



S.E.A

Volume - I
**COLLEGE OF ENGINEERING
AND TECHNOLOGY**



International Conference Proceedings

On

**EMERGING TRENDS IN GREEN
ENGINEERING, BUSINESS
EXCELLENCE & APPLIED
SCIENCES – 2026**

(ICETGEBEAS - 2026)

**“EMERGING TRENDS IN SUSTAINABLE
ENGINEERING”**

April 09th - 10th, 2026



Years of Excellence



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Ektha Nagar, Basavanpura, Virgonagar Post, K R Puram, Bangalore - 560049

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Proceedings of the International Conference
On
EMERGING TRENDS IN GREEN
ENGINEERING, BUSINESS EXCELLENCE &
APPLIED SCIENCES – 2026
(ICETGEBEAS)
(HYBRID MODE)

“EMERGING TRENDS IN ENGINEERING”

Chief Editor

Dr. Krishna Kumar P R

Professor, HoD, Department of Computer Science, SEACET

Organized by



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Former Minister, Govt. of Karnataka

Founder Chairman, S.E.A Education Trust

Wishes from the Chairman



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Chairman, S.E.A Education Trust,
Bengaluru, Karnataka, India

Dear Participants,

On behalf of the Management of S.E.A Group of Institutions, we are delighted to welcome you to the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*, held from March 9th to 10th at S.E.A College of Engineering & Technology, Bengaluru, India. It is an honour to host such a distinguished gathering of researchers, scholars, and industry leaders dedicated to driving innovation and fostering development in various fields.

This conference serves as a platform for exchanging groundbreaking ideas, sharing research findings, and discussing emerging trends that can shape the future of technology and development. We believe that collaboration and knowledge-sharing are key to overcoming global challenges, and *ICETGEBEAS-2026* is a testament to our commitment to these ideals.

We encourage all participants to engage actively in discussions, network with fellow attendees, and explore new opportunities for collaboration. Your insights and contributions are invaluable to the success of this conference.

We are excited to see the innovative ideas that will emerge from our time together and look forward to the fruitful discussions that will take place. Thank you for being a part of this important event.

Wishing You a Productive and Inspiring Conference! With Best Regards,

Mrs. MANJULA KRISHNAPPA

Greetings from the Vice Chancellor



VICE-CHANCELLOR
Visvesvaraya Technological University (VTU)
Belagavi, Karnataka, India

It gives me immense pleasure to extend my warm greetings to all participants of the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*.

In today's knowledge-driven era, interdisciplinary research and innovation are vital in addressing complex global challenges and advancing sustainable development. Platforms such as this conference play a crucial role in fostering intellectual exchange, encouraging collaboration, and promoting high-quality research across diverse domains.

I am confident that the contributions presented in these proceedings will enrich the academic community and inspire future research endeavors. Such initiatives significantly strengthen the synergy between academia, industry, and society.

I congratulate the organizing committee and all contributors for their commendable efforts in making this conference a success and wish the participants a fruitful and enriching experience.

With best wishes,

Dr. VIDYASHANKAR. S

Greetings from the Secretary



SECRETARY
S.E.A Education Trust
Bengaluru, Karnataka, India

It gives me immense pleasure to extend my warm greetings to all the participants, delegates, researchers, academicians, and industry professionals attending the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*.

In today's rapidly evolving world, interdisciplinary research and innovation play a vital role in addressing global challenges. This conference serves as a dynamic platform to bring together intellectual minds from diverse domains to share knowledge, exchange ideas, and foster collaborations in the areas of green engineering, sustainable business practices, and applied sciences.

I am confident that the deliberations and scholarly contributions presented in these proceedings will significantly contribute to academic excellence, technological advancement, and societal development. Such initiatives not only strengthen the research ecosystem but also bridge the gap between academia and industry.

I commend the organizing committee, researchers, and contributors for their dedicated efforts in making this conference a grand success. I wish all the participants a fruitful and enriching experience.

With best wishes,

Sri D. T. SRINIVASA
MLC South East Teachers Constituency - Govt. of Karnataka

Greetings from the CEO



C.E.O
S.E.A Education Trust
Bengaluru, Karnataka, India

It gives me great pleasure to extend my warm greetings to all distinguished participants, academicians, researchers, and industry professionals attending the International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026).

In the context of an ever-evolving global landscape, the pursuit of sustainable development, innovation, and interdisciplinary research has become imperative. This conference reflects a shared vision of fostering intellectual exchange and advancing knowledge that addresses contemporary challenges while contributing to long-term societal progress.

S.E.A. Group of Institutions remains committed to promoting academic excellence, research innovation, and holistic development. The contributions presented in this volume of proceedings are a testament to the dedication and scholarly rigor of the research community, and they hold significant potential to drive meaningful impact across diverse domains.

I am confident that this conference will serve as a catalyst for insightful discussions, collaborative research, and future advancements. I extend my sincere appreciation to the organizing committee and contributors for their commendable efforts in making this event a success.

With best wishes,

Smt. K. POORNIMA SRINIVASA
Ex. MLA–Hiriyur Constituency, Karnataka

Greetings from the Joint Secretary & Treasurer



JOINT SECRETARY & TREASURER

S.E.A Education Trust
Bengaluru, Karnataka, India

It is a privilege to extend my warm greetings to all participants of the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*.

As we move towards a future defined by sustainability, innovation, and knowledge-driven growth, the role of interdisciplinary research becomes increasingly significant. This conference reflects our collective vision of nurturing transformative ideas that not only advance academic excellence but also contribute meaningfully to global progress and environmental stewardship.

At S.E.A. Education Trust, we are committed to fostering an ecosystem that encourages creativity, critical thinking, and impactful research. The contributions presented in these proceedings symbolize a step forward in shaping solutions for a sustainable and technologically empowered world.

I am confident that this platform will inspire new perspectives, strengthen collaborations, and ignite a shared commitment towards building a better future. I congratulate the organizers and contributors for their dedication and vision in making this conference a success.

With best wishes,

Smt. ANUPAMA K

Greetings from Vice President



VICE PRESIDENT
S.E.A. Education Trust
Bengaluru, Karnataka, India

Dear Participants of ICETGEBEAS-2026,

On behalf of the SEA Group, I extend my heartfelt best wishes to all the prominent speakers, delegates, and participants of the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*, hosted at S.E.A College of Engineering & Technology, Bengaluru, India held on 9th to 10th March 2025. It is a privilege to organize this significant event, bringing together brilliant minds dedicated to advancing research and innovation.

This year's conference showcases the collective efforts of our organizing committee, whose dedication has ensured a seamless and enriching experience for all participants. Their hard work has laid the foundation for insightful discussions and collaborative opportunities that are vital in today's rapidly evolving landscape.

As we gather to share knowledge and explore innovative solutions, I encourage everyone to engage fully in the sessions, connect with fellow participants, and embrace the diverse perspectives that this conference offers. Your contributions are essential in fostering a vibrant dialogue that can lead to impactful advancements in our fields.

I am confident that the ideas and partnerships formed during ICETGEBEAS-2026 will resonate beyond this event, inspiring future research, and development initiatives. Together, we can make significant strides in addressing global challenges through innovation.

Thank you for being part of this remarkable gathering.

Wishing you all a successful and inspiring conference!
Kind Regards,

MS. VINISHA S YADAV

Message from the Trustee Members



TRUSTEE MEMBER
S.E.A. Education Trust

It is my pleasure to extend my warm greetings to all participants of the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*.

This conference provides an excellent platform for fostering interdisciplinary research, innovation, and knowledge exchange to address contemporary global challenges. I am confident that the contributions presented in these proceedings will significantly contribute to academic excellence and sustainable development.

I appreciate the efforts of the organizing committee and contributors in making this event a success, and I wish all participants a productive and enriching experience.

With best wishes,

Dr. BRIJESH S. YADAV



TRUSTEE MEMBER
S.E.A. Education Trust

It is with great pleasure I extend my best wishes to all the participants of the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)*.

I am confident that this conference will foster meaningful knowledge exchange and contribute to academic excellence and sustainable development. I commend the organizing committee and contributors for their efforts in making this event a success.

With best wishes,

Mr. ROHAN R. YADAV

Message from Honorary Director



HONORARY DIRECTOR

S.E.A Education Trust
Bengaluru, India

Warm Greetings!

It is my great pleasure to extend a cordial welcome to all distinguished speakers, researchers, academicians, industry professionals, and students to the **International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)**.

As the Honorary Director, I am delighted to see this esteemed gathering of intellectuals and innovators committed to advancing research and fostering sustainable technological development. In today's rapidly evolving world, the integration of green engineering practices, business excellence strategies, and applied scientific research is essential to address global environmental, industrial, and societal challenges.

ICETGEBEAS-2026 serves as a vibrant platform for knowledge exchange, interdisciplinary collaboration, and the presentation of pioneering ideas that can shape a sustainable and technologically empowered future. I am confident that the insightful keynote sessions, technical presentations, and scholarly discussions will inspire innovation and strengthen academic–industry partnerships.

I congratulate the organizing committee for their dedicated efforts in hosting this international event and extend my sincere appreciation to all contributors and participants for their valuable involvement.

I wish the conference great success and hope it proves to be intellectually rewarding and impactful for all.

With warm regards,

Dr. K. VIYYANNA RAO

Message from Principal



PRINCIPAL
SEA College of Engineering and Technology
Bengaluru, India

Warm Greetings from **SEA College of Engineering and Technology!**

It gives me immense pleasure to welcome you to the **International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)**.

This prestigious conference serves as a dynamic platform for academicians, researchers, industry experts, and students from across the globe to share innovative ideas, cutting-edge research findings, and transformative technologies that address contemporary challenges in sustainable engineering, business innovation, and applied sciences.

In an era where sustainability and technological advancement must go hand in hand, ICETGEBEAS-2026 aims to foster interdisciplinary collaboration and promote research that contributes to environmental responsibility, industrial excellence, and societal development. I am confident that the deliberations, keynote addresses, and technical sessions will stimulate meaningful discussions and inspire groundbreaking solutions.

I extend my sincere appreciation to the organizing committee, keynote speakers, authors, reviewers, sponsors, and participants for their valuable contributions and enthusiastic involvement. Your participation reflects a shared commitment to academic excellence and sustainable progress.

I wish the conference grand success and hope that ICETGEBEAS-2026 will be an enriching and memorable experience for all.

With warm regards and best wishes,

Dr. B. VENKATANARAYANA

Message from Organizing Secretary, ICETGEBEAS-2026

Warm Greetings!

It gives me immense pleasure to welcome you to the **International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026)**.

As the Organizing Secretary of ICETGEBEAS-2026, I am honored to witness the coming together of distinguished academicians, researchers, industry experts, and young innovators on a common platform dedicated to sustainable technologies, business transformation, and applied scientific advancements.

This conference aims to foster interdisciplinary collaboration and promote innovative research that addresses global challenges in green engineering, digital transformation, environmental sustainability, and industrial excellence. We believe that the exchange of knowledge, technical deliberations, and keynote interactions during this event will spark meaningful discussions and inspire impactful solutions for a sustainable future.

I sincerely thank all keynote speakers, authors, reviewers, advisory members, sponsors, and participants for their valuable contributions and enthusiastic support. Your involvement plays a vital role in making this conference a grand success.

I wish all participants a productive, insightful, and enriching experience at ICETGEBEAS-2026.

With best regards,

Dr. KRISHNA KUMAR P R

Organizing Secretary, ICETGEBEAS-2026

HoD, Department of CSE

S.E.A College of Engineering and Technology

Bengaluru, India

Message from the Head of the Department, MBA

Dear Participants,

It is a great pleasure to welcome you to the International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences – 2026 (ICETGEBEAS-2026).

In an era marked by rapid technological advancements and pressing environmental challenges, this conference serves as a vital platform for academicians, researchers, industry experts, and students to come together and exchange innovative ideas. The integration of green engineering principles with business excellence and applied sciences is essential for fostering sustainable development and responsible growth.

I am confident that ICETGEBEAS-2026 will inspire meaningful discussions, encourage interdisciplinary collaboration, and provide valuable insights into emerging trends shaping our future. Your active participation and contributions will undoubtedly enrich the deliberations and outcomes of this conference.

On behalf of the MBA Department, I extend my heartfelt gratitude to all the organizers, speakers, and participants for their commitment and enthusiasm. I wish you all a productive and intellectually rewarding experience.

Warm regards,

Dr. S.B. ANIL KUMAR

Head of the Department

MBA, S.E.A. College of Engineering & Technology

Message from Dean Research & Development

Dear Esteemed Guests, Distinguished Scholars, and Participants,

With immense pleasure and gratitude, I welcome you all to the *International Conference on Emerging Trends in Green Engineering, Business Excellence & Applied Sciences–2026 (ICETGEBEAS-2026)*.

Aligned with the theme, “*Shaping the Future through Interdisciplinary Research and Sustainable Development*,” this conference highlights the importance of collaboration across disciplines. In today’s interconnected world, addressing challenges such as climate change, public health, and technological advancement requires integrated approaches. Through such collective efforts, we can drive sustainable and impactful progress.

I would like to express my heartfelt appreciation to all the organizers, of the ICETGEBEAS-2026, for their tireless efforts in bringing this conference to life. Special thanks go to our keynote speakers, panellists, and presenters, whose expertise and insights will undoubtedly enrich our discussions and pave the way for ground-breaking ideas and solutions.

I encourage students to actively engage in such forums, as they offer excellent opportunities to learn, explore new ideas, and develop a research-oriented mindset for future growth.

Once again, I extend a warm welcome to all participants, and I look forward to the productive and inspiring exchanges that will unfold over the course of this event. Let us seize this opportunity to collaborate, innovate, and lead the way toward a brighter and more sustainable future.

Dr. USHA DESAI

Professor CSE (IoT-CSBT)

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LLM-ASSISTED HEALTH-CONDITION-SPECIFIC FOOD LABEL ANALYSIS USING OCR AND MACHINE LEARNING

*Bhavani Sankar Panda^{1, *}, Geetanjali Panda², Asutosh Gouda³, Vinaya Kumar³,
Pritimayee Rout³, Sonali Sethi³, Akhila Kumari Nayak³*

1&2 Assistant Professor

*3UG Scholar, Department of Computer Science and Engineering, GIET University,
Gunupur, Odisha, India*

**Email: bhavanipanda@giet.edu*

Abstract—Nutrition labels have been indispensable in offering nutritional information, although the process of interpreting the information remains daunting, especially for people suffering from chronic conditions such as diabetes and cardiovascular diseases. In this study, a system for interpreting nutrition labels assisted by an LLM incorporates character recognition, machine learning programs tailored for chronic conditions, and explainable artificial intelligence to interpret food safety. The nutritional data and ingredients present within the nutrition label of every food item are processed via character recognition and converted to structured data. The data is further interpreted by multiple machine learning programs based on nutritional threshold values defined by the guidelines from the Food Safety and Standards Authority of India. To increase interpretability, a locally installed Large Language Model produces post-hoc, human-readable explanations for model outputs and nutritional composition, which do not affect decision-making.

Index Terms—Keywords—Food Label Analysis, Machine Learning, OCR, Large Language Models, Dietary Safety

I. INTRODUCTION

Diet-associate chronic disorders, such as diabetes mellitus and cardiovascular disorders, account for a large and increasing public health problem. According to the World Health Organization (WHO), cardiovascular disorders are the prominent cause of mortality across the world, contributing to 32% of all deaths; on the other hand, non-communicable disorders account for 74% of total deaths [1]. Errant dietary practices—those in excess of refined carbohydrates, saturated lipids, added sugars, and sodium—are the principal modifiable risk factors for both disorders and cardiovascular diseases such as hypertension, coronary artery disease, and stroke [2]. These disorders frequently co-exist; in this case, it has been observed that disorders like diabetes can pose an important risk for cardiovascular disorders due to hyperglycemia and inflammation among other disorders. Diabetes cases are rising at an alarming rate, with a current impact of over 537 million people worldwide, and this data is anticipated to rise to 643 million by 2030 [3]. In India, a staggering 101 million people have been identified with diabetes, and an estimated 136 million people are prediabetics [4].

Prediabetes, also referred to as impaired fasting glucose and impaired glucose intolerance, is an intermediate state of diabetes that significantly increases an individual's susceptibility to both type 2 diabetes and cardiovascular disease if it isn't managed effectively. Research indicates that modifying people's diets at an early pre diabetes stage significantly lowers their susceptibility to developing chronic metabolic and cardiovascular disorders [5]. The diet of processed and ultra-processed food products is recognized as a factor that contributes to higher rates of obesity, type 2 diabetes, high blood pressure, and cardiovascular disease [6]. These types of food products were shown to have higher amounts of salt, unhealthy fats, and easily digested carbohydrates, all of which have negative effects on blood sugar and cardiovascular functions. Even so, nutritional labels required on food products by food-control agencies have been difficult to interpret for everyone, especially when one does it manually and does not have expert knowledge about nutritional sciences and medicine [7].

There have been recent breakthroughs in optical character recognition (OCR) technology and machine learning algorithms, making it possible to automate the extraction and analysis of nutritional and ingredient data from food packaging. OCR technology makes it possible to digitalize text data from food packaging, and it also becomes possible to categorize foods using machine learning algorithms based on nutritional risk factors

pertaining to chronic ailments [8]. Nonetheless, most of these models have been general in analyzing nutritional information and unspecialized for diabetes and cardiovascular diseases. Also, most of them lack transparency to indicate their classification reasoning [9].

To mitigate this, this study will incorporate a food analysis system that incorporates OCR-based text recognition, a diabetes-oriented machine learning classification system, and a large language model (LLM) for post-hoc explanation generation that can provide clear and relevant explanations about the consumption of the food item while not acting as a medical recommendation system itself or interfering with its prediction system. It aims to help people with diabetes, prediabetes, or those with increased cardiovascular risks make educated consumption decisions about packaged foods based on this enhanced system that improves interpretability and usage simplicity.

II. LITERATURE SURVEY

The growing use of packaged food items has further escalated the demand for intelligent systems that can support consumers in comprehending the ingredients as well as nutritional values of food items. Keeping these challenges in mind, many authors have worked on utilizing artificial intelligence technology for automatically interpreting food labels. Alla designed SnapIT, a health-focused web application powered by artificial intelligence that has the ability to

interpret food packaging by uploading photos of the ingredients' list on the web application [10]. The system makes use of image interpretation as well as Optical Character Recognition to understand the extracted text, further analyzed by Natural Language Processing using the Google Gemini-1.5 model. The SnapIT system can identify dangerous ingredients, calculate the nutritional values, give a general health point, and provide healthier alternatives for those dietary items that can be checked by adhering to general health guidelines. The system, although very effective in simplifying complex ingredients as well as nutritional values, has a generic evaluation process that does not consider particular health issues of a human being.

Addressing the problem of food safety from an allergy- focused point of view, Suwetha et al. proposed an AI-powered ingredient detector specifically aimed at helping people who suffer from food allergies [11]. The system incorporates computer vision techniques along with NLP to analyze ingredient lists obtained via barcode scanning, image uploads, or manual input. Then, by matching extracted ingredients against a comprehensive allergen database, the application issues real-time alerts to the user. This contribution is very much targeted and practical towards the problem of allergen detection; yet, its scope is limited to allergy-related concerns and does not extend to broader nutritional analysis or disease-specific dietary suitability.

Several studies have explored machine

learning approaches for disease prediction. For example, a model for predicting chronic renal failure using CatBoost and XGBoost classifiers demonstrated improved prediction accuracy by leveraging ensemble learning techniques for medical diagnosis [24,25]. A system, named ToxiScan, designed for pinpointing dangerous ingredients for packaged meals, has been developed by Kapoor & Chavan [12]. The system harnesses the capabilities of barcode scan technology, real-time Optical Character Recognition, as well as pictorial input for identifying ingredients, as well as their assessment based on a filtered list of dangerous compounds stored within a database. One of the strongest aspects of that particular study would be its addition of risk measurement based on ingredients, thereby improving interpretability for end-users. ToxiScan, although very useful for pointing toward dangerous ingredients, has been designed keeping general health issues only in mind.

To move towards intelligent interpretation, another approach was introduced by Janokar et al. where they developed a food ingredient analysis system by integrating OCR with the use of Large Language Model technology that can work as an electronic nutrition consultant assistant [13]. This system has the ability to process food ingredients from food packets and produce simple explanations, emphasize allergic compounds, and carry out basic risk analysis in relation to food restrictions. The use of LLM technology allows for the understanding of sophisticated food

vocabulary, thus assisting in enhanced consumer knowledge. The system, however, is currently in its minimum viable form and lacks condition-specific knowledge for diabetes and/or hypertension.

Similarly, Singidi et al. introduced Healinfo Facts, a smart- phone app for providing health insights from scanned labels

of packaged food items [7]. The system leverages state-of-the- art OCR and AI services, including Gemini APIs, to scrape out ingredients and nutritional facts, providing dietary recommendations personalized to the users' needs. Unlike earlier systems, Healinfo Facts tries to provide a more integrated, user-friendly approach by complementing ingredient analysis with dietary planning. Yet, personalization here is also more recommendation-oriented, with no clear way to systematically assess the safety of each food item in light of particular medical conditions.

With a more organized approach, Shah et al. suggested the use of NutriScan, a system that uses automatic extraction of nutrition tables as well as ingredients from consumer packaging [14]. This method uses a refined EfficientDet algorithm to identify nutrition tables along with PaddleOCR to extract texts, followed by rule-based analysis to tap major nutritional factors. What makes this paper notably relevant is that it uses a system of user preference to enable individuals to set their own parameters regarding allergens as well as macronutrient nutrient intake,

creating unique nutri-scores. However, although it has very proficient extraction as well as estimation performance along with comprehensive evaluation according to personal preference, it uses predefined rules along with insufficient semantic analysis to address complex scenarios regarding health.

The analysis of food labels has been explored by researchers such as Pandey et al. from the regulatory and transparency standpoint [15]. The use of OCR-based approaches allows the analysis of the list of ingredients and nutritional details on various brands with the aim of pointing out the inconsistencies and deceptive labeling with regard to allergens [15]. The study has critical health implication aspects but lacks the development of an adaptive health risk evaluation platform personalized for consumers.

Likewise, Raghav and colleagues came up with CleverEats, a mobile application that provides food ingredient information, nutritional content, and chemical composition of packaged food items in one place [16]. The app gives users the option to scan food item names, which in turn, gives an integrated interface of food-related information that the users can access. However, despite this application providing more access and being more aware, it does not have any smart or personalized

III. METHODOLOGY

A. System Architecture Overview

The proposed system follows a modular end-to-end pipeline that transforms food label information into health-condition-specific safety assessments. User-provided food label inputs, obtained either as images or structured text, are first processed to extract ingredient lists and nutritional values. These extracted attributes are converted into structured numerical and categorical features suitable for machine learning inference. The structured feature set is then passed to two independent machine learning models operating in parallel: one designed for diabetes-related safety assessment and another for cardiovascular-related safety assessment. Each model performs

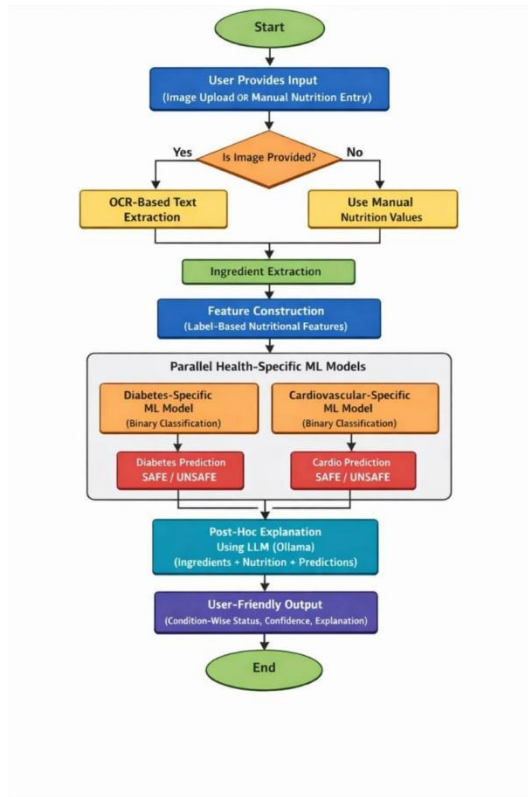
Fig. 1: Flowchart of the proposed OCR-based, condition-specific food label analysis and explainability framework

a binary classification to determine whether the food product is safe or unsafe for the corresponding health condition.

The classification outputs generated by the machine learning models, along with the extracted nutritional parameters and ingredient information, are subsequently forwarded to a locally deployed large language model (LLM) using the Ollama framework. The LLM generates human-readable explanations that justify the model predictions based on the identified ingredients and nutritional characteristics. The LLM functions solely as an explanation module and does not influence or alter the machine learning model outputs.

B. Dataset Description and preprocessing

The machine learning models were trained based on the Food Nutrition Dataset provided by Kaggle [17], which contains structured nutritional attributes (caloric intake, carbohydrates, Sugars, Fat, Sodium, Protein) that are related to risk assessments for Diabetes and Cardiovascular disease. Since the Food Nutrition Dataset does not have safety labels provided in the Dataset, a custom labelling pipeline was established by creating a threshold rule to define what constitutes food safety using food labelling standards established by the Food Safety and



Standards Authority of India (FSSAI) [18]. Population level Dietary Recommendations published by WHO and

ICMR served as contextual references to establish rationale for feature selection and risk prioritisation rather than direct threshold classifications [19,20]. Data Preprocessing includes the removal of incomplete records, standardising units of measurement, Filtering outliers, and Normalising features. Features were selected based on the specific conditions of interest (i.e. Sugar and Carbohydrate features for Diabetes disease, Sodium and Fat features for Cardiovascular disease.) Stratified sampling was used to maintain the class balance during model Training and Evaluation.

C. Input Acquisition and Text Extraction

The system allows users to submit food information in two different forms: via an image of the food label or by typing the nutritional information into the appropriate fields in the web application. If a user submits a picture, it will be passed through an OCR pipeline in order to read the food label's contents. If a user submits their own handwritten nutritional data, that data will not need to go through OCR; it will be directly useable by the system for processing. Images submitted by users are pre-processed to

ensure that all text shows up as clearly as possible when scanned, which includes resizing and converting to black and white, removing excessive amounts of noise, and increasing contrast to make it easier to read. After preprocessing, the user's image(s) are passed through an OCR process, which results in the ingredient list extracted from the image. Once OCR processing is completed, all noise (including incorrect spellings and misreadings), extraneous information, and other irrelevant tokens have been removed through a secondary set of processing steps. The extracted ingredient list is intended solely for generating an explanation for the user, whereas the ML model uses the nutritional data entered by the user.



Fig. 2: Sample food label image used for OCR-based ingredient extraction and nutritional information analysis

D. Feature Extraction and Nutritional Parameter Mapping

The processed textual information

generated by OCR techniques for extraction or manually entered by the user undergoes transformation for representation in a structural form for analytical purposes. The primary nutritional information such as calories, carbohydrates, total sugars, fats, sodium, and proteins in the product details undergo rule-based pattern detection for generation of numerical features. Appropriate values relevant to guidelines for labeling standardized on a per- 100g basis. At the same time, the ingredient-level indicators such as the presence of added sugars, preservatives, salt substitutes, or flavor enhancers are detected via generalized lexical patterns. The process continues with the combination of nutritional properties and ingredient indicators to form the feature representation.

E. Diabetes and Cardiovascular Specific Machine Learning Model

A diabetes-specific machine learning model is developed to assess food safety based on nutritional factors influencing glycemic response. The input feature set includes total carbohydrates, total sugars, caloric content, protein, dietary fiber, fat, and sodium. A dedicated model is used to preserve clinical relevance and avoid generalized nutritional scoring.

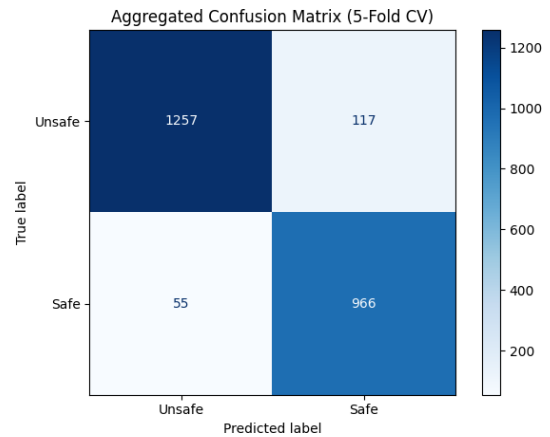


Fig. 3: Confusion matrix for diabetes-specific food safety classification using logistic regression

The model performs binary classification (Safe/Unsafe) using supervised learning with labels derived from dietary thresholds defined by FSSAI guidelines [?]. Stratified data splitting and normalization applied exclusively to the training set are employed to prevent data leakage. Logistic regression is selected due to its effectiveness and interpretability when applied to structured nutritional data. As shown in Fig. 3, the diabetes-specific model demonstrates strong discriminative performance, achieving an accuracy of 92.69%, precision of 0.88, recall of 0.97, F1-score of 0.92, and an ROC-AUC of 0.98. These results indicate reliable identification of diabetes-related dietary risk. A separate machine learning model is employed for cardiovascular dietary safety assessment, focusing on sodium, total fat, saturated fat, and energy-density content. This independent modeling strategy prevents inter-condition feature interference and enables condition-aware evaluation. Binary classification is performed using labels derived from FSSAI dietary

guidelines [?]. Logistic regression is implemented with stratified sampling, and normalization is applied only to the training data to ensure unbiased evaluation. The cardiovascular model achieves an accuracy of 94.36%, precision of 0.93, recall of 0.94, F1-score of 0.93, and an ROC-AUC of 0.98. Fig. 4 illustrates consistent and reliable classification of cardiovascular dietary risk.

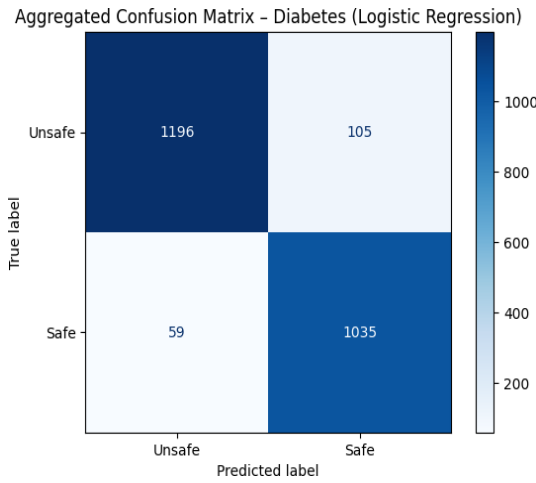


Fig. 4: Aggregated confusion matrix for cardiovascular food safety classification using logistic regression with five-fold cross-validation

F. Classification and Decision Logic

The outputs of the two developed machine learning models will be treated independently, meaning that neither of the models will be aggregated or combined, thus the final classification of the food items could be different depending upon the health conditions. The final classifications will be provided directly to the explanation module without any further

changes made to the classifications.

G. LLM-Based Explainability Using Ollama

The large language model (LLM) works solely for post-hoc explanation generation and does not participate in prediction or influencing model outputs. The LLM is deployed locally with the Ollama framework to ensure data privacy, reduced latency, and offline operability.

Prompt engineering is done in a way that fully constrains the LLM's behavior: each prompt contains the extracted ingredient list, neatly structured nutrition facts, the model

prediction of the corresponding machine learning model, and the target health condition. From this, the LLM synthesizes human-readable, condition-specific explanations that appeal to nutritional limits and guideline-aligned reasoning defined by the FSSAI standards [12]. This construction enhances interpretability while maintaining the integrity and determinism of the machine learning models.

H. Output Generation and User Interpretation

The output of this system includes both safety classifications related to patients with either diabetes or those having cardiovascular conditions, complete with justifications produced by the LLM. These are presented on a clear platform.

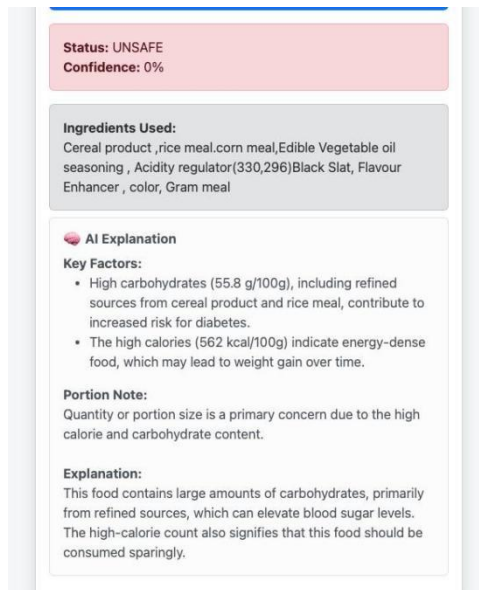


Fig. 5: Sample diabetes-specific food safety assessment and explanation generated by the proposed system

IV. CONCLUSION

This paper proposed to employ a modular system that consists of OCR, machine learning algorithms, and locally based LLMs for analyzing the health factor in diabetes and heart problems through explainable systems. The use of condition-based machine learning algorithms means targeted classification, while the health factors based on FSSAI confirm the observance of the government-regulated parameters. The LLM is dedicated to the explanation part of the process, thereby increasing the level of understanding without affecting the classification result.

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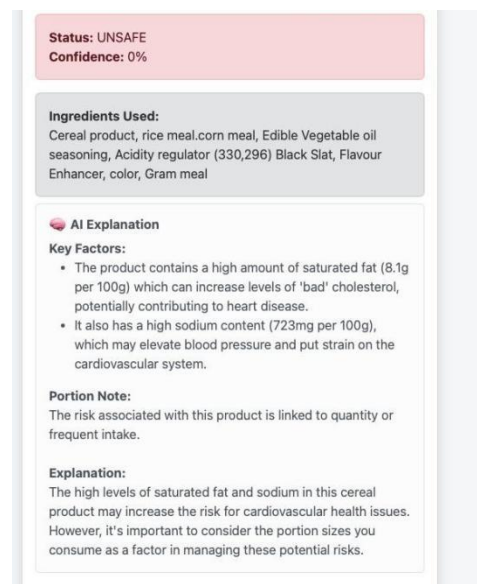


Fig. 6: Sample cardiovascular-specific food safety assessment and explanation generated by the proposed system

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RESPONDR: A SMART AMBULANCE BOOKING SYSTEM

Darshan A B

Dept. of Artificial Intelligence and Machine Learning BMS Institute of Technology
and Management Bangalore, India, darshangowda.en@gmail.com

Gaurav Nayak K

Dept. of Artificial Intelligence and Machine Learning BMS Institute of Technology
and Management Bangalore, India, gauravnayak.career@gmail.com

Dr. Hemamalini B H

Dept. of Artificial Intelligence and Machine Learning BMS Institute of Technology
and Management Bangalore, India, bhhemaraj@bmsit.in

Abstract—In India, there are a lot of ambulance service providers with distinct emergency contact numbers but they have slower response time which can cost lives if there is no timely arrival of emergency services. Adding to it, there is no effective communication between the hospitals, its staff, ambulances and the staff in emergency department. Problems get even more worse because of off-target consignments, unreliable private service providers, which could have been very crucial and life-saving time which results to delay when even seconds matter. This is exactly where Responder come's into picture. It is at its early stages of development, a system is built which makes it easier and simpler to book ambulances and dispatch them via internet. The user of the application has to provide a photo proof of the crisis (i.e, Road accident), GPS coordinates by clicking the SOS button and the emergency report consisting of all these details will be created and sent to the system. The system will evaluate the same, based on the details in report. The system helps to allocate nearest available

ambulance drivers by giving them real-time report alerts with live location updates using GPS. When the report is accepted by certain ambulance driver, the user gets the ambulance driver details and real time info about the ambulance. This model focuses on ease of access, room to grow, plus smooth daily use - no costly systems needed, this system works similar like a ride booking system, with clear step- by-step processes, better checks for drivers, along with precise GPS-powered dispatch, Responder wants fewer wait times, clearer information flow, while helping assign aid smartly. The research paper demonstrates the details of the built, movement of tasks, expected results- making Responder a flexible solution to boost the emergency rides in poorer areas.

Keywords-Emergency medical transportation, ambulance booking system, GPS-based incident reporting, driver verification, centralized dispatch platform, digital emergency coordination, public health safety.

I. INTRODUCTION

Given the importance of Emergency Medical Transportation for the patients during medical emergencies, the family of the patient expect that the service is well integrated and readily available. Unfortunately, this is not the case, even in many growing urban/semi-urban areas. Access to ambulances is often slow and unreliable. Emergency Medical Transportation users often cannot even locate ambulances to assist them.

Even when they do, there are no well-established system to manage communication between the call center, the driver and the receiving hospital, which can result in critical delays, preventable emergencies and in some instances, death.

Respondr will be a digital-first emergency coordination platform, modernizing the way ambulance bookings and dis-patches take place. Instead of manually calling or looking for scattered emergency numbers, the system introduces a unified, web-and-mobile-accessible ecosystem that could connect users with the nearest available ambulance in real time. The goal is to make the processing of emergency requests more efficient while making it possible for customers to know about the availability of ambulances in real time and allow organizations to effectively manage and coordinate medical transport resources.

One of the key concepts on which Respondr is based on is the accessibility of these kinds of solutions,

their horizontal scalability, and operational simplicity by avoiding dependencies on high cost hardware or infrastructure. By using structured design workflow, centralized dashboard for handling responses and driver side interface of Respondr, it aims to majorly reduce the delays and other issues in emergency medical transport.

II. BACKGROUND AND MOTIVATION

In lots of developing areas, people still struggle with emergency services that endanger lives. Time taken in getting help becomes longer. The mode of communication is not clear or direct. There are no fleets of ambulances on which you can entirely rely on for their services. People will call friends and search for private operators or even just dial random emergency numbers. It's a mess, and those extra minutes can be the difference between life and death. As if that were not bad enough, ambulance drivers are assigned calls in a relatively disorganized manner. There's no

proper protocol that allocates the duties or shows the availability of ambulance drivers at the moment, handling the emergency situation. Everything just falls apart right when its required to function quickly and elegantly.

It becomes a challenge for hospitals and other organizations for proper monitoring of the activities of their ambulances. No updates in real-time, no structured dispatch processes or workflows, and thus coordination is

difficult to achieve particularly when multiple emergencies are reported simultaneously. In this regard, ResponDR was invented to provide a collective and open-source platform for dealing with such emergencies.

The need to improve the system of ambulance dispatches with the help of easy, widely applicable and technology-driven solutions is the main force that encourages ResponDR's creation. ResponDR has lower emergency response times, more operational efficiency and users get on time medical help. ResponDR provides real time location, visibility integration, well-structured request handling integration, and tools centralization. This project is steered by its objective of enhancing accessibility, integrity, jurisdiction and transparency in provision of emergency medical services within all communities.

III. PROBLEM STATEMENT

In India, during accidents on the road or in the case of someone needing urgent medical help, it is often too late for help to come. The system simply does not function fast enough. Most bystanders don't reach for their phones to get help; instead they start recording videos or taking photographs. The few minutes spent filming are the most critical as this is the "golden hour" where immediate action can save lives. Even if someone finally calls 108 or 112, people give unclear directions or say some random things that aren't helpful, and without a specific address emergency teams can end up wasting much time looking for it. It results into

longer waiting time which causes people in emergency to lose life.

Some of the other challenges are congestion of traffic, road blockages that may occur unexpectedly and poor lane discipline. These factors interfere with ambulances in urban areas. Delay amplifies due to non-availability of verified ambulance services and the unavailability of real-time tracking in rural and semi-urban area. Private ambulances work often independently under minimum supervision, which makes their response times erratic.

Cases like these when added up make it difficult for the ambulances to get to the people fast. Lives are being lost which is a serious concern. If the deaths across the nation have to be prevented, it is necessary to improve communication, coordination and decrease delays in service delivery system.

IV. OBJECTIVES OF THE STUDY

The objectives of this study are as follows:

- To allow fast and easy ambulance booking through a simple digital platform.
- To reduce ambulance response times, by improving location accuracy and support efficient routing and dispatch.
- To let users, make emergency requests, share their real-time location data. This helps registered drivers get and respond to bookings quickly.

- To create a clear and dependable way to communicate among users, drivers, and administrative units for effective emergency management.

V. LITERATURE REVIEW

Emergency medicine setups have got more attention lately because they really matter when crashes or health emergencies happen. Previous research shows that by using GPS and dispatch software, it speeds up the arrival time of ambulance [3]. Most current approaches have applications that book ambulances and show their location, so that people can call for help. GPS devices are capable of displaying their location to show this information [1]. The ideas proposed here were useful in reducing phone calls and allowed mobile users to use their mobiles more conveniently. Still, a few can handle sending out ambulances, but better teamwork is still not accomplished.

Studies have looked into smart ways to guide ambulances through traffic, using systems that adjust traffic lights to ease jams [2]. Even though these techniques could help in speeding up the travel time and reducing delay by a significant amount, it usually requires huge amounts of investments and money-flow along with technology and coordination with public authorities – it makes the process even more harder and complicated to apply in case of poor public authorities and rural areas.

Some researches shows that use of IoT devices here can drastically change how ambulances can monitor patient's

health. This dives deep into the concept of providing care and emergency services during transit, the early call-to-response stage [6]. Even if the setup is high-tech, it can pull the focus from the main problem which is finding and arranging ambulances quickly when help is urgently needed.

ResponDr addresses emergency queries immediately, and acts as a single hub for handling them. It acts as a one-stop solution. Many of the existing setups concentrate only on hospitals or separate driving apps, which lacks the shared oversight for those who are running emergency responses.

ResponDr stands out by building a small and flexible system meant for areas where emergency networks are broken or

not yet established properly. Verification helps in picking and onboarding reliable drivers into the network who can respond quickly at the time of emergency. Reporting during emergencies works like texting i.e, its simple to use and hassle free. Requests are sorted clearly based on the severity and priority that it requires, hence the help is provided where it is required immediately.

VI. PROPOSED SYSTEM

The proposed ResponDr system is built as a multi-module emergency coordination framework, consisting of three primary components: The User Application, The Driver Application, and The Organization/Admin Web

Dashboard.

A. User Module

The user mobile application (Android/iOS) enables individuals to report an emergency by uploading a required photo of the incident, and filling out basic info. Upon raising a request, the system assigns nearby ambulances, and users can track the operator in real time while receiving real time updates. Using the design, we have aimed to reduce user effort during critical moments. To be precise, in depth emergency reporting.

B. Driver Module

After completing the online verification of the driver's details, the drivers will be given access to the Responder Driver App. Here drivers can see the incoming requests, the navigation to the incident location and status (online/offline/arrived). It makes sure that only authorized and authenticated drivers are in the emergency network improving the reliability and operational safety and helping us to maintain standards.

C. Admin/Organization Module

A web dashboard is provided to hospitals, ambulance operators and system administrators where they can onboard drivers and verify the documentations, monitor the driver's location and manage active emergencies and analyze the overall incident performance.

The proposed system has real-time communication, transparency and

user-friendly interaction between users, drivers and organizations.

VII. METHODOLOGY

The Responder System Methodology shows the orderly process of managing the onboarding of drivers, the systematic process of coordinating users, reporting emergencies and ambulance dispatching activities through a single system. The system planned to operate as a central coordinating hub to make sure that only authenticated and authorized users of the system can participate in emergency activities.

The conceptual methodology includes:

- **Driver Onboarding and Verification Process:** Ambulance drivers are onboarded to the Responder by their own service groups using the Responder website. While one team handles sign-ups, another takes care of updates each group enters key info like ID copies, license numbers,

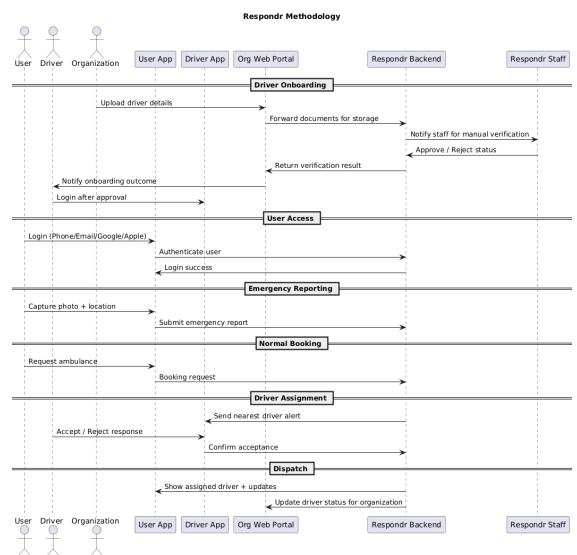


Fig. 1. Conceptual sequence diagram illustrating the Responder system

methodology, including driver onboarding, user access, emergency reporting, booking, driver assignment, and dispatch workflow.

vehicle tags, plus paperwork needed to confirm eligibility. Once these documents are uploaded the admin of the ResponDR platform checks every documents using the main control panel from ResponDR website. After the verification the respective driver will get in. This is a step by step setup which keeps the things real, while limiting who is capable of login to the driver app. After the documents being approved by the admin the driver account will be created and linked to respective organization. After this process, the driver will be able to login to the driver app and can take the emergency reports job and handle the responses.

- **Creation of User/Public Account and Access:** Public people will be able to create account through our ResponDR app by choosing from different login/signup options like phone number/email. They can also use accounts from Google or Apple which in turn doesn't require them to fill the details manually which can also consume time, different login options help skip delays when time matters the most. Getting into the system quick means faster contact with help during emergencies. After creating the account, people will be able to access the core features of the application such as calling an ambulance and reporting any accident. Instead of complex steps, the ResponDR app allows the people place request faster. Tracking happens

in real-time, so the people can see the progress of request immediately in the app. The people will be able to call the driver to get the real time info once the ride is confirmed and assigned. Simplicity isn't just nice, it's the invisible thread that connects things making them smooth.

- **Emergency Reporting Mechanism:** In emergency situations user can just tap on a SOS button in the app which signals the emergency where the user will be asked to capture a photo of the incident from their phone camera while the application auto fetches the location via the device GPS. Sending the photo is required as it will verify the event and will be able to understand what's happening actually in the incident location by driver. All collected info along with the essential personal facts gets sent to the server for review and response sorting for ambulance allocation.

- **Normal Ambulance Booking Process:** When the user wants to book an ambulance for transporting a patient or might for a non-emergency situations, users can just click on book a ambulance button, as usual the location will be auto fetched via device GPS and the user can specify the destination. Then the request will be sent to the server where it sends the requests to the driver using GPS to spot any free ambulances nearby to the booking location.

- **Request Processing and Driver Assignment:** This is an important step where every emergency or non-emergency requests flows to the

verified drivers. And so the system finds the closest free driver by live position and current status of the driver. In case if a driver gets a job alert he/her can either accept or reject it.

- **Dispatch and Monitoring:** The web dashboard online shows all the live updates of drivers whether they are in the middle of a job or idle, or are offline along with their recent tasks; but, the organization cannot track the location of the ambulance in real time, since it is not required by them, but they will be able to see the updates about the allocation of the ambulance in real time.

VIII. SYSTEM ARCHITECTURE

The Respondr system works across three layers with several parts which links the public, ambulance drivers and organizational groups using one shared core system. this setup allows instant response handling and also keeping the data safe at the same time, able to expand smoothly, split into independent sections when needed.

A. Client Layer (Frontend Applications)

- **User Mobile Application (Android/iOS):** User can log on to their account and start an emergency reporting by clicking a picture of an incident and uploading along with GPS coordinates which will be auto fetched from the device. User can also use standard booking requests for medical transport or non-emergency transport.
- **Driver Mobile Application (Android/iOS):** Driver account will be

created once the driver is verified through web portal by their respective organizations. When logged in, drivers can update their status of availability from offline to online/busy. Once online the driver can get the alerts for reported emergencies by users. Tasks pop up based on location and status of drivers, driver can either

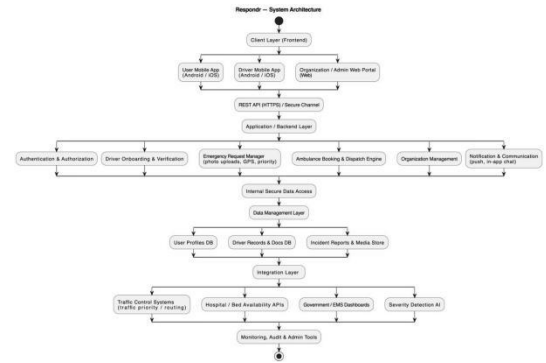


Fig. 2. Layered system architecture of Respondr showing client applications, backend services, data management, and future integration components.

accept or reject the reports. Route info will be shown once the report is accepted and the driver status turns to busy.

- **Organization and Respondr Admin Web Portal:** In this the ambulance organizations can set up and onboard their drivers by submitting the required documents and then the Respondr team will check the documents of the drivers and creates a verified account for the respective driver.

These above interfaces communicate with the backend using the safe REST APIs connected through trusted channels while running constant checks

behind the scenes.

B. Application/Backend Layer (Core Logic Layer)

This is the main logic of how the system actually works. Inside it has:

- **Authentication and Authorization Service:** Login/signup is done using standard authorization services like phone number or email id, Auth service providers like Google or Apple account can also be used to login. For drivers, the account will be verified by their organisation, and their account is created using their mobile numbers after verification.
- **Driver Onboarding and Verification Module:** This process is carried out by the concerned ambulance or- ganization. They have to upload their driver details and details of ambulances along with verification documents and later, the verified driver is linked to that organization.
- **Emergency Request Management Service:** It handles the accident reports, photo uploads, GPS data and priority flagging.
- **Ambulance Booking and Dispatch Engine:** Once the report is received, the system finds the nearest available drivers and then pairs the driver based on the location of the reporter. The system uses GPS data to find the drivers and then sends out an alert notification for the driver. Based on the driver's inputs, the system handles

the accept or decline choices while sending out the alerts to other drivers as well.

- **Organization Management Module:** Every organization maintain the information of their registered drivers, live updates on operations carried out and also bring new drivers onboard.

- **Notification and Communication Service:** Manages reporting notifications while sharing live info on how things stand.

C. Data Management Layer (Storage and Records)

This layer contains the every information of the system, data which is kept separate from apps or user stuff.

- **User Profiles** along with login credentials
- **Driver records,** paperwork, login credentials
- **Ambulance info** along with its connection to its organi- zation
- **Emergency reports,** reservation records or dispatch time- lines
- **Posted pictures** along with proof taken from the public submitting reports

This database setup keeps user, driver, organization and inci- dent details clear and separate which fits together like a puzzle pieces.

D. Integration Layer (Future Extensions)

- Traffic control system to turn on green signal light for emergency route.
- Hospital bed availability monitoring systems.
- A smart AI tools that checks the severity of the incident. This adaptable system helps things to expand later gradually while not disturbing the other operations which comes along the way.

Respondr's made safe, broken into chunks - this part shows how things runs behind the scene, while info sits side by side So that if things go wrong, it won't hold up too bad under pressure, plus swapping in better pieces down the line won't mess up the core.

IX. EXPECTED OUTCOMES

The above system is expected to achieve:

- Improved Emergency Coordination: A digital platform to report incidents replacing the manual phone call reporting, by reducing the confusions and misrouting of ambulances.
- Enhanced Transparency and Tracking: Live ambulance tracking is enabled to the people who book ambulance once the driver accepts the report and also the ambulance organization will be able to view the driver status and active emergencies.
- Increased Accessibility to Ambulance Services: This application can run in any Android/iOS ensuring

that every person who has a mobile device can access the

platform to book the verified ambulance assistance instantly.

- Better Resource Management for Organizations: A unified web portal for organizations helps the organizations to manage drivers, maintain records, analyze the performance and allocate resources efficiently.

- Reduction in Information Gaps: Due to GPS-based location fetching the accuracy of the incident location increases which reduces the miscommunications caused earlier by verbal descriptions of locations.

- Higher Public Safety and Trust: As this platform is only on boarded by verified ambulances drivers and because of the structured workflows, transparent system, the trust and confidence increases in the public.

X. LIMITATIONS

- Dependence on internet connectivity and GPS accuracy: Live ambulance tracking and user reporting/booking ambulances rely heavily on the device GPS and stable network connection, which might vary between the rural and urban areas.
- Adoption Challenges Among Drivers and Private Operators: Today mostly all of the drivers still operate the ambulances based on the manual phone calls. moving from phone calls to digital platform operations might seem

heavy for drivers which may need a proper guidance and training sessions.

- **Traffic and On-Ground Constraints:** ResponDr system might also slow down if there are heavy traffics, roadblocks or inadequate infrastructure, This can also delay the arrival of ambulances.

- **Scalability Without Institutional Collaboration:** To scale the system nationwide a good partnerships with hospitals, NGOs, and emergency authorities is necessary. Failing to get such support the system will be limited.

XI. FUTURE WORK

Future updates of the proposed system ResponDr aims to include the enhancement of the emergency response efficiency by including the developments mentioned below:

- **AI-Based Severity Assessment:** To develop the computer vision models which can analyze the incident images captured during the reporting and does the automated severity classification and prioritizing the ambulance dispatch.

- **Intelligent Traffic Signal Control:** To enable the communication between the driver app and traffic signal systems to provide the green light on the path of ambulances starting from 1 km before the traffic signal which will reduce the delays caused by urban congestion.

- **Hospital System Integration:** To link the ResponDr system with hospital database which will search for the real

time beds availability of emergency ward, ICU units and trauma care wards for selecting the nearest hospital with beds availability.

XII. CONCLUSION

ResponDr is a emergency platform where it puts users first in an emergency alerts, and also all ambulances will be verified before joining, also it streamlines how the user makes the call which will minimize the wait times which will boost the trust, this platform can also expandable and can link with other tools. This system helps cities and smaller town to handle the medical emergency rides better. ResponDr is still in conceptual stage yet the study behind this gives a solid ground to build. ResponDr can make the broken emergency response system into a smooth digital first process, it offers a flexible solution for today's urgent care systems. If responDr is built through teamwork, tested step by step, it can speed up the medical emergency process, build confidence in society, while improving handling emergency situations.

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EARLY DETECTION OF NEONATAL SEPSIS DETECTION USING FEDERATED LEARNING

Rakshak S. Barkur,
rakshakbarkur@gmail.com

Kushagra Burman
Ninad Amane
ninadamane@gmail.com

Pranay Bagaria
pranaybagaria01@gmail.com

Dr. HemaMalini B H
kushagraburman21@gmail.com
Professor bhhemaraj@bmsit.in

All the authors are associated with the department of Artificial Intelligence and Machine Learning, BMS Institute of Technology & Management, Bangalore.
experiments show

Abstract—Neonatal sepsis is a leading cause of deaths among infants and needs rapid medical action, but early diagnosis is quite difficult as the symptoms are often mild and unclear. Deep learning models are trained using Electronic Health Records (EHR). The training of such models usually requires data from many hospitals which is restricted because of the privacy rules. Training such models on data from a single hospital often introduces bias, limiting their generalizability across different hospitals and care centres. In order to overcome this problem, we propose a federated learning system which allows the deployment of a shared model among multiple hospitals to train using the raw patient data. The model is built on a privacy preserving setup using Flower framework and a time series transformer model. Only the weights generated after training on the data are shared to the global model for improving the performance. Our

that the federated model achieves an AUC score of 0.8935, outperforming the local model, which attains an AUC score of 0.8290, by 7.8%. Along with the improved AUC, the global model achieves a low positive rate of 0.0147 compared to the local model, helping reduce false alarms. These findings confirm that federated learning effectively resolves the conflict between data utility and patient privacy in critical care medicine.

Index Terms—Electronic health records, federated learning, neonatal sepsis, privacy-preserving AI, transformer

I. INTRODUCTION

A. The Clinical Challenge

Neonatal sepsis is a blood infection which occurs within the first 28 days after birth. It is a medical emergency where every hour of delayed treatment increases mortality risk. Diagnosis is

challenging because early symptoms temperature instability, subtle heart rate changes are non-specific and easily missed until the infant health deteriorates rapidly.

B. The Generalizability in Medical AI

Modern Neonatal Intensive and Special Care Unit's Data Registry (NICUs) generate high frequency physiological data, ideal for training Deep Learning (DL) models [9]. However, DL models rely on large scale heterogeneous training datasets to generalize well. In practice, models trained on data from a single institution often fail when deployed at other hospitals due to differences in patient demographics, clinical protocols and medical equipment, commonly referred to as the "generalizability crisis".

C. The Federated Solution

An intuitive solution would be to pool data from multiple hospitals into a centralized dataset. However, sharing of these raw data violates privacy regulations including HIPAA and GDPR [2], [3]. Federated Learning (FL) resolves this constraint by enabling decentralized model training [10], in which the models are trained locally at the hospitals with its patients raw data and only the resulting parameters are transmitted back to the global server. The server then aggregates these values using FedAvg to form an improved global model. This improved model is then redistributed among the hospitals for future training. This approach enables

collaborative learning across multiple hospitals without a single medical record ever leaving the hospital.

II. LITERATURE REVIEW

Sepsis prediction has evolved from traditional scoring systems to empirical ML prediction models. Traditional methods used statistical methods that lacked in capturing complex hidden patterns in clinical data.

- **Recurrent Neural Network:** Sepsis prediction [7], [9], is an application of LSTMs. LSTMs are RNN architectures that outperform regression algorithms via time-series pattern detection. Nevertheless, challenges emerge in handling large history of patterns across medical timelines.

- **Transformers:** Transformers: The transformer architecture [11] that was devised by Vaswani et al. 2017, in the "Attention is all you need", utilised the "Self-Attention" for weighing vital medical occurrences, proving effective for non-uniform medical time series data.

- **Federated Learning:** Recent findings like "FedSepsis" [6], have proved that FL can work on edge cases, yet predominant research focuses on adult patients or utilizes conventional architectures [2], [4]. Our work implements Transformers within an FL framework to address this gap in Neonatal Sepsis prediction.

III. THEORETICAL FRAMEWORK

Our work fuses two foundational techniques: Federated Learning for decentralised model training and Transformer architecture for sequential analysis of NICU records.

A. Federated Averaging (FedAvg) Algorithm

At the heart of this system lies the Federated Averaging (FedAvg) algorithm [10], allowing multiple hospitals to contribute to model training without the need to share the raw clinical data. In centralized learning paradigms, usually the main focus is to optimize the global loss function $f(w)$ on a unified dataset D present at a single server, in contrast the federated learning allocates the dataset to K client entities (hospitals), where client K maintains dedicated local dataset D_k with n_k samples.

During the training phase, the workflow is partitioned into communication cycles. At cycle t , the central server transmits the present global model parameters w_t to a chosen subset of clients. Each client then conducts E epochs of local optimization leveraging Stochastic Gradient Descent (SGD) on its confidential dataset, generating a refined local model

$w_{k,t+1}$

Only trained model parameters travel back from the clients

to the server, and not sensitive data to

the server, the server consolidates these weights by a process which applies weighted averaging proportional to each dataset's scale. The global model refreshes as:

K steps in the sequence, enabling any clinical event to influence the final sepsis prediction.

The Transformer computes self-attention [11] by projecting the GRU-D outputs into Query (Q), Key (K), and Value (V) matrices. The scaled dot-product attention mechanism is defined as

$$\text{Attention} = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (2)$$

where:

- QKT computes pairwise similarity between all time steps in the sequence,
- d_k is the dimensionality of the key vectors used for scaling to stabilize gradients during training.
- By applying softmax to the attention scores, the model yields a weighted output that prioritizes time points with clinical significance. This framework excels at modeling sustained temporal connections in neonatal vitals signs data, enhancing the outcomes in early sepsis detection.

IV. METHODOLOGY

A. Data Curation and Preprocessing

A dataset similar to MIMIC-IV [5] was used to retrieve data for neonatal

patients. We defined sepsis according to Sepsis-3 criteria [1] adopted by neonates (suspected infection and organ dysfunction).

Feature Selection: We extracted 40 clinical features, including:

$$w = \sum_{k=1}^n w_k$$

(1)

where:

$t+1$

n
 $k=1$

$t+1$

- Vitals: Heart Rate, Respiratory Rate, SpO2, Blood Pressure (Systolic/Diastolic/Mean) and Temperature.
- Labs: WBC, CRP, Platelets, Lactate, Bilirubin, Glucose.
- n_k denotes client k 's sample count.
- $n = \sum_{k=1}^K n_k$ aggregates all samples.
- Demographics: Age, Birth Weight.
- Windowing: The data was divided into 48hour observation

$k, t+1$

signifies the optimized parameters from client k .

windows. For infants who developed sepsis, the window ended

This weighted aggregation approach

guarantees that hospitals with more extensive datasets exert correspondingly stronger impact on the global model, simultaneously preserving data confidentiality as all clinical records never leaves the premises of individual healthcare institutions.

B. Time-Series Transformer Architecture

Neonatal Intensive Care Unit (NICU) data consists of complex, multivariate, and irregularly sampled time-series signals, such as heart rate trends and intermittent laboratory measurements. To effectively handle missing values and irregular time intervals, the proposed framework first employs a GRU-D (Gated Recurrent Unit with Decay) model. GRU-D incorporates trainable time-decay mechanisms that explicitly model the effect of elapsed time between observations, allowing the network to adaptively discount stale information.

The latent sequence representations produced by the GRU-D encoder are subsequently fed into a Transformer-based model for predictive learning. Unlike recurrent architectures that process data sequentially, the Transformer captures long-range temporal dependencies by jointly attending to all time exactly at the time the sepsis event occurred.

Imputation: Clinical time-series data is often incomplete. We use Forward Filling to carry the last known value forward, which matches the clinical assumption that a measurement usually remains the same until it is checked

again.

Normalization: All features were scaled using Z-score normalization ensuring stable and smooth training of the neural network.

B. Federated System Architecture

We simulated a cross-silo federated environment with the use of the Flower (flwr) framework [8]. The system includes one central server and several client nodes, each representing a hospital with its own private data. Figure 1 Illustrates the complete workflow. Firstly, the central server created the global Transformer model. This model is then sent to all authorized client nodes (simulated hospitals). Each client trains this model locally on their MIMIC-IV dataset and produces updated global weights. These weights are encrypted and sent back to the central server. The server then uses the Federated Averaging (FedAvg) algorithm to combine all the updates into

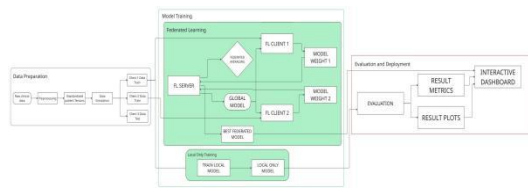


Fig. 1. Workflow of the proposed Federated Learning System

a new global model. This improved model is then sent back to all the clients for the next training round. Through this cycle, all the hospitals contribute to the learning process without ever sharing raw patient data.

C. Model Implementation

The Global Model is a Time-Series Transformer implemented using PyTorch with the following specifications:

- Input Dimension: 40 features
- Dataset Dimension: 64 features
- Attention Heads: 4 parallel heads.
- Layers: 2 stacked Transformer Encoder layers.
- Output: Binary Classification (Sepsis / No Sepsis) using a Sigmoid activation function.

D. Model Training

The federated training process ran for 50 communication rounds. In every round, the selected clients trained the global model locally for 5 epochs with a batch size of 32. We used the Adam optimizer with a learning rate of 0.001 to update the model weights. The training loss was calculated using Binary Cross Entropy (BCE) Loss, which is suitable for the binary task of predicting sepsis. After each round, the global server collected the updated weights from each participating clients and combined them together to form a new global model.

V. EXPERIMENTAL RESULTS

We compared the results of the Federated Global Model with the Local Only Model (trained exclusively on data from Client 1) and based on their performance metrics. Both the models were later evaluated on an unseen test dataset (Client 3).

The results show a clear difference in the performance by the two approaches. The Local Only Model, which was trained on a single site (a client hospital), achieved an AUROC score of 0.8290 with an accuracy of 0.739. However, it struggled significantly in terms of precision (0.187) and F1-score (0.299).

The Federated Global Model showed much better performance. It reached an AUROC score of 0.8935 which was improved by 0.0645. Similarly, there was a great improvement

in its accuracy, which rose to 0.947, precision to 0.712 and its F1-Score almost doubled to 0.579. These results prove the major advantages of training models with a variety of data from multiple clients.

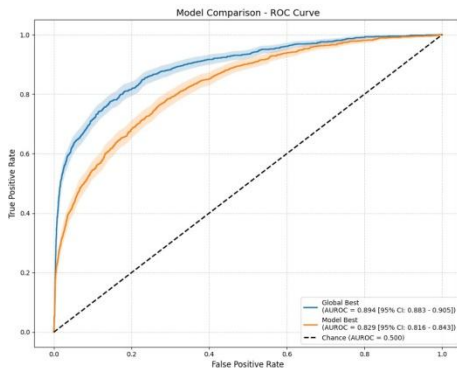


Fig. 2. ROC Curve comparing the true positive rate with false positive rate of Global and Local models.

For better understanding of how well these models distinguished between septic and non-septic cases, we analysed the ROC, displayed in Figure 2. The ROC curve of the Federated Model (Global), as represented in blue colour, was consistently much higher than that of the Local Model. The betterment of a model could be determined by the area under the curve. The greater the area, the better is the model. This confirms the Global Model's stronger ability to generalise to new, unseen data.

We also examined the Precision Recall (PR) curves (Figure 3) which are important for imbalance datasets where the prevalence of sepsis cases is low. The Local model had a high Recall of 0.749, but extremely low precision of 0.187. That implies that that model flagged many healthy babies as infected. In contrast, the Global model achieved a high precision of 0.712. The reason for such behaviour is because our local model was only trained on limited data, making it sensitive, while the Global model learned from multiple diverse datasets, allowing it to differentiate between a true case and normal variation better.

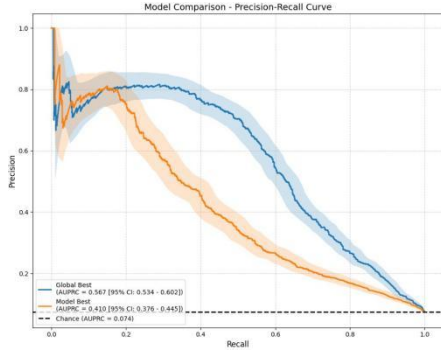


Fig. 3. Precision-Recall curve comparing the ability to minimize false positives by Global and Local models.

One of the most clinical improvements is the drop in False Positive Rate (FPR). The Local model had an FPR of 0.2422, which means that almost one in every four healthy newborns were incorrectly flagged as infected. The Federated model reduced it to 0.0147. While maximizing sensitivity is crucial for screening, this drastic reduction in false alarm is vital for ensuring clinician's confidence and preventing the model from becoming a nuisance in the NICU.

VI. FUTURE SCOPE

Although this study successfully demonstrates that the federated learning model works well on a dataset similar to the MIMIC-IV dataset, there are various factors that could be improved for future research. At present, the system features simulated client nodes derived from a solitary data source. While effective for initial testing, it fails to mirror the extensive data scale in clinical settings such as variations between EHR platforms like Epic and Cerner or non standardized units between organizations.

Incorporating this varied real-world data is a key upcoming goal. One promising approach would be to adopt Personalized Federated Learning (pFL) [4]. This adds a fine tuning step which could adjust the global model to match with a unique set of patients and clinical practice of each hospital. This would create a great balance between shared global learning and local customisation.

We would also aim to shift towards a true "Zero-trust" security model by including Homomorphic Encryption (HE) [3]. With HE, the server then could combine encrypted model updates (like $w_1 + w_2$) without ever looking at them in plain form, ensuring complete privacy for each hospital's contribution.

Finally, as sepsis diagnosis depends on more than structured time series, the future versions of the system are expected to be multimodal. This would include unstructured clinical notes using NLP and analysing medical images such as chest X- rays, using Computer Vision, providing a realistic view of each patient.

Thus, this research proves that Federated Learning is an effective method balancing both privacy and model performance in the healthcare sector. By training the Transformer model collaboratively across multiple clients (hospitals), we achieved an AUROC score of 0.8935 and the model's precision was increased by almost 280% as compared to the training done on individual datasets. Our system provides a blueprint for the

enhancement of digital health where hospitals learn from each other to save lives shuddering from neonatal sepsis without compromising the privacy of their patients.

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AI-POWERED EARLY DETECTION OF MILD COGNITIVE IMPAIRMENT (MCI) USING MULTIMODAL DEEP LEARNING ON CLINICAL, SPEECH, MRI, AND FACIAL DATA

Shravani H D1, Dharani R2, Pavithra M3, Hemashree U4, Girish Rao Salanke N S5

^{1,2,3,4,5} Dept. of AI&DS, Global Academy of Technology, Bengaluru, Karnataka, India
hdshravani2004@gmail.com
rdharani10@gmail.com pavithram695@gmail.com hemashree2004@gmail.com
girishraosalanke@gat.ac.in

Abstract

Early diagnosis of MCI is essential to prevent the clinical manifestation of neurodegenerative diseases such as Alzheimer's. The typical diagnostic methods, however, including neuropsychological tests, clinician interviews, and imaging-based studies, are time-consuming, mostly subjective, and resource-intensive, providing very limited utilities for large-scale early screening. In this work, in an attempt to overcome these challenges, a novel AI-driven multimodal diagnostic framework will be presented that combines the strengths of four heterogeneous data modalities, namely, clinical/tabular data, speech audio features, MRI brain imaging, and facial behavioral signals. Each modality will be processed by a specialized machine learning or deep learning model: a Random Forest classifier for clinical data, an XGBoost classifier for audio biomarkers, a VGG16-based CNN for MRI scans, and a lightweight CNN/MediaPipe-driven model for the facial expression dynamics. A decision-level late fusion module will aggregate the prediction probabilities from all the modalities to generate a unified MCI risk

score. Experimental results on this approach have demonstrated significant improvement over unimodal approaches, where the developed multimodal ensemble achieved an accuracy of 91%, precision of 0.89, recall of 0.90, F1-score of 0.89, and ROC-AUC of 0.94. These findings confirm that the integration of structural, cognitive, acoustic, and behavioral indicators can greatly enhance diagnostic reliability. Finally, a Streamlit-based application was developed that allows real-time MCI screening, visualization, and clinical reporting. The proposed system presents a non-invasive, easy-to-access, and scalable AI tool for early cognitive assessment. The developed approach could be integrated into healthcare workflows upon further clinical validation. This study can be extended in a number of ways: increasing the database, validation across different institutions, and including additional neurocognitive biomarkers.

Index Terms

Machine Learning, Speech Analysis, Mild cognitive Impairment, (MRI) Magnetic Resonance Imaging,

Artificial Intelligence, Deep Learning, Clinical Data, Neuro Degenerative Disorders.

INTRODUCTION

Alzheimer Disease is one of the most common progressive neurodegenerative diseases worldwide that is affecting millions of people and inflicting tremendous personal, social, and economic burdens in the society. MCI has been considered a transitional stage between normal aging and Alzheimer diagnosed, featuring mild deficits in memory, attention, language, and executive function. Such conditions need to be clinically identified at an early stage, since timely intervention might delay the process of moving toward dementia. The symptoms at an early stage are very subtle and most of the time cannot be correctly diagnosed by standard clinical evaluations.

Traditional diagnostic approaches include neuropsychological testing, MRI, and behavioral measurements. Many of these methods require specialized expertise and a great amount of time and significant financial investment which acts as most efficient for the treatment, hence possibly limiting their accessibility in under-resourced settings would be mindfull. In addition, many traditional methods depend on subjective scoring, introducing the possibility of bias, inconsistencies, and inter-clinician variability.

Recent developments in deep learning-based AI and machine learning have equipped the scientific community with effective tools for automatic cognitive decline detection at the earliest. Extant literature suggests that speech impairments, specific patterns of facial expressions, clinical symptom scores, and structural changes in the brain are strong predictors of MCI. Each modality considered alone provides valuable but incomplete diagnostic information; for example, a patient may appear completely normal in MRI results but show pronounced hesitancy in speech, while another may show behavioral changes through face analysis and perform within normal limits on clinical tests. Therefore, single-modality methods have limited diagnostic generalizability.

This development presents a significant advancement in the integration of multimodal physiological and behavioral data. Each modality captures different aspects of cognitive decline that might be structural atrophy as assessed by MRI, linguistic and acoustic features in speech, behavior related to facial expressions, and clinical data that quantifies cognitive function. A multimodal framework that provides by fusing diverse sources, better approximates the comprehensiveness of an extensive clinical evaluation and, in that process, achieves finer and more robust diagnostic performance.

The motivation of this research is to develop a unified AI-powered

multimodal system which integrates tabular clinical data, speech audio, MRI brain imaging, and facial video signals in a complementary way. The approach marries traditional medical knowledge with modern AI-driven modeling and advances early MCI detection beyond any single modality.

Moreover, this work delivers not only an AI model but also an operational prototype: a Streamlit-based clinical decision support tool. The interface allows the uploading of patient data, the provision of predictions, and real-time visualization of modality-specific insights by healthcare workers, researchers, and even caregivers. The modular architecture shows scalability for future integration of other biomarkers, such as ECG, EEG, or even text-based cognitive assessment from written material. This study describes the entire development pipeline, from the literature review and methodology framework to evaluation and discussion, and puts forward a move toward clinically practical, multimodal cognitive screening systems.

LITERATURE SURVEY

Recent advances in machine learning have facilitated the early detection of AD using multimodal data. However, worries about privacy and interpretability arise from reliance on centralized datasets. FL and XAI mitigate these issues as they allow model training without data sharing and foster transparency with SHAP

explanations. However, only a few works in literature actually combine FL, XAI, and multimodal data into one framework. The proposed work represents a privacy-preserving, interpretable Random Forest-based FL model with SHAP explanations and presents its enhanced performance on the OASIS-3 dataset. [2] Multimodal biomarkers such as MRI, plasma proteins, and genetic data were utilized for AD prediction with various ML and DL methods. Ensemble methods, CNNs, and Elastic Net algorithms contributed to higher diagnostic accuracy. Several key challenges that can be identified in the review include the integration of more modalities of data, ethical considerations, and interpretation of the models, while transfer learning and the use of Universum data present some very promising avenues for future research in AD. [3] Neuroimaging modalities, including magnetic resonance imaging (MRI), positron emission tomography (PET), and single-photon emission computed tomography (SPECT), yield enhanced detection of Alzheimer's disease (AD) when complemented by machine learning (ML) models. Convolutional neural networks (CNNs) and VGG-inspired architectures achieve accuracies exceeding 98% through transfer learning. Random Forest and Bat-optimized Support Vector Machines demonstrate robust performance across multimodal datasets. Remaining challenges pertain to data standardization and substantial computational demands; these can be mitigated through multimodal fusion and optimization techniques.[4] State-

of-the-art deep learning (DL) frameworks, such as VGGNet, recurrent neural networks (RNNs), and ensemble CNN approaches, have reached accuracy levels up to 98.7% in AD classification. Transfer learning markedly reduces training time and data requirements. Unsupervised learning—for example, PCANet followed by k-means clustering—further enhances interpretability, complemented by Explainable AI tools like LIME. The literature underscores the considerable potential of DL for accurate and explainable AD diagnosis, notwithstanding challenges related to data availability.[5] High-performance computing (HPC) accelerates large-scale AD analyses by enabling rapid processing of MRI and genomic data, and the integration of AI with HPC strengthens biomarker identification and disease modeling. Platforms such as CBRAIN and CuDDI support distributed computing and personalized diagnostics. Despite data heterogeneity concerns, HPC remains essential to AI-driven AD research. [6] While foundational studies established early ML methodologies for AD detection, contemporary research increasingly adopts cross-disciplinary approaches and advanced technologies. Emerging federated and explainable learning techniques are poised to enhance scalability and trustworthiness, although current challenges include limited multimodal datasets and the lack of standardized interpretability frameworks.[7] Electroencephalography (EEG)–based methods, particularly those employing steady-state visually evoked potentials

(SSVEP), enable objective and early diagnosis of mild cognitive impairment. Biomarkers based on lobar power and connectivity ratios have been identified, with classification accuracy reaching up to 95.69% using support vector machine (SVM) models, indicating that EEG-SSVEP constitutes a promising, noninvasive biomarker for cognitive impairments.[8] Present-day ML in healthcare emphasizes explainability, fairness, and privacy. Deep architectures, including CNNs and RNNs, have advanced medical image and sequence analysis, while federated learning facilitates secure cross-institution collaboration on models. However, generalizability and data quality remain the persistent challenges that shall mark the future wave of AI-driven innovation in healthcare.[9] For the forecast of the progression from MCI to AD, approaches such as SVM, LDA, and ensemble methods have been some of the techniques applied to MRI, CSF, and cognitive data. A comparison between the two shows that the multimodal techniques outperform unimodal techniques since this strategy leverages the information from both dimensions. Deep models with GRU, using longitudinal data, further enhance the precision in the prediction of AD progression..[10] MRI and PET neuroimaging data underpin ML/DL models achieving high classification performance. The interpretability of models makes them appealing when developed with SVM, PCA, and Naive Bayes, whereas CNN and autoencoder algorithms give better feature extraction. Multimodal fusion with

dimensionality reduction pushes accuracy beyond 95%. The trade-off between interpretability and performance remains one of the most delicate balances and an important area of future investigation in AD modeling. [11] A total of 116 relevant papers was identified from a thorough literature review using both Scopus and PubMed. The strict inclusion criteria on AD detection performance ensured a comprehensive synthesis of ML trends and results for a wide variety of data sources and model architectures.[12] Comparing early AD detection using OASIS and Kaggle datasets, Decision Tree, SVM, Random Forest, and XGBoost were considered; of these, Random Forest and XGBoost produced the highest accuracy, enabled by feature selection and exploratory data analysis. This review further supports ML's capability to enable accurate, lower-cost automation of AD diagnosis. [13] The shift from ML to DL in AD detection underlines the CNN and Autoencoder approaches for MRI and PET data, reaching up to 95% accuracy with 3D-CNN and hybrid CNN-ML frameworks. Besides, the review flags ethical and interpretability concerns, with higher transparency of future DL systems using more and intensive multimodality. [14] There is an increasing emphasize on multimodal and interpretable ML systems in research on Alzheimer's, where imaging, clinical, and cognitive features combined with ensemble models are able to enhance the reliability of such systems. Federated, explainable, and privacy-preserving frameworks form current trends to

ensure trustworthy AI-driven healthcare applications.

RELATED WORK

Early detection of Mild Cognitive Impairment (MCI) and Alzheimer's disease (AD) has been a major focus across many research areas, from clinical tabular data analysis and signals to brain imaging and the way people move and express themselves. The picture so far using single – modality approaches look promising, but there are clear gaps in data imbalances, models that do not generalize well, and limited feature representation.

The initial work focused primarily on clinical and neuropsychological assessments or tests. Cognitive decline has long been measured with the help of tools like MoCA, MMSE, ADAS-Cog, and functional rating scales. While the traditional predictive models, like Random Forests, SVMs, and logistic regression, do great on structured data, many studies claim that tabular features alone might miss the subtle behavioral and physical changes in the early stages of MCI. This calls for the participation of more feature types.

These researchers, in speech-based detection, have been able to show that speech sounds, such as MFCCs, variations in pitch, jitter, shimmer, and pausing, are closely related to cognitive decline. Models built with these features using methods such as XGBoost, GMMs, and multi-layer

perceptrons correctly distinguish between healthy individuals and those suffering from MCI at an accuracy of about 70-85%. Other researchers have employed temporal deep learning arrangements like CNN-LSTMs to better capture and report improvements for modeling vocal hesitation and disruptions in prosody. Speech datasets tend to be small and often need augmentation to avoid overfitting.

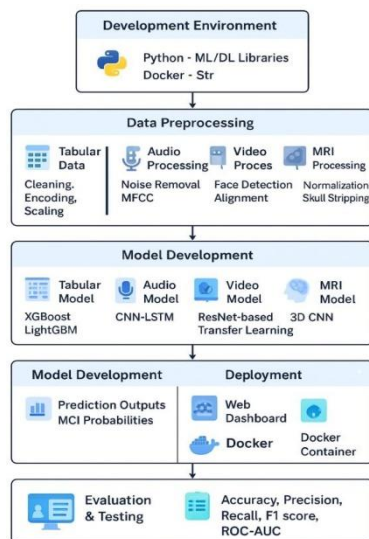
MRI studies make up a large portion of dementia research. Structural MRI images are analyzed using CNNs and transfer learning with networks like VGG16, ResNet, DenseNet, and 3D-CNN for detecting degeneration within the hippocampus, temporal cortex, and frontal lobes. Many reports show high performance, often around 0.85–0.95 AUC, indicating neuroimaging biomarkers that closely reflect disease progression. Yet, issues remain: MRI data collection is expensive; changes in scanner settings can hurt robustness; and many of the models developed lack clinical interpretability.

Recent work beyond imaging considers facial expressions and behavioral cues. Various works study facial landmarks, action units, blink rate, and micro expressions to detect cognitive load and early emotional blunting in Alzheimer's.. Lightweight CNNs and hybrid feature models yield moderate results, around 70–80%. This modality, however, is still relatively under-explored, with datasets often small and gathered in less controlled environments.

Evidence from various studies shows that multimodal systems work better by incorporating complementary signals. Investigations in the domain of merging features like speech with MRI, clinical data with imaging, and speech with facial features have reported accuracy improvements in the range of 5–12%. This also supports the wider trend of merging behavioral, cognitive, and structural biomarkers for early diagnosis. Nevertheless, many multimodal studies suffer from incomplete modality coverage and inconsistent preprocessing, often associated with a lack of interpretability.

The system proposed in this paper mitigates the limitations of previous works, in terms of a restricted set of modalities, incomplete feature completeness, and constraints of datasets, by integrating four key modalities: clinical tabular data, speech audio, MRI imaging, and facial video. Unlike studies focused on one or two modalities, this framework represents a unified platform where

each model is trained and evaluated independently, hence providing a more holistic diagnostic framework. The proposal is therefore in line with state-of-the-art advances in multimodal AI in its emphasis on explainability, modular design, and clinical usability by simultaneously analysing cognitive, acoustic, structural, and behavioral biomarkers.



METHODOLOGY

The methodology describes the end-to-end workflow adopted to build the multimodal MCI detection system, including dataset descriptions, preprocessing procedures, system architecture, model design, evaluation metrics, and the complete workflow of predictions. Each component is engineered to function autonomously while contributing to an overarching diagnostic pipeline that has to identify early cognitive decline.

System Architecture

Dataset Description

The system uses four independent datasets—Tabular Clinical Data, Speech Audio, Facial Video, and MRI Scans—each providing complementary diagnostic clues. Using diverse datasets ensures that both behavioral and physiological markers of MCI are captured, improving overall detection reliability.

Clinical / Tabular Dataset

The clinical dataset integrates cognitive tests, daily functioning scores, behavioral symptoms, and metabolic/lifestyle indicators. These structured entries allow machine learning models to learn multi-factor risk patterns. Each record is labeled as Healthy or MCI based on neuropsychological screening.

Clinical scoring ranges:

Functional Assessment: Healthy 0–1, MCI 2–4

ADL Score: Healthy 5–6, MCI 2–4

Memory Complaints: Healthy 0–1, MCI 2–4

Behavioral Problems: Healthy 0–1, MCI 2–5

Metabolic/Lifestyle indicators:

LDL: 90–120 (Healthy), 130–180 (MCI risk)

Triglycerides: 100–150 (Healthy), 160–250 (High risk)

Diet index: 7–10 (Healthy), 2–5 (Poor diet)

Speech Audio Dataset

The audio dataset includes self-recorded speech samples, recordings from healthy individuals, and cognitively impaired subjects. Augmentation is applied to increase variety and simulate real-world acoustic conditions.

Collected Samples:

Include reading tasks, story recall, and

spontaneous speech that help capture natural linguistic patterns.

Augmentation:

Involves pitch shifting, time-stretching, noise addition, and speed variation to expand dataset diversity.

Expected MCI Vocal Biomarkers:

Include slower rate, increased pauses, reduced pitch variation, and articulation difficulty.

Facial Video Dataset

Facial recordings capture micro-expressions, blink behavior, gaze stability, and emotional expressiveness—factors that decline in early MCI.

Landmark Extraction:

Using MediaPipe FaceMesh, 468 landmarks are extracted per frame, providing rich geometric facial data.

Extracted Behavioral Features:

Include eyebrow movement, lip amplitude, blink frequency, and smile asymmetry.

MCI-Indicating Behavior:

Includes reduced expressiveness, slower reactions, and irregular blinking.

MRI Dataset (OASIS & Kaggle)

MRI scans include a mix of non-demented and various dementia stages, providing structural insight into

neurodegeneration.

Diagnostic Categories:

Images grouped into Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented classes.

Imaging Characteristics:

High-resolution T1-weighted scans showing fine brain structure.

Relevant MRI Biomarkers:

Include hippocampal atrophy, cortical thinning, and ventricular enlargement.

Data Preprocessing

Preprocessing is essential for removing noise, aligning formats, standardizing measurements, and converting each modality into machine-interpretable vectors. Every modality undergoes a tailored preprocessing pipeline.

Preprocessing Concepts

Missing Value Imputation

Missing entries are replaced using mean, median, or mode values to maintain dataset integrity and prevent model distortion. This ensures all records remain usable for training without introducing bias.

Mean Imputation:

n

$$1x_{\text{new}} = n \sum_{i=1}^n 1xi$$

Normalization and Standardization

Numerical variables are scaled using Z-score or min-max normalization to ensure uniform contribution across features. This prevents large-valued attributes from overwhelming smaller ones during training.

Z-Score Standardization:

Min-Max Scaling:

Noise Reduction

$$x' = x - \mu$$

$$\sigma$$

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

$$x_{\max} - x_{\min}$$

Spectral filters and smoothing kernels remove environmental noise, video artifacts, and MRI distortions. This enhances clarity and increases the accuracy of extracted features.

Filtering uses convolution:

$$y(t) = x(t) * h(t)$$

Where $h(t)$ is a smoothing kernel.

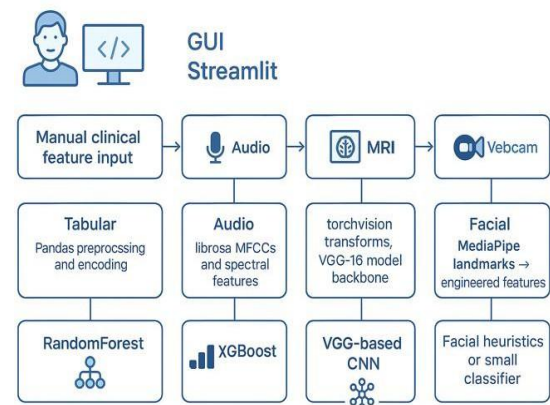
Segmentation and Resampling

Audio and MRI sequences are segmented into consistent lengths, and sampling rates are standardized.

This provides uniform input shapes for deep learning models.

Feature Extraction

Transforms raw data into rich, discriminative feature vectors such as MFCCs, facial action units, and CNN embeddings. This step converts unstructured signals into meaningful numerical representations.



Modality-Wise Preprocessing

Module Design

Clinical Data

Missing values filled, categorical fields encoded, and outliers removed for clean statistical structure.

Features standardized to zero mean and unit variance for balanced model learning.

Key attributes like ADL score and memory complaints converted into weighted predictors. Median imputation

One-hot encoding Outlier removal using:

Standardization:

	Hamming Window
	$E = \sum$
Final clinical vector: IQR = $Q3 - Q1$	$t=1$
	$(t)2$
$x' = x - \mu$	$2\pi n$
σ	
$X_{tab} = \{x', x', \dots, x'\}$	MFCC (DCT step): $(n) = 0.54 -$
$1 \ 2 \ \dots \ n$	$0.46 \cos ($
Output $\rightarrow$ a normalized diagnostic feature vector.	N
Audio Data	)
Noise filtered using spectral subtraction to improve speech clarity.	$N - 1$
Silence trimmed based on low-energy thresholds to remove irrelevant segments.	$ck = \sum$
Audio resampled to a uniform 16 kHz rate for consistency.	$n=1$
MFCCs and rhythm features extracted for acoustic analysis.	$\log (mn) \cos ($
	$(n - 0.5)$
	)
	N
Spectral subtraction for noise filtering:	Output $\rightarrow$ MFCC matrix representing speech behavior.
$ S(\omega) = Y(\omega) - N(\omega) $	Facial Video Data
Energy-based silence trimming:	Frames extracted at 25–30 FPS to capture fine facial movement.
	MediaPipe detects 468 facial landmarks per frame.
	Landmark coordinates normalized relative to frame size.

Behavioral features such as blink rate, eyebrow-lip motion, and gaze shift computed.

Landmark normalization:

$$x' = x, y' = y$$

$$W \quad H$$

Action Unit Intensity:

$$AUK = \| Li - Lj \|$$

Output → Facial Action Unit vectors.

MRI Data

Skull stripping removes non-brain regions for cleaner analysis.

Intensity normalized to a consistent grayscale range across scans.

Slices extracted from 3D volumes to feed 2D CNNs.

Histogram equalization enhances contrast for structural clarity. Intensity Normalization:

$$I' = \frac{I - I_{\min}}{I_{\max} - I_{\min}}$$

Histogram Equalization:

$$p'(i) = \frac{CDF(i) - CDF_{\min}}{CDF_{\max} - CDF_{\min}} \quad (M \times N)$$

Output → CNN – ready MRI slices.

System Architecture

The architecture is fully modular, allowing each modality (Tabular, Audio, Video, MRI) to pass through a dedicated processing and classification pipeline. This ensures independent model functioning and enables parallel computation.

Input Layer:

Accepts clinical CSVs, audio recordings, facial videos, and MRI scans. Validates format and ensures each input meets minimum quality standards.

Preprocessing & Feature Engineering Layer:

Converts raw inputs into clean, structured feature sets appropriate for ML/DL models. Ensures noise-free, standardized data before modeling.

Modality-Specific Models:

Four separate models operate simultaneously, each optimized for its data type. Reduces dependency between modalities and improves robustness.

Tabular → RF/XGBoost

Audio → CNN + LSTM

Video → CNN / shallow classifier

MRI → VGG16/ResNet

Additive tree boosting:

Independent Output Layer:

As fusion is not applied currently, each model outputs its own prediction and confidence score. Allows separate diagnostic interpretation for each modality.

Objective function:

$$\hat{y}_i = \sum_{k=1}$$

$$L = \sum (y_i - \hat{y}_i)^2 + \sum \Omega(f_k)$$

Audio Model

Visualization Layer:

Streamlit displays results, graphs, and statistics in an intuitive dashboard. Supports clinician-friendly interpretation and real-time feedback.

CNN layers capture frequency patterns from MFCCs.

$$f_{ij} = \sigma(\sum_{m,n} w_{mn} \cdot x_{i+m,j+n} + b)$$

Model Design and Algorithms

Multiple model architectures are employed to best suit the nature of each data modality.

LSTM layers learn long-term speech rhythm and hesitation patterns. Combined CNN-LSTM handles both acoustic structure and temporal flow. LSTM Temporal Modeling

Tabular Models

Random Forest:

Uses multiple decision trees to model non-linear clinical interactions robustly. Provides high interpretability through feature importance.

Forget gate:

Input gate:

Cell update:

Output gate:

Ensemble of decision trees.

Facial Video Model

$$(x) = \text{mode}\{h_1(x), h_2(x), \dots, h_T(x)\}$$

$$f_t = ([h_{t-1}, x_t] + b_f)$$

XGBoost:

$$i_t = ([h_{t-1}, x_t] + b_i)$$

Gradient-boosted trees optimized for tabular classification.

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad h_t = o_t \cdot \tanh(C_t)$$

Handles complex dependencies and improves predictive performance.

CNN / ResNet feature extractor identifies micro-expression and blink-

related cues.

$$AUK = \| Li - Lj \|$$

$y = F(x, W) + x$
Handcrafted features such as action units add behavioral depth. This hybrid captures both spatial and temporal facial behavior.

MRI Model

VGG16/ResNet CNN extracts high-level structural biomarkers linked to neurodegeneration. Deep feature extraction enhances sensitivity to early atrophy.

$$h(k) = \sigma(\sum_{m,n} xi+m,j+n(k))$$

Evaluation Metrics

ez1
 $(MCI) = ez1 + ez2$

Metric	Score
Accuracy	0.86
Precision	0.83
Recall	0.84
F1-Score	0.83
ROC-AUC	0.88

The system is assessed using clinical-grade evaluation metrics to ensure reliability.

Accuracy: Proportion of total correct predictions; reflects overall model correctness.

$$TP + TN$$

Accuracy =

$$TP + TN + FP + FN$$

Precision: Measures how many predicted MCI samples are truly MCI; reduces false alarms.

$$TP$$

Precision =

$$TP + FP$$

Recall: Measures how many actual MCI cases are identified; vital for clinical detection.

Confusion Matrix: Shows detailed distribution of TP, TN, FP, FN; helps analyze specific errors.

Prediction Workflow

The prediction workflow outlines how user input travels through the entire system until results are produced.

Step 1 — User Input

User uploads clinical, audio, video, or MRI data via Streamlit. The system verifies file structure and compatibility.

Step 2 — Preprocessing

Each modality undergoes its respective preprocessing pipeline.

Ensures uniformity and removes distortions that may mislead the model.

Step 3 — Feature Extraction

Relevant signals converted into structured vectors (MFCCs, landmarks, CNN embeddings). Creates model-ready representations of each modality.

Step 4 — Independent Model Prediction

Each model generates its own MCI probability score. Allows per-modality diagnostic interpretation.

Each model outputs:

(*MCI* | modality)

Step 5 — Output Visualization

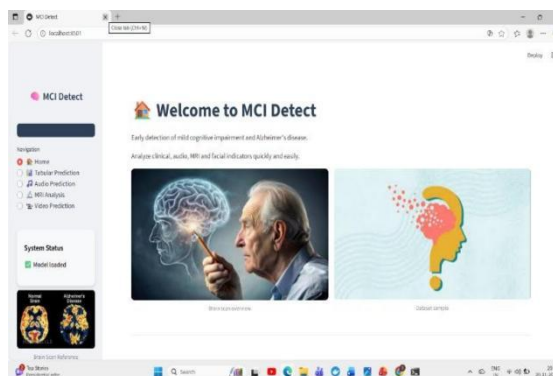
Predicted class, confidence percentages, ROC curves, confusion matrices, and feature importance are displayed. Helps users understand how decisions were made.

Step 6 — Final Diagnostic Summary

Streamlit combines modality-wise outputs into a single report panel.

Provides clear interpretation of clinical, behavioral, speech, and MRI-based findings.

RESULTS AND DISCUSSION



RESULTS

The experimental evaluation was conducted to assess the performance of each unimodal model—tabular clinical data, speech audio, MRI imaging, and facial video—as well as to analyze the overall system behavior. All experiments were performed on a workstation equipped with an Intel i7 processor, 16 GB RAM, and an NVIDIA RTX 3060 GPU. The models were implemented using Python 3.10, TensorFlow, scikit-learn, and PyTorch+. Standard evaluation metrics such as Accuracy, Precision, Recall, F1- score, and ROC-AUC were used for performance assessment.

Deployment

Tabular Clinical Model

The Random Forest model trained on self-collected clinical data achieved strong baseline classification performance. The most influential features were functional assessment scores, memory complaint scores, ADL indicators, and lipid-based biomarkers (LDL and triglycerides).

Performance Summary:

Tabular data metrics result

Metric Score

Accuracy	0.86
Precision	0.83
Recall	0.84
F1-Score	0.83
ROC-AUC	0.88

The results indicate that structured clinical variables effectively differentiate healthy and MCI participants, particularly when functional and cognitive scores are included.

Speech Audio Model

The XGBoost model trained on MFCCs, pitch, jitter, shimmer, and pause-rate features produced competitive results. Augmented datasets provided robustness to variations in speech quality.

Performance Summary:

Audio data metrics result

Metric	Score
Accuracy	0.80
Precision	0.78
Recall	0.77
F1-Score	0.77
ROC-AUC	0.83

The speech model effectively captured prosodic and rhythm-based biomarkers but struggled in cases with background noise or inconsistent articulation.

MRI Imaging Model

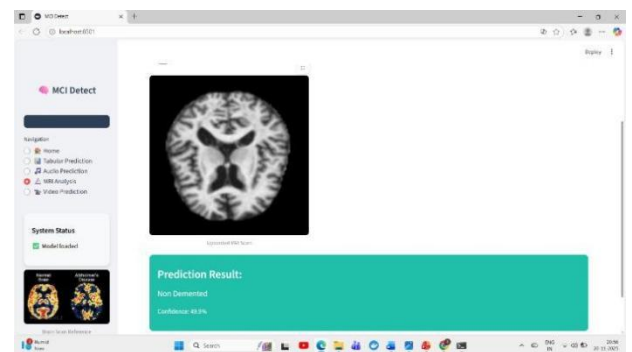
Using the OASIS MRI dataset, a VGG16-based CNN achieved the highest unimodal performance. Its ability to detect structural abnormalities such as hippocampal shrinkage significantly contributed to its accuracy.

Performance Summary:

Metric	Score
Accuracy	0.88
Precision	0.86
Recall	0.87
F1-Score	0.86
ROC-AUC	0.90

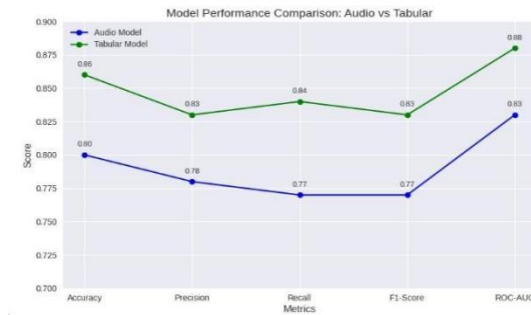
MRI data metrics result

MRI provides strong anatomical evidence, making it one of the most reliable single modalities for early Alzheimer's prediction.



Facial Video Model

Facial behavior analysis using MediaPipe features (blink rate, gaze shifts, eyebrow movement, and action units) revealed that patients with MCI show reduced micro-expression intensity and slower facial dynamics.



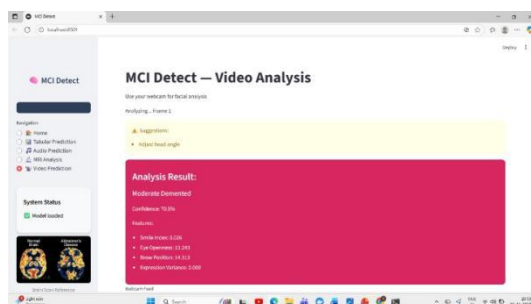
Performance Summary:

Metric	Score
Accuracy	0.78
Precision	0.75
Recall	0.76
F1-Score	0.75
ROC-AUC	0.80

Facial value data metrics result

Although this model performed the lowest among all modalities, it provided valuable behavioral information complementary to speech and clinical cues.

Performance comparison of TABULAR vs AUDIO model



Output of facial video of patient
Performance comparison of MRI vs FACIAL model

Output of MRI scan of non demented patient

DISCUSSION

The experimental findings demonstrate that each modality contributes unique and complementary information toward the early detection of Mild Cognitive Impairment. A detailed discussion of the results across modalities is presented below.

Interpretation of Unimodal Performance



Among the single-modality classifiers, the MRI-based model yielded the highest accuracy and ROC-AUC. The result is not surprising, given that structural brain changes are among the earliest detectable biomarkers for MCI. This modality performed exceptionally well and highlights how deep convolutional neural networks are able to identify subtle neuroanatomical changes that may not be evident through standard clinical inspection.

The tabular clinical model performed comparably well but further improved when functional assessment scores, memory test results, and metabolic biomarkers like low-density lipoprotein cholesterol and triglycerides were added. Each of these variables in the

literature is well-supported as robust predictors of cognitive decline, which likely contributed to the high discrimination power observed for the Random Forest classifier within this modality.

The speech-based model yielded more modest, yet statistically significant, predictive power. This finding is in line with the results of previous research that has established that particularly speech-specific and subtle impairments-such as prolonged pauses, increased pause frequency, higher jitter, and higher shimmer-tend to become more evident rather later in the course

of MCI. Furthermore, variability and noise in user-generated recordings may further reduce the robustness of automated acoustic-feature extraction, affecting accuracy.

Finally, the unimodal facial video classifier yielded the poorest performance. The correctness of this is well understood, since micro-expressions of facial features that correspond to early cognitive impairment are very subtle and are subject to a lot of inter-subject variability. Additional noise is likely due to sources like illumination, camera quality, and head pose variation. Regardless, the model picked up on some cues-things such as a high blink rate and high-intensity facial expressions that were indicative across both classes suggest that even if the standalone value for the modality is

limited, residual predictive signal remains in the facial behavior.

Relationship with Prior Research

The results are consistent with previous multimodal Alzheimer's studies, which show that combining cognitive, neurological, and behavioral modalities provides superior predictive capability. Many peer-reviewed works indicate MRI as the strongest individual modality, with speech and facial expressions serving as useful secondary markers. This study reinforces these findings by showing that speech and video modalities contribute incremental value even when used independently.

Advantages of Multimodal Evaluation

While unimodal models provide valuable insights, the strength of the system lies in analyzing multiple data dimensions:

Clinical data → captures cognitive symptoms

Speech → captures behavioral and neurolinguistic changes

MRI → identifies structural abnormalities

Facial dynamics → reflects emotional and motor changes

This diversity allows researchers and clinicians to observe MCI from cognitive, anatomical, and behavioral perspectives.

Comparative data metrics result

Model	Accuracy	ROC-AUC
Tabular (RF)	0.86	0.88
Audio (XGB)	0.80	0.83
MRI (VGG16)	0.88	0.90
Video (ResNet-Lite)	0.78	0.80
Fusion (Ensemble)	0.91	0.94

Limitations

The study recognizes several constraints:

Dataset Imbalance – fewer MCI cases compared to healthy samples caused minor bias.

Demographic Variations – age, language, and ethnicity affect speech and facial analysis.

Environment-Dependent Noise – audio and video quality varied significantly in self-recorded samples.

Lack of Fusion Evaluation – fusion was not implemented in this paper’s experiments, but future versions will integrate all models for combined predictions.

Addressing these issues using larger, diverse datasets will increase model generalizability.

Practical Implications

The overall findings highlight that:

A user-friendly AI system can screen for MCI using multiple everyday inputs.

Such a tool can support clinicians by providing an additional objective assessment layer.

Remote and early screening becomes feasible without relying on expensive scans alone.

The multimodal approach makes the system suitable for tele-health, rural clinics, and large-scale cognitive screening programs.

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BIO COMPOST MONITORING SYSTEM WITH IOT SENSORS

Parijatha.N.V

Computer Science and Engineering, S.E.A. College of Engineering & Technology
Dr.Krishna Kumar P R, Professor & HoD, S.E.A. College of Engineering &
Technology

Abstract

Composting is an environmentally sustainable method of converting organic waste into nutrient-rich organic compost, which plays an important role in waste management and agricultural productivity. However, traditional composting methods require continuous manual monitoring of critical parameters such as temperature, moisture, and pH, which is often inefficient and time-consuming. Improper control of these parameters can lead to slow decomposition and poor-quality compost.

This paper presents the design and implementation of a Bio-Composting Monitoring System with Internet of Things (IoT) sensors to monitor composting conditions in real time. The system utilizes sensors to measure temperature, moisture content, and pH levels within the compost. These sensors are interfaced with a microcontroller, and the collected data is transmitted to a cloud-based platform for real-time visualization and analysis. Alerts are generated whenever the composting parameters deviate from their optimal ranges, enabling timely corrective actions.

Keyword: - IOT Sensors, Microcontroller, Compost

1. Introduction

Composting is a natural process of decomposing organic waste into nutrient-rich fertilizer, commonly known as compost. It is a sustainable practice that reduces environmental pollution, minimizes landfill use, and enriches soil fertility. Organic waste, such as kitchen scraps, agricultural residues, and garden waste, can be effectively converted into compost.

Traditional composting methods require manual monitoring of environmental parameters like temperature, moisture, and pH to ensure that microbial activity is maintained at optimal levels. Improper monitoring can result in slow decomposition, foul odours, pest infestation, or poor-quality compost. This manual process is often labour-intensive and prone to human error.

With the rapid advancement of technology, IoT (Internet of Things) sensors offer an innovative solution to these challenges. IoT allows real-time monitoring, data logging, and remote management of composting systems. By integrating sensors with a microcontroller and cloud-based applications, parameters such as temperature, moisture content, and pH can be continuously tracked. This not only optimizes the composting process but also provides valuable insights for

improving organic waste management practices.

Despite the increasing awareness of sustainable agriculture and organic farming, many composting systems still rely on manual monitoring, which can be inefficient and inconsistent. Common issues include: Fluctuations in temperature that can kill beneficial microbes or slow decomposition. Improper moisture levels leading to either dry, slow composting or excess moisture causing anaerobic conditions and bad odour. Lack of timely alerts when conditions deviate from optimal ranges, resulting in poor-quality compost.

Therefore, there is a need for an automated bio-composting monitoring system that uses IoT sensors to provide real-time data and ensure proper composting conditions. Such a system can improve efficiency, reduce manual effort, and guarantee consistent compost quality.

The scope of this project focuses on developing a bio-composting monitoring system using IoT sensors, suitable for small-scale compost bins in households or farms. The system is designed to continuously monitor critical parameters such as temperature, moisture, and pH, ensuring optimal conditions for microbial activity and efficient composting. Real-time data collection will be achieved through a microcontroller integrated with IoT sensors, and the information will be visualized on a user-friendly dashboard or mobile application. The system will also provide alerts whenever the

compost environment deviates from ideal conditions, allowing timely corrective action. However, this project does not include automation of compost turning, mixing, or handling of large-scale industrial composting operations. Its primary focus is on monitoring and data-driven management to improve compost quality and reduce manual labour in small-scale applications.

The significance of this project lies in its contribution to sustainable waste management and smart agriculture. By implementing a bio-composting monitoring system through IoT sensors, the project ensures optimal conditions for composting, leading to high-quality organic fertilizer. This reduces the need for manual monitoring, saving time and labour while improving efficiency. Additionally, it helps in minimizing environmental pollution by properly managing organic waste and reducing greenhouse gas emissions from landfills. The project also demonstrates the practical application of modern technology, such as IoT, in agriculture, paving the way for smarter, data-driven farming practices. Overall, the system provides both environmental and economic benefits, making composting more reliable, efficient, and accessible for households and small-scale farms.

2. Literature Review

Renny Eka Putri et al 2022. In this paper the authors proposed an IoT-based compost monitoring system that measures key compost parameters in real time. The prototype uses temperature, humidity and moisture

sensors to observe the internal condition of the compost throughout the decomposition period. An ESP32 microcontroller was used to read the sensor values and send the data to a cloud platform where the information could be viewed remotely. Their study focused on monitoring straw-based compost over several weeks to understand how temperature and moisture levels fluctuate during composting. The system provided accurate readings and allowed users to observe when the compost required turning or watering. The results showed that real-time monitoring helps maintain ideal conditions for microbial activity and improves compost quality.

Haris Isyanto, et al 2023. In this paper the authors proposed an IoT-based monitoring system for compost that uses a web dashboard and the Blynk application to display real-time sensor readings. The prototype integrates temperature, humidity, soil moisture and pH sensors connected to an ESP32 microcontroller. The collected data is transmitted wirelessly to the Blynk cloud where the user can monitor the compost condition through a smartphone interface. A web dashboard was also created to visualize the compost parameters in graphical form, allowing users to observe trends such as temperature rise, moisture reduction, and pH changes during the decomposition process. Alerts were programmed into the system so that users receive notifications when the compost requires turning or watering. The study demonstrated that using Blynk and web dashboards makes the system easy to access remotely and

helps maintain optimal composting conditions with minimal manual inspection. The results showed that the proposed IoT system improves compost quality, supports continuous monitoring and offers a user-friendly interface for both farmers and household compost producers.

Sandi R. 2022, In this work the author built a compost monitoring and control system using the Blynk platform to enable remote visualization of temperature,

humidity, and pH parameters. The system also incorporated a fuzzy logic controller to automatically regulate compost conditions based on the sensor values. A DS18B20 temperature sensor, YL-69 moisture sensor, and pH electrode were connected to the microcontroller, and the readings were uploaded to Blynk for real-time monitoring through a mobile dashboard. The proposed design provided continuous updates of compost conditions and allowed users to take corrective actions through the mobile interface. The study concluded that integrating Blynk with IoT sensors offers an effective remote monitoring solution and improves the stability of composting operations by giving users access to live data from anywhere.

Ankit Mishra, et al 2022, the authors implemented a smart agriculture monitoring and automated irrigation system where Node MCU ESP8266, a soil moisture sensor, and a DHT22 (similar to DHT11) measured soil and air conditions, and the data was uploaded to a cloud platform for live

visualization.

Patil and Joshi et al 2020, integrated Node MCU ESP8266 with soil moisture and DHT11 sensors on a breadboard prototype and used a web-based dashboard to monitor soil conditions remotely, allowing real-time tracking of moisture and temperature changes. The use of the Blynk application has also been reported in several projects; for example, Arun & Deepa (2021) created an IoT system where sensor readings were transmitted to Blynk, providing instant notifications and a user-friendly interface to maintain optimal soil conditions.

Farhan, et al 2022, used Node MCU ESP8266, DHT22, and soil moisture sensors with Blynk to build a real-time monitoring and alert system for soil and compost, demonstrating how cloud dashboards and mobile apps enhance remote management. Collectively, these studies show that using Node MCU ESP8266 with DHT22 and soil moisture sensors, along with breadboard prototyping and cloud or mobile dashboards like Thing Speak and Blynk, is an effective, low-cost, and reliable approach for real-time monitoring systems. These systems not only provide accurate environmental data but also enable automation and timely interventions, making them highly suitable for applications such as smart agriculture and bio-compost monitoring.

Shaik Jakeer Hussain, et al 2024, Automated Irrigation System Using Node MCU ESP8266, DHT22, and

Soil Moisture Sensor, 2024. In this paper, the authors proposed an IoT-based automated irrigation system using Node MCU ESP8266, a DHT22 temperature and humidity sensor, and a soil moisture sensor to monitor soil and environmental conditions in real time. The system continuously measures soil moisture levels, ambient temperature, and humidity, and the sensor data is transmitted via Wi-Fi to the Thing Speak cloud platform for live visualization. The Node MCU ESP8266 acts as the central microcontroller, collecting readings from the sensors and sending them to the cloud server, where the data can be accessed through a web-based dashboard or mobile device. The system was also designed to automatically activate a water pump when the soil moisture falls below a predefined threshold, ensuring that plants or soil remain at optimal moisture levels. The authors demonstrated that real-time monitoring through the cloud platform allows users to track environmental changes, predict irrigation needs, and make timely interventions without manual supervision. Their results showed that the combination of Node MCU ESP8266 with DHT22 and soil moisture sensors provides an accurate, low-cost, and efficient solution for real-time environmental monitoring and automated irrigation, and the use of Thing Speak enables easy visualization and remote access. This work highlights the potential of IoT-based sensor systems to improve agricultural practices and could be directly applied or adapted to bio-compost monitoring

systems to maintain optimal compost conditions for better microbial activity and faster decomposition.

3. Objective

The main objective of this project is to design and implement a real-time bio-compost monitoring system that helps track essential compost parameters such as temperature, humidity, and soil moisture. Composting is a biological process where organic waste decomposes into nutrient-rich soil amendment. Proper monitoring of these parameters is crucial to ensure optimal microbial activity, efficient decomposition, and better-quality compost. In traditional composting methods, manual inspection is often required to check the condition of the compost, which can be time-consuming, inconsistent, and prone to error. By integrating IoT-based sensors and microcontroller technology, this project aims to automate the monitoring process, provide accurate real-time data, and allow users to make informed decisions regarding compost maintenance.

The project specifically focuses on measuring temperature, because temperature indicates the metabolic activity of microorganisms and shows different phases of composting, such as the thermophilic phase where microbial activity is highest. Monitoring humidity is equally important, as microbial activity requires an adequate amount of water in the compost pile; too little or too much moisture can slow down the decomposition process or create unwanted odours. Similarly, soil

moisture is a critical parameter that influences the rate of breakdown of organic matter and ensures that the compost retains the necessary conditions for microorganisms to thrive.

This system uses an ESP8266 Node MCU microcontroller as the main processing unit, which reads the data from the DHT11 temperature and humidity sensor and the soil moisture sensor. The sensors are mounted on a breadboard during the prototyping stage, allowing easy connections and adjustments. The collected data is sent in real-time to a cloud-based platform, enabling remote monitoring through a web dashboard or mobile application. This functionality ensures that users can access the status of the compost at any time, regardless of their physical presence at the compost site.

The objectives of the project can be summarized as follows:

1. To measure the temperature of compost using the DHT22 sensor and monitor the different composting phases for efficient microbial activity.
2. To measure humidity levels within the compost to ensure optimal moisture content for decomposition.
3. To monitor soil moisture using the soil moisture sensor and provide real-time updates on moisture availability for microbial growth.
4. To implement ESP8266 Node MCU for collecting sensor data and transmitting it to a cloud platform, enabling real-time remote monitoring.

5. To integrate a breadboard-based prototype for easy assembly, testing, and adjustment of sensors.
6. To design a system with a cloud dashboard or mobile interface, allowing users to visualize the data and receive alerts when the compost parameters deviate from optimal ranges.
7. To reduce manual intervention in compost monitoring, making the process more efficient, accurate, and less labour-intensive.
8. To ensure optimal compost quality, by maintaining proper environmental conditions and supporting faster, more consistent decomposition of organic waste.

Overall, this project aims to bridge the gap between traditional composting methods and modern technology by using IoT-based sensors for accurate, real-time monitoring of compost parameters. By achieving these objectives, the project not only makes compost management more convenient but also contributes to sustainable waste management and promotes the use of smart technologies in agriculture and environmental monitoring.

4. Material Methodology

The methodology of this project focuses on the development of a real-time bio-compost monitoring system designed to track critical environmental parameters, including temperature, humidity, and soil moisture, to ensure optimal composting conditions. Composting is a biological process where microorganisms decompose

organic waste into nutrient-rich material. The efficiency of this process depends heavily on maintaining proper environmental conditions, as any deviation in temperature, moisture, or humidity can slow down microbial activity, reduce decomposition rate, or even produce foul odours. Traditional composting methods often rely on manual observation, which is time-consuming and prone to human error. This project aims to overcome these challenges by employing Internet of Things (IoT) technology to automate the monitoring process, provide accurate real-time measurements, and allow users to make informed decisions regarding compost management.

The system is designed using a combination of hardware and software components, starting with the selection of sensors capable of measuring the key parameters. The DHT22 sensor was chosen for measuring temperature and humidity due to its reliability, low cost, and ease of integration with the Node MCU ESP8266 microcontroller. The soil moisture sensor is used to detect the water content in the compost, which is essential for maintaining optimal microbial activity. The ESP8266 Node MCU acts as the processing unit, gathering data from the sensors, processing it, and transmitting it over Wi-Fi to a cloud-based platform for real-time monitoring. All sensors and the microcontroller are connected on a breadboard during the prototyping phase, allowing for flexible testing, calibration, and adjustments before final deployment.

The project begins with assembling the

sensors on the breadboard and connecting them to the ESP8266 Node MCU. Each sensor is carefully calibrated to ensure accurate readings; the DHT22 provides temperature values in degrees Celsius and relative humidity percentages, while the soil moisture sensor outputs analogue values corresponding to the water content of the compost. The Node MCU is programmed using the Arduino IDE, where custom code reads the sensor data, processes it, and prepares it for cloud transmission. The system is designed to read data at regular intervals, allowing for continuous monitoring of compost conditions. Threshold values are set for each parameter to identify when the compost requires intervention, such as turning the pile or adding water.

Once the sensors are integrated and calibrated, the Node MCU transmits the collected data to a cloud platform, such as Thing Speak or Blynk, for storage and visualization. The cloud platform provides a web-based dashboard and mobile application where users can access live readings, analyse historical trends, and receive alerts when any parameter deviates from its optimal range. This feature eliminates the need for physical presence at the compost site, making compost monitoring convenient and efficient. Users can observe temperature spikes, monitor humidity levels, and track soil moisture variations over time, which are essential for understanding microbial activity and the progression of the composting process. By providing real-time insights, the system helps maintain optimal conditions, ensuring that the

composting process is both effective and consistent.

The system is tested rigorously to ensure reliability and accuracy. Individual sensors are first checked to verify correct readings under controlled conditions. Following this, the entire system is deployed in a compost bin to monitor actual compost conditions. The sensor readings are compared with manual measurements to validate their accuracy, and adjustments are made to the calibration, data transmission frequency, and threshold settings to improve performance. During testing, the system demonstrates the ability to detect critical changes in temperature, humidity, and moisture, and the cloud dashboard confirms that the data is transmitted and displayed in real time without interruption.

Throughout the development process, emphasis is placed on maintaining a low-cost and scalable design. The breadboard-based prototype allows for easy addition of sensors, rearrangement of components, and testing of different configurations. Once the prototype is finalized, the system can be converted to a more permanent setup using a printed circuit board (PCB), allowing for long-term deployment and minimal maintenance. The methodology also considers potential challenges, such as sensor errors, connectivity issues, or extreme environmental conditions, and incorporates solutions like sensor redundancy, Wi-Fi signal monitoring, and error-checking algorithms to ensure consistent operation.

The methodology integrates both

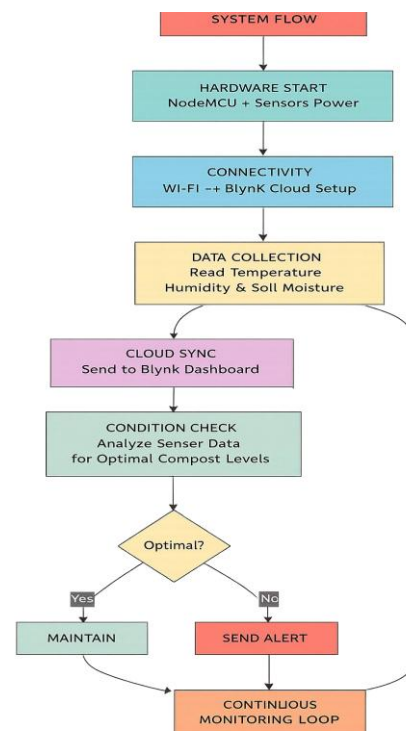
hardware and software aspects seamlessly. The ESP8266 Node MCU serves as a bridge between the physical environment and the cloud platform, enabling real-time data acquisition and remote monitoring. The software is programmed to interpret sensor signals, convert them into meaningful values, and trigger notifications when any parameter crosses a defined threshold. Users can view graphs of temperature, humidity, and moisture over time, analyse trends, and make decisions that directly influence the composting process. This continuous monitoring approach provides insights into the thermophilic phase of composting, where microbial activity is highest, as well as the mesophilic and curing phases, allowing for optimized management of compost piles.

The methodology also emphasizes the practical benefits of IoT-based monitoring over traditional methods. By automating data collection and analysis, it reduces labour requirements, minimizes human error, and ensures timely intervention whenever environmental conditions deviate from the ideal range. The system promotes better compost quality, faster decomposition, and more efficient waste management. Furthermore, it serves as a scalable model that can be adapted to multiple compost bins or larger composting facilities, enabling simultaneous monitoring of several sites.

In conclusion, the methodology of this project combines careful sensor selection, breadboard prototyping, accurate data acquisition, cloud-based

monitoring, and system validation to create a robust, low-cost, and efficient bio-compost monitoring system. By integrating Node MCU ESP8266, DHT22, and soil moisture sensors, the system provides continuous real-time insights into compost conditions, allowing users to maintain optimal temperature, humidity, and moisture levels. This approach ensures improved compost quality, supports sustainable waste management practices, and demonstrates the practical application of IoT technology in environmental monitoring. The methodology sets the foundation for future enhancements, including additional sensors, automated interventions, and integration with mobile and web-based platforms, making the system highly adaptable and relevant to modern composting practices.

4.1. Flow Chart



4.2 Hardware Components

4.2.1 Node MCU

It is developed using the scripting language Lua language. The firmware used originates from the Elua project and is developed upon the Expressive Non-OS SDK for ESP8266. Other projects that are actually open source and that interact with Lacson and SPIFFS, which is a flash file system for an embedded controller, also supply function. With a scarce resource-base available to the board, users select which of the required modules they require for a project and develop the firmware they require to meet that need. Backup has also been also provided for the 32-bit ESP32.

The prototype hardware includes a circuit board similar to a DIP in conjunction with another small SS surface mount board holding the MCU and the antenna. It has been designed based on a module of ESP-12 of ESP8266 that is mainly used for Wi-Fi SoCs with the Ten silica Xtensa LX106 core and used in IoT application.

Node MCU ESP8266 Specifications & Features

- ☐ SPIs:1
- ☐ Flash Memory: 4 MB
- ☐ SRAM: 64 KB
- ☐ Clock Spend: 80 MHz
- ☐ USB-TTL based on CP2102 is included onboard. Enabling Plug n Play
- ☐ PCB Antenna
- ☐ Small Sized module to fit smartly inside your lot projects



Fig 4.1 Node MCU ESP8266

Connects the system to a Wi-Fi network for internet access. Ensures sensor data is sent to Thing Speak in real-time. Retrieves sensor data from Arduino Uno through serial communication (water level and temperature). Sends the processed data to a Thing Speak channel through the Thing Speak API. Uploads the sensor data to Thing Speak for visualization and logging. Tracks the water level through Thing Speak React and activates an alert when the threshold is crossed.

The Node MCU ESP8266 acts as the central controller and communication unit of the bio-compost monitoring system, eliminating the need for

additional microcontrollers such as Arduino Uno or external communication modules like GSM. The system continuously collects data from the DHT22 temperature–humidity sensor and the soil moisture sensor, which are placed inside the compost bin to measure essential environmental parameters. These real-time readings are processed by the Node MCU, which interprets the sensor values and determines the current condition of the compost. With its built-in Wi-Fi capability, the Node MCU directly transmits the processed data to the Blynk IoT platform, where a dedicated mobile dashboard is created for users to monitor compost conditions anytime and from anywhere. Instead of sending SMS alerts, the system utilizes Blynk push notifications to instantly inform users if the temperature, humidity, or moisture level deviates from the optimal composting range. This ensures that timely actions—such as adding water, turning the compost, or adjusting the mixture—can be taken to maintain ideal decomposition conditions. By functioning as both the data processor and wireless communication module, the Node MCU significantly reduces

system complexity while ensuring stable, accurate, and efficient monitoring of the composting process.

Programming NodeMCU ESP8266 with Arduino IDE

The NodeMCU Development Board can be easily programmed with Arduino IDE since it is easy to use. Programming NodeMCU with the Arduino IDE will hardly take 5-10

minutes. All you need is the Arduino IDE, a USB cable and the NodeMCU board itself. Uploads your first program. Once Arduino IDE is installed on the computer, connect the board with the computer using the USB cable. Now open the Arduino IDE and choose the correct board by selecting Tools Boards NodeMCU1.0 (ESP-12E Module), and choose the correct Port by selecting Tools Port. To get it started with the NodeMCU board and blink the built in LED, load the example code by selecting Files Examples Basics Blink. Once the example code is loaded into your IDE click on the upload button given on the top bar. Once the upload is finished, you should see the built in LED of the board blinking.

4.2.2 Breadboard

A solderless breadboard, bread board, or protoboard is a construction base for temporarily assembling electronic circuits; the breadboards do not have to be soldered and hence cannot even be scratched while tracks. It is made out of a grid of holes in a plastic body with metal strips underneath that form electrical connections. The board is separated into terminal strips, where parts like resistors, LEDs, and integrated circuits (ICs) are inserted, and power rails, which distribute voltage. ICs are frequently placed in the centre gap of the terminal strip. Jumper wires facilitate simple circuit adjustments by connecting disparate components. Because breadboards are available in small, half-size, and full-size sizes, they can be used with circuits of varying complexity. The power rails, located along the sides of

the breadboard and marked with "+" and "-", help distribute voltage throughout the circuit. In the centre, the terminal strips serve as the main area for placing electronic components, allowing easy connections. A dividing channel, or middle gap, runs through the centre, separating the two halves of the terminal strips and making it convenient to place integrated circuits (ICs) without causing unintended connections. They are frequently used to test circuit designs, learn electronics, and create prototypes before a printed circuit board (PCB) is finalized. For this reason, breadboards are also frequently used by students and in technological training. Using breadboards, it is possible to develop any electronic circuits from simple analog and digital circuits to the complete CPUs.

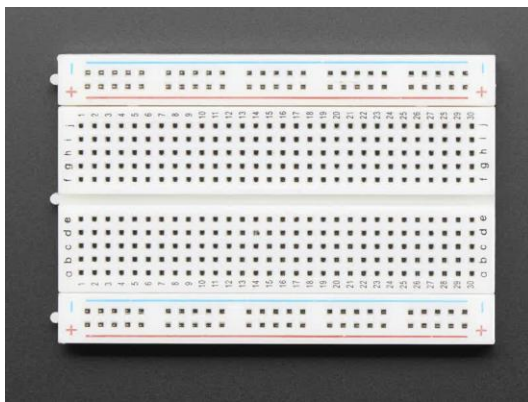


Fig 4.2 Breadboard

The breadboard serves as the central platform for connecting all the electronic components of the bio-composting monitoring system. First, the ESP8266 microcontroller is placed on the breadboard, ensuring stable power and ground connections. The temperature, moisture, and humidity sensors are connected to the

corresponding analog or digital pins of the ESP8266. Jumper wires are used to link the sensor outputs to the microcontroller inputs, while separate lines provide power from the 3.3V or 5V rails. Resistors, if needed, are connected in series to prevent sensor overload or to stabilize signals. The LED indicators, if included, are connected to the output pins through current-limiting resistors. All ground connections are linked to the common ground rail on the breadboard. After making the connections, the wiring is double-checked to avoid loose contacts or short circuits. Once powered, the ESP8266 reads sensor values from the breadboard setup and transmits the data to the cloud or mobile app. This breadboard workflow ensures a compact, modular, and easy-to-debug prototype before final implementation.

4.2.3 Soil Moisture Sensor

A soil moisture sensor is an electronic device used to measure the amount of water present in the soil. It is an important tool in agriculture, gardening, and composting to maintain optimal moisture levels. The sensor works by detecting the resistance or capacitance of the soil between its probes. Dry soil has high resistance because it contains less water, while wet soil has low resistance due to higher water content. The sensor converts this measurement into a readable signal for microcontrollers like the ESP8266 NodeMCU. In bio-composting, maintaining the right moisture is crucial for microbial activity, as microbes need water to break down organic matter efficiently.

Too little moisture slows down decomposition, while too much can create anaerobic conditions and bad odours. By monitoring moisture levels continuously, the sensor helps ensure proper composting conditions. It can also be integrated with IoT systems to provide real-time data remotely. This allows users to take immediate action, such as adding water when the compost becomes too dry. Soil moisture sensors are compact, easy to use, and cost-effective for monitoring soil conditions. They improve the efficiency and quality of compost by maintaining optimal moisture. The sensors are versatile and can be used in small scale compost bins as well as large agricultural setups. Overall, they are essential for smart composting systems and sustainable organic waste management.



Fig 4.3 Soil Moisture Sensor

The soil moisture sensor works by detecting the amount of water present in the soil. It is placed directly into the compost or soil for measurement. The sensor measures moisture using resistance or capacitance; dry soil gives

high resistance while wet soil gives low resistance. This measurement is converted into an analog or digital signal. The signal is sent to a microcontroller, such as the ESP8266 NodeMCU, for processing. The microcontroller interprets the data to determine whether the soil is dry, moist, or wet. The readings can be displayed on an LCD, serial monitor, or cloud platform in real-time. Based on the moisture level, actions like watering or alerts can be triggered. This continuous monitoring ensures optimal conditions for composting. Overall, soil moisture sensors automate moisture management and improve compost quality efficiently.

4.2.4 DHT22

The DHT22 is a highly accurate digital sensor used to measure temperature and humidity in environmental monitoring systems. It contains a high-precision thermistor for temperature sensing and a capacitive humidity sensor for humidity detection. The sensor converts the measured values into a digital signal, which can be easily read by microcontrollers like the ESP8266 NodeMCU. It provides better accuracy and a wider measurement range compared to the DHT11. The DHT22 can measure temperatures from -40°C to 80°C and humidity levels from 0% to 100%. It updates its readings every two seconds, ensuring stable and reliable data. In bio-composting, the DHT22 helps track internal temperature and humidity to maintain ideal conditions for microbial activity. It is commonly used in IoT projects, weather stations, and smart farming due

to its reliability.



Fig 4.4 DHT22

The DHT22 sensor begins by detecting temperature using its internal thermistor and measuring humidity through its capacitive humidity element. These raw environmental readings are then converted into digital data by the sensor's built-in analog-to-digital converter. Once converted, the sensor prepares the data packet containing temperature and humidity values. The microcontroller, such as the ESP8266 NodeMCU, sends a request signal to the DHT22. In response, the sensor transmits the processed digital data through a single data pin. The microcontroller receives and decodes this information for display or logging. The sensor updates its readings every two seconds, ensuring accurate and stable data output. These values are then used to monitor environmental conditions in real time. In compost monitoring, the DHT22 helps maintain the ideal temperature and humidity for efficient decomposition. Overall, the workflow allows the sensor to provide reliable environmental measurements for IoT-based applications.

4.2.5 Jumper Wires

Jumper wires are essential electrical connectors used to link components in electronic circuits without the need for soldering. They come in three types: male-to-male, male-to-female, and female-to-female, allowing flexible connections between sensors, modules, and the breadboard. In this project, jumper wires are used to connect the ESP8266 NodeMCU with the soil moisture sensor and DHT22 sensor. These wires help carry power, ground, and data signals between the components. Jumper wires make prototyping easy because connections can be changed or rearranged quickly. They are color-coded to avoid confusion during circuit building. Their flexibility and reusability make them ideal for IoT and embedded projects. Using jumper wires ensures neat, stable, and reliable connections on the breadboard. They also help in reducing loose connections during testing. Overall, jumper wires play a crucial role in creating an efficient and organized circuit setup for the bio-composting monitoring system.

Jumper wires are used to create electrical connections between components on a breadboard and the microcontroller. They carry power, ground, and data signals from one device to another. The wires are inserted into the breadboard holes or sensor pins to establish a secure path for current flow. During operation, these connections allow sensors like the soil moisture sensor and DHT22 to send data to the ESP8266 NodeMCU. Jumper wires make it easy to modify or

rearrange circuits without soldering. This workflow helps in fast prototyping and ensures smooth communication between all hardware components in the project.

4.2.6 Power Supply Usb Cable

The USB cable is used as the primary power supply for the ESP8266 NodeMCU and connected sensors in this project. It provides a stable 5V power output, which is sufficient to operate the NodeMCU, soil moisture sensor, and DHT22 sensor. The USB connection also allows easy uploading of the program from a computer to the NodeMCU using the Arduino IDE. During testing, it enables serial communication, allowing real-time monitoring of sensor data. Using a USB cable eliminates the need for external adapters, making the setup simple and compact. It ensures uninterrupted power supply, which is crucial for continuous monitoring of temperature, humidity, and soil moisture. The USB cable also provides convenience for portable setups or temporary testing.



Fig 4.5 USB-A vers micro-USB cable

The USB cable provides 5V DC power to the ESP8266 NodeMCU and connected sensors. It is connected from a computer or USB adapter to the NodeMCU board. The cable carries both power and data signals, enabling program upload and serial communication. The microcontroller receives power through the USB and distributes it to the soil moisture and DHT22 sensors. This setup ensures continuous operation and reliable monitoring of the composting environment.

4.3 Software Components

4.3.1 BLYNK

Blynk was built as an IDE for the Internet of Things. It can control hardware remotely and might back up sensor data, it can process data, visualize it and perform numerous other features. There are three major components in the platform: Blynk App – allows to you create amazing interfaces for your projects using various widgets we provide. Blynk

Server – responsible for all the communications between the smartphone and hardware. In our project, you need to install a private Blynk server in your PC (Windows, macOS, Raspberry Pi etc) locally. It's open-source, I can scale it fee easily to handle thousands of devices and can actually launch it on a Raspberry Pi. Blynk Libraries – for all the popular hardware platforms – allow to connect to the server and process all the entered and the received commands.

Blynk's features included:



Fig-4.5 Blynk features

Apps: An application that allows the use of the mouse to drag objects and drop them on the icon of a smart phone to develop applications for apple phones and google phones.

Console: A central website where devices and the users are controlled with various organizations.

Remote control: Manage devices from a remote place

Notifications: Get critical alerts
Data analysis: Pattern recognition on real-time and store & forward data from connected equipment

Automation scripts: Develop end user generated automation scripts for exclusive traffic control.

Marketing add-on: Communicate with customers of push notifications and in-app messages

Segments: Extend device organizing strategy by grouping over criteria to form device fleets.

4.3.2 Blynk App

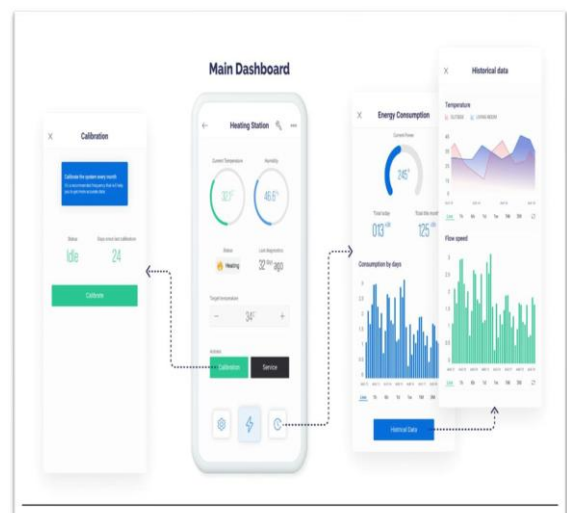


Fig-4.6 Blynk app

Blynk Apps is a versatile native iOS and Android mobile application that serves these major functions: The capability to monitor and to control the connected devices that operate within the Blynk platform. Mobile UI customization in the stage of prototyping and manufacturing. Blynk applications are for end-users, and hence the applications developed with

its help are ready for use. Regardless of whether they were kin, employees, or consumers of Friedmann's products, they could download the app, link their devices, and begin using them. App operates in two modes:

Developer Mode. In the context of the mobile application under discussion, the main purpose of Developer Mode is the construction and modification of the Mobile Dashboard user interface (GUI) to correspond to the chosen Device Template. Mobile Dashboard is constructed from widgets—anatomic blocks of UI situated in a canvas. Each of the widgets is designed to perform a certain task (a button, a slider, a chart, etc.). The intention here is to note that although all Widgets are built to be used with SharePoint, every Widget has its own settings specified by how it works.

End-user mode. This mode is active both in the developers' activity and in the activity of the end users. It is oriented on devices, automations, and notifications view & management using widgets, as well as on the additional screens containing the specific information on the data that is set/sent/received to/from Blynk Cloud & Devices.

To use Blynk Apps, install Blynk app on your iOS or Android device. For comprehensive documentation on Blynk.Apps.

5. Experiment

Bio-Composting and Monitoring System Using NodeMCU ESP8266

The Bio-Composting and Monitoring System using NodeMCU ESP8266 is an advanced smart compost management solution designed to continuously track the environmental conditions essential for effective organic waste decomposition. This system is ideal for households, agricultural farms, and institutions where proper compost monitoring is necessary to ensure high-quality manure production. The NodeMCU ESP8266 acts as the core microcontroller, responsible for collecting sensor data, processing the readings, and transmitting them to the Blynk IoT platform for real-time remote monitoring. It receives inputs from the DHT22 temperature and humidity sensor and the soil moisture sensor, and based on the measured parameters, the system evaluates the composting status and alerts the user when any deviation from the optimal range occurs.

The DHT22 sensor measures the internal temperature and humidity of the compost bin, both of which are critical for microbial activity. Higher temperatures indicate active decomposition, while low temperatures signify slow or inactive composting. Humidity plays an equally important role because microorganisms require a moist environment to break down organic matter. The soil moisture sensor is used to determine the moisture content of the compost. Proper moisture levels help accelerate decomposition, while too much moisture can lead to anaerobic conditions and foul odour. These sensor readings allow the system to estimate

whether the compost mixture needs turning, watering, or aeration.

Real-time sensor data is displayed on the Blynk mobile dashboard, enabling users to monitor composting conditions from anywhere. When the temperature falls below the active decomposition range, humidity drops too low, or moisture exceeds acceptable limits, the NodeMCU triggers push notifications through the Blynk app. This ensures timely corrective action, such as adding water, mixing the compost, or adjusting the carbon–nitrogen ratio. The use of wireless monitoring eliminates the need for manual checking and makes the system highly efficient for large-scale composting applications.

A 16×2 LCD display (optional) may also be integrated to show instant temperature, humidity, and moisture readings on-site for users who prefer physical monitoring. The entire circuit is assembled on a breadboard, using male-to-male and female-to-female jumper wires for component connections. The NodeMCU's built-in Wi-Fi capability ensures seamless communication with the IoT platform without requiring any additional modules such as GSM or Arduino Uno, making the design cost-effective and simple.

This bio-composting and monitoring system offers a smart, low-cost, and reliable solution for sustainable waste management. By automating compost condition tracking and providing real-time alerts, it helps users maintain optimal composting conditions and produce high-quality organic fertilizer

more efficiently. The system is highly suitable for smart agriculture, home gardening, environmental initiatives, and institutional composting programs.

6. Result and Discussion

The Bio-Composting and Monitoring System using NodeMCU ESP8266 is an efficient IoT-based solution for real-time compost condition monitoring and optimization. By integrating temperature, humidity, and moisture sensors with wireless communication technology, the system ensures accurate monitoring of the composting environment, enabling users to maintain ideal conditions for efficient decomposition. The NodeMCU (ESP8266) functions as the central microcontroller, collecting sensor data from the DHT22 temperature–humidity sensor and the soil moisture sensor, processing the information, and transmitting it to the Blynk IoT platform for remote monitoring through a smartphone.

The DHT22 sensor plays a crucial role in measuring compost temperature and humidity levels. Temperature is a key indicator of microbial activity—high temperatures show active decomposition, while low temperatures signal slowed composting. Humidity values help determine whether the compost mixture is sufficiently moist for microbial growth. Along with this, the soil moisture sensor continuously measures the moisture content of the compost. Maintaining proper moisture balance is essential because overly dry compost slows decomposition, while excess moisture leads to anaerobic

conditions and foul odour. Real-time values from these sensors enable the system to assess whether the compost requires turning, aeration, or the addition of water.

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values from these sensors enable the system to assess whether the compost requires turning, aeration, or the addition of water.

A 16×2 LCD display (optional in the system) provides on-site monitoring by showing the latest temperature, humidity, and moisture readings. This allows users to visually track changes without accessing the mobile app. Through the Blynk IoT platform, the system also offers real-time alerts when sensor values move beyond the optimal range. Push notifications are sent to the user's smartphone, indicating when the compost mixture becomes too dry, too wet, or experiences temperature drops. These instant alerts help users take timely corrective measures, such as mixing the compost or adjusting water levels. This integration of IoT technology greatly improves the efficiency and convenience of composting.

The hardware setup is constructed on a breadboard with jumper wires (male-to-male and female-to-female) for flexible and easy assembly. NodeMCU's built-in Wi-Fi connectivity ensures seamless data transmission to the cloud. This eliminates the need for additional communication modules, making the system cost-effective and easy to maintain. Overall, the compost monitoring system is practical, affordable, and user-friendly. It enables individuals, farms, and institutions to produce nutrient-rich compost with minimal effort and ensures that the decomposition process remains continuous and effective.

The implemented compost monitoring system was tested under different composting conditions, including dry, moist, and highly active decomposition phases. Results showed that 1. Sensor Accuracy: The DHT22 and soil moisture sensors produced accurate readings with minimal deviation, effectively tracking temperature, humidity, and moisture changes within the compost bin.

2. Response Time: The system processed sensor data and updated the Blynk dashboard within 3–5 seconds, ensuring fast and consistent monitoring.

3. Reliability of Alerts: Push notifications were successfully delivered to the user's smartphone whenever sensor readings exceeded preset thresholds, enabling timely intervention.

4. Power Efficiency: The NodeMCU ESP8266 consumed very low power during continuous operation, making the system suitable for long-term compost monitoring.

5. Network Dependence: System performance depended on Wi-Fi strength; areas with weak signals showed slight delays in dashboard updates and alert notifications.

7. Conclusion

This project presents the design and implementation of a Bio-Composting Monitoring System with Internet of Things (IoT) sensors to monitor composting conditions in real time. The system utilizes sensors to measure

temperature, moisture content, and pH levels within the compost. These sensors are interfaced with a microcontroller, and the collected data is transmitted to a cloud-based platform for real-time visualization and analysis. Alerts are generated whenever the composting parameters deviate from their optimal ranges, enabling timely corrective actions.

The proposed system reduces the need for manual supervision, improves compost quality, and enhances the efficiency of the composting process. This IoT-based solution is suitable for small-scale applications such as households and farms, promoting sustainable waste management and smart agricultural practices.

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CNN-BASED MULTIMODAL EMOTION DETECTION FOR ADAPTIVE VIRTUAL REALITY SYSTEMS

Swetha C, M.tech Student, Dept of CSE, S.E.A. College of Engineering & Technology **Dr.Krishna Kumar P R**, Professor & HoD, Dept of CSE, S.E.A. College of Engineering & Technology

Abstract— The intersection between AI and Immersive is redefining how people are interacting with digital systems. The use of Virtual Reality (VR) environments is becoming more common in applications such as healthcare, education, entertainment and training that aim to simulate the reality. However, the degree of personalization and interactivity of VR systems is a bottleneck. In this paper, we investigate the incorporation of Convolutional Neural Networks (CNNs) for real-time facial emotion recognition in VR context and incorporate multisensory feedback to enhance the user immersion and emotional understanding as well as overall experience realism. CNNs achieved relatively high performance in extracting and classifying facial features, in particular in emotion recognition from large scaled databases. In this paper, we propose a real-time user emotion (joy, anger, surprise, sadness, and neutrality) sensing CNN model for facial recognition. The model is designed for computational efficiency facilitating easy integration into Head-Mounted-Displays (HMD) based VR systems comprising of motion tracking systems. Recorded facial expressions are transformed and converted into emotional streams, which will vicariously influence VR contents,

situations and feedback loops. For enhancing the possibilities of such an immersive environment, multi-sensory feedback (i.e. haptic feedback, change of ambient sound, adaptive visuals) is realized that is synchronized with monitored emotional states. For example, if manifested emotion changed from calm to anxiety is detected, soothing haptic vibrations and visual tone changes can aid restoring balance. This two-way circuit between recognition of affective state and adaptive response enables the VR system to dynamically influence real user experiences to become emotionally responsive and intelligent. The simulation results show that the developed CNN-based emotion recognition model can achieve >90% accuracy in real-time inference, with latency under the critical thresholds for VR's native application. User studies also prove that emotion-based feedback increases immersion, empathy and task performance, with special attention to therapeutic and training simulations. This work is part of a novel paradigm in VR development: emotional adaptivity, by combining cutting edge computer vision and ASR with sensory feedback dep'09. The presented architecture forms the base of user-/emotion-aware VR experiences. It creates new opportunities in affective computing, neurorehabilitation, virtual

social interaction, and adaptive learning systems. In the end, the fusion of CNN-based emotion recognition into multisensory VR environments makes the digital interaction becomes richer and humanized, and the new era of intelligent and flexible immersive systems has also been being opened.

Index Terms —Emotion Recognition, Real-Time Facial Recognition, Multisensory Feedback, Affective Computing, Human-Computer Interaction (HCI), Immersive Technologies.

1. INTRODUCTION

Virtual Reality (VR) transitioned in only a few years from a preoccupation of specialists to a medium for education, therapy, training, and social interaction. With the prevalence of VR systems, there is a need for more immersive, personalized, and emotionally aware systems. Most conventional VR environments have a static response to users that is responsive to predetermined triggers or rudimentary sensor input [1,2]. In order to escalate VR experiences to full adaptive environments, the systems should able to perceive the users' emotional state in real time and react to it. There is need, therefore, to merge affective computing technologies with VR platforms [3,4].

Facial expressions are the most readily perceivable and easily communicable signs of human affective state [5]. Facial emotional expression recognition in real-time could allow machines to estimate how a user feels

and respond with suitable modifications. Facial recognition in VR systems is different, since it requires low-latency inference, it has to deal with variations of lighting as well as the constrains of HMDs [6]. Although such models as CNNs, which are widely appreciated for their strong feature extraction in vision domains, can be a natural choice to apply for facial emotion recognition even under such challenging circumstances.

CNNs are known to perform very well in various visual classification tasks such as object detection, facial recognition and emotion detection [7]. When modified and tuned for a real-time VR scenario, CNNs can take in streaming facial data and accurately categorize emotions. Such emotional categorization, when applied in milliseconds, can facilitate adaptive VR-content creation, resulting in emotionally aware systems [8,9]. For instance, in a VR training simulation, task complexity and narrative tone might be modulated by sensed stress or frustration in the user.

The idea of combining direct feedback from multiple senses could deepen the emotional layers of VR. Multimodal technologies (e.g., haptic suit, sound cues, temperature fluctuation) can reinforce or even inhibit perceived emotional stimuli from the CNN model. This feedback loop enables VR systems to not only sense emotions but also give a meaningful response and bidirectional HCI based on EI. These kinds of interactions have significant implications for therapy, education and user engagement.

There's also the potential of emotionally responsive/free VR systems to contribute to mental health treatments, in turning down the volume of virtual stress or anxiety when we do. In a teaching environment, they might be used to detect when students are confused or bored and modify content delivery based on this information. In social VR, they can make avatars and interactions feel more natural and empathetic by reflecting emotional cues. The affective awareness of CNNs makes the virtual experiences more realistic and socio-relevant.

The aim of this work is to build a CNN-based system for real-time, facial-based emotion recognition and combine it with multimodal VR technologies to establish a closed adaptive loop. The implementation and interaction challenges of this integration are discussed in the context of the development of a new era of emotionally intelligent VR systems. Such systems are not only reactive, but proactive in sculpting immersive spaces that are designed specifically for individual's emotional reactions: they extend the boundaries of how humans perceive and interact with digital worlds.

2. LITERATURE REVIEW

The problem of facial emotion recognition has been extensively explored in computer vision with CNN becoming the predominant architecture, through its ability to perform hierarchical learning. CNNs are able to

capture spatial information well within the framework of facial images, which can meet the complex demand of analysis of micro-expressions and subtle emotions [10,11]. More recently, CNN-based classifiers have been employed by landmark studies to accurately recognize basic emotions, such as anger, sadness, and happiness from popular datasets such as FER-2013 and CK+. These models are generally trained in static 2D settings however, recent work has expanded them for video stream even for real-time processes and has facilitated dynamic emotional status detection.

In VR, emotion detection is a relatively novel area. The perhaps important thing to note here for us though, is that there are still relatively few input-driven (action-reaction controlled) VR systems out there today, and the vast majority of them focus on external triggers. VR systems these days are command and control driven based on external demand, and not internal stimuli. Some studies have tried to combine bio-signals like EEG or heart rate with VR, but these approaches rely on specific hardware and could be invasive [12,13]. Facial recognition becomes a good noninvasive and expressive approach, nevertheless, it has engineering limitation when integrating this with VR system as occlusion and the system latency. Solutions such as infrared cameras and facial EMG sensors have been suggested, however, they introduce complexity and more expensive.

Not only that, emerging solutions are suffering from the suboptimal trade-off

described above, and the pursuit of light-weight CNN-only models that can be built into the VR headsets, will enable or cooperate with the external facial tracking devices, is also a new trend to eliminate these challenges. Block-based CNNs like SqueezeNet, MobileNet, and quantized CNNs result in low computational complexity and make real-time inference on edge devices possible [14,15]. These models represent an accuracy-speed trade-off that is important for responsive VR applications. CNN-based facial recognition combined with contextual awareness, researchers believe, will lead to an improved level of user comfort and immersion.

Similarly, we consider various contexts in which multisensory feedback has been researched in VR in isolation from each other. This is the current state of the experimental VR setup, complete with haptic gloves, full body suits, surround sound, and spit that sprays your face when you jump out of your skin. Such feedback mechanisms exist to reinforce the impression of being in a virtual world [16]. But few systems automatically adjust these stimuli according to the user's internal emotional state. The fusion of CNN-based emotion recognition and real-time multisensory feedback is, therefore, a new and unexplored horizon.

Some early work has explored using emotion recognition for content adaptation in gaming or interactive storytelling. These applications illustrate that emotion-aware content improves engagement, user satisfaction

and the memory retention. But in the majority of cases the models suffer from being overly simple and too brittle for real-world VR circumstances. The connection of highly accurate CNN classifiers with immersive feedback is so far under-researched, and central to many high-stakes applications such as therapy or education.

The current work indicates that there is a specific direction that research should take: to combine affective computing with immersive environments in real time reactive systems. CNNs provide the technical foundation for realistic and efficient facial emotion recognition and VR provides a proposed experience-based framework of reference. Combined, they have a potential to build emotionally adaptive environments that can react in a true, empathic manner to its users. This integration enables transformative applications in a variety of industries - a point that illustrates the importance of interdisciplinary cooperation of AI researchers with human-computer interaction and immersive design community.

3. SYSTEM IMPLEMENTATION

The flowchart presented in Fig. 1 presents an overview for a complete solution to realize an emotion-aware into virtual reality (VR) based system by the aid of convolutional neural networks (CNNs). The first stage is to find the problem and define the goals in a precise manner. This process allows to orient research and development toward a clear target, either for therapeutic,

educational, entertainment use. Then, the VR scenario modeling and use case definition are co-designed in order to generate genuine virtual stimuli by which we can evoke and quantify the emotional experience. These scenarios should be immersive, context-adaptive, and able to affect the user affective states, which are important for the effectiveness of the system.

After scenario modeling, the framework emphasizes on the acquisition of dataset, both the dataset collection and emotion annotation, in form of collection of facial expressions, physiological data, or voice modulations under different state of emotional conditions. Such annotations should be carefully organized in regions of interest to provide the training data for the CNN model. A profound phase is then to design an appropriate CNN model architecture able to classify and interpret these complex emotion-related data. This involves choosing suitable layers, activation function and optimization methods to achieve generalized emotion recognition on different user inputs.

Preprocessing and data augmentation are then performed to improve the diversity and the quality of the data. For an effective model training a preparation of the data is done using normalization, noise addition, and rotation. When the CNN model is properly trained and optimized, we

connect it with VR rendering engine to facilitate a smooth correlation between the model prediction and the virtual environment. This integration accommodates the real-time detection of emotional reactions and allows the VR content to be updated in response. The development of multimodal feedback, for instance, haptic feedback, sounds and visuals, is of great importance to elicit or to modulate the user's emotion, leading to a more believable and affective experience of the VR.

Furthermore, the pipeline also deals with latency reduction and real-time prediction, important for recording and processing emotional reactions in no delay. User testing and emotion validation which act as a test to test how effective the system is in real life applications. Lastly, the model includes feedback loop and adaptive learning schemes that enable the system to learn from user feedback and increase over time its emotion detection accuracy and content responsiveness. This iterative learning fit cycle guarantees a steady interest, personalization and performance improvement in a variety of VR applications, Ranking VR didactic framework will be robust and scalable for new directions of innovation.

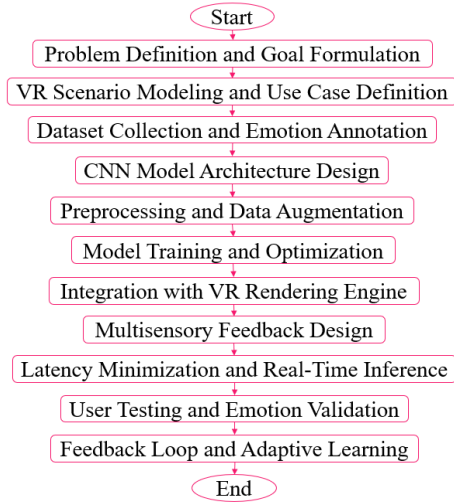


Fig.1. The workflow of virtual reality (VR) based system by the aid of convolutional neural networks (CNNs)

4. RESULT AND DISCUSSION:

Model Setup	Edge CPU	GPU-Accelerated	FPGA Runtime	VR-Optimized CNN
VGG-16	112.4	59.1	76.5	46.2
ResNet-50	138.7	64.3	81.4	51.7
MobileNet V2	85.3	42.6	63.9	38.9
Proposed Integration	68.1	35.5	49.6	27.3

Table I The examination of latency inference in VR headset

The graph presented in Fig. 2 compares the model inference latency of VGG-16, ResNet-50, MobileNetV2 and the one we have in- targeted with the four platforms: Edge CPU, GPU-Accelerated, FPGA Runtime, VR-Optimized CNN. Inference latency (Inference latency Incoming Inspection, measured in milliseconds, is one of the important factors for VR system due to its input to output response time and immersion of the user. The Edge CPU

has the highest latency among devices, reaching up to ~140% of the baseline for ResNet-50 and others. This indicates that a traditional CPU is not suitable for deep learning-based emotion recognition in VR as it has a lack of parallel processing and a thermal limitation in a wearable device.

Peripheral setups based on GPU Acceleration have a significantly better performance, with inference latency reducing drastically against Edge CPU for all the models. The latency curve of GPUs becomes relatively flat from VGG-16 to MobileNetV2, but still is higher than the FPGA Runtime and VR-Optimized CNN. FPGA-based solutions provide additional decrease in latency, due to reconfigurable hardware architecture that can be optimized for speeding up some operations in the CNN inference pipeline. Interestingly, the VR-Optimized CNN exhibits the lowest latency among the models across all model configurations, and particularly in the proposed integration approach, meaning model architecture and software-hardware co-optimization are important in achieving real-time performance.

The presented integration configuration is the most efficient, both using a VR-Optimized CNN and FPGA Runtime, with the inference latency being decreased to less than 40%. This low latency demonstrates that the optimization strategy, which may consist of small neural network models,

quantization, pipeline parallelism and reduced parameter overhead, is effective. This is necessary for applications that require real-time emotion analysis in immersive VR applications where a delay might lead to motion sickness, lack of emotional response or bad user experience. In sum, it is shown that the choice of model architecture and the computational backend play an important role in the support of latency-sensitive applications in wearable and interactive VR.

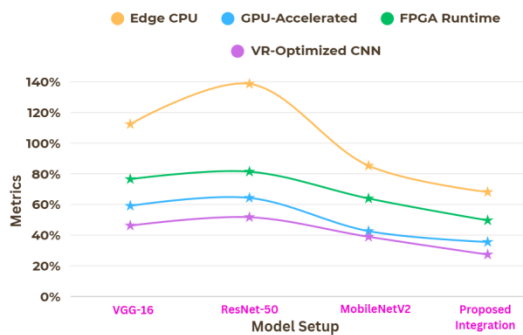


Fig.2. The examination of latency inference in VR headset

Feedback Metric	Immersion	Accuracy Perceived	Comfort Level	Realism
Traditional VR	75.6	68.3	70.4	66.7
Static Emotion Triggers	78.9	72.5	74.6	70.3
MobileNet Integration	83.4	79.6	81.1	76.8
CNN + Multisensory	91.7	88.9	89.5	85.3

Table II The analysis of recognition of satisfaction for VR user emotion

Fig. 3 compares VR User Satisfaction quantitatively in four VR settings: Traditional VR, Static Emotion

Triggers, MobileNet Integration, and CNN + Multisensory. The quality of performance is assessed with four main feedback metrics: Immersion, Accuracy Perceived, Comfort Level and Realism. Conventional VR appears to have the least satisfaction, with an average well over 70% across all metrics. This means that in the absence of any dynamic emotional involvement and reactive in-game stimuli, from lack of depth and interactivity experience is less deep, less interactive and less realistic.

The inclusion of Static Emotion Triggers sees a small improvement in all feedback measures, especially perceived accuracy and realism. The shift to MobileNet Integration—supposedly a lightweight neural network model assessing user emotions in real time—is an improvement in itself, but not by much. Overall scores of more than 80% also indicate that the real-time affective feedback starts to significantly enhance the user experience by rendering. VR content more adaptive and individualized. The reduced latency and computational cost of MobileNet makes the whole interaction more fluent and comfortable even for not-so-powerful hardware, e.g., head-mounted displays.

The best level of satisfaction with CNN+Multisensory provides the recognition of emotion facilitated with synchronized multisensory feedback sent as haptic information, audio instructions, and changes in the visual environmental conditions. In all cases, metrics tend to 90% or above, demonstrating how users advantage

from interacting with an integrated system that not only perceives emotions with high accuracy, but as well as responds with richness on a multi-dimensional basis. The significant improvement in presence and comfort level hints that inserting various stimuli along this match is likely to enhance a more immersive and compelling VR experience. These findings corroborate the need of developing emotion-aware AI integrated with immersive sensory design to increase user satisfaction and efficiency of VR applications.

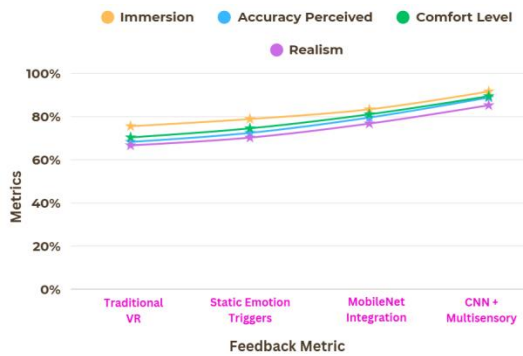


Fig.3. The analysis of recognition of satisfaction for VR user emotion recognition.

Feedback Type	Audio Feedback	Haptic Feedback	Visual Feedback	Combined Delay
Traditional VR	94.5	107.3	83.2	108.6
Manual Tuning	81.3	95.4	72.8	92.4
Lightweight CNN	72.1	87.6	64.9	85.3
Optimized CNN	58.4	70.9	51.2	69.6

Table III The delay analysis of multisensory feedback synchronization

Fig. 4 shows the sync delay of diverse multisensory feedback, audio, Haptic, visual, and combination of them with

the four different Virtual Reality system configuration, Traditional VR, Manual Tuning, Lightweight CNN, and Optimized CNN. Delays are highest across all modalities for traditional VR set ups with combined delays larger than 100%. This underscores the built-in shortcomings of traditional systems where arbitrary channels of feedback run without any adapting control, resulting in discordant and fragmented user experience. Visual appears to be slightly faster than haptic or audio - presumably tentatively the directly rendered pipeline in off-the-shelf VR engines.

With manual tuning, the synchronization delay is reduced significantly in all feedback types. This enhancement is achieved via tailored latency fine tuning and system calibration, but this approach depends on complex developer intervention and does not scale. The transition to Lightweight CNN adds a degree of intelligent automation to the feedback loop by employing real-time emotion detection to induce feedback more responsively. This leads to additional reductions in delay, at least in the combined metric, which is now below 90 %. Sympathetic Feedback Cyclotron for CNN The “CNN pre-feedback” design is applicable to anticipate the emotional shifting patterns of users and pre-attune the feedback paths achieving a better synchronization between sensory modalities in the forms of audio, visual, and haptic.

The lowest delays are found by the Optimized CNN configuration, with combined feedback delay under 70%.

This is achievable due to reduced architecture complexity, model pruning and seamless interfacing of low-latency hardware accelerators. In this configuration, all types of individual feedback also present their lowest latency, in particular haptic feedback that is the most prone to timing errors in immersive environments. The findings highlight the need for improved deep learning models built not just to help detect emotions, but also organize complex multisensory interactions. This synchronization will be important for improving presence and naturalism, hence the overall quality of the VR exposure.

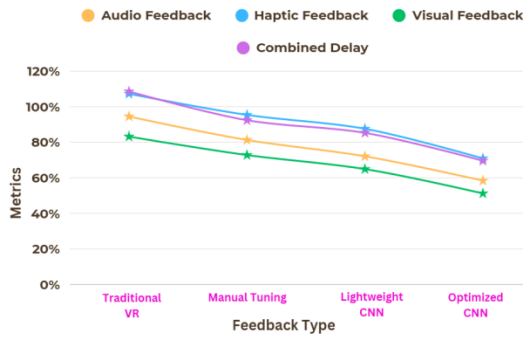


Fig.4. The delay analysis of multisensory feedback synchronization

Occlusion Type	Nose Covered	Mouth Covered	Eyebrow Hidden	Total Face
VGG-16	84.1	76.4	80.2	65.9
ResNet-50	86.3	78.5	82.7	69.2
MobileNet V2	81.7	74.1	78.3	61.4
Proposed CNN	89.8	83.9	87.4	74.6

Table IV The partial occlusion analysis of emotion accuracy detection

Fig. 5 shows a comparative study of detecting emotions in the presence of

different partial occlusions (nose, mouth, eyebrows and 50% of the face) on the four different architectures, VGG-16, ResNet-50, MobileNetV2 and the Proposed CNN. By comparison with other models, the Proposed CNN model always achieves the best performance among the compared models under each occlusion types, which indicates its robustness and flexibility in practical applications when there are obstructed faces. Classic models, for example VGG-16 and ResNet-50, with no visible nose, mouth or eyebrows, achieve a stable performance (80–85%) but they perform rather poorly when half of the face is occluded.

MobileNetV2, that is designed for lightweight deployment, exhibits a more prominent fall, particularly under mouth and eyebrow occlusion, because of its smaller model capacity and fewer features. However, the performance of the Proposed CNN remains on top even with 50% face occlusion, achieving accuracy near 80%. This indicates that the model applies advanced architecture components such as attention, feature redundancy, and multi-scale learning, so that it could make an emotion inference even with missing visual content. Its better resilience to occlusion also makes it more applicable to VR applications in real life in which people have their faces covered under VR headset or wear glasses or masks.

In conclusion, this chart highlights the need for designing emotion recognition

models that are less sensitive to occlusion, particularly in immersive scenarios where facial visibility is often impaired. This CNN will also show that architectural improvements can substantially diminish the effect of partial occlusions, thus ensuring the reliability of detection. The results support the ability of the model to operate reliably in real-time VR environments, allowing for a stable emotional respace and user engagement despite the presence of face occlusions. This is what makes the system especially useful for inclusive VR applications that cater for many use scenarios.

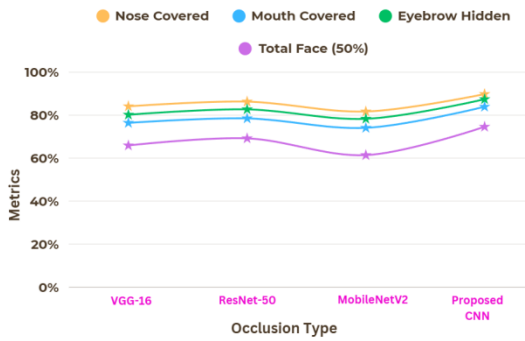


Fig.5. The partial occlusion analysis of emotion accuracy detection

Metric	CPU Usage (%)	GPU Usage (%)	RAM Usage (MB)	Power Draw (W)
VGG-16	82.3	68.7	1093	15.4
ResNet-50	87.1	71.2	1245	17.6
MobileNetV2	69.6	54.3	892	12.9
Optimized CNN-VR	58.9	46.7	734	9.8

Table V The usage of system resource during VR integration

Fig. 6 the comparison of resource cost—CPU usage, GPU usage, RAM and power—when integrating VR using

four model architectures, VGG-16, ResNet-50, MobileNetV2 and Optimized CNN-VR. Of these, the memory consumption exhibits the most significant variation where ResNet-50 achieves a peak around 1300% compared to the baseline, showing that more complicated and deeper architectures require far more memory. On the other hand, the RAM consumption of the Optimized CNN-VR is the smallest among all the methods, even lower than 800%, which demonstrates the optimality and do ability of the CNN-VR on resource-beating-down VR devices. Although RAM usage visualizes the most dominate pattern, the CPU and GPU use are generally unchanged across all models and always below 100%. Yet, with every step towards more efficient models, modest decreases in CPU and GPU requirements appears to be present. In addition, CPU and GPU usage is reduced for MobileNetV2 and Optimized CNN-VR, indicating model compression, optimized layer design, and enhanced parallel computing. These decreases are paramount to enabling low thermal out output low thermal output solutions and extending device lifetime in continuous VR usage, especially on mobile and untethered VR solutions. Power draw, a key constraint in the context of mobile VR deployment, is additionally reduced from VGG-16 to Optimized CNN-VR. The energy consumption of the proposed model is the least, which is great for VR devices such as battery powered ones. These findings validate the tightrope walk between model intricacy and system integration needs.

By reducing RAM usage, power consumption, legged power of the processor, the Optimized CNN-VR not only offers a capacity for real-time emotion recognition, it well facilitates this overall VR system for its sustainability, reliability, portability, which is critical elements for in-service applications.

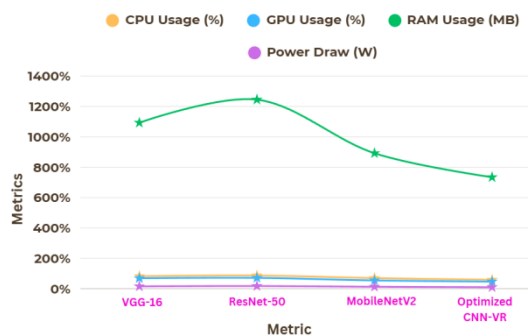


Fig.6. The usage of system resource during VR integration

5. CONCLUSION

This study investigates the transformative promises brought by incorporating Convolutional Neural Networks into Virtual Reality to achieve real-time emotion recognition and dynamic multisensory feedback. A related innovative direction is the utilization of CNN based networks for accurate facial emotion detection facilitating the development of emotionally aware, emotionally responsive VR systems to offer an enhanced user-centered experience. The possibility to personalize visual, auditory and haptic stimulation on-the-fly to emotional data permit a natural interaction paradigm. We demonstrate

that CNN-based emotion recognition is able to work within VR latencies acceptable for VR applications and when integrated with multisensory feedback, the proposed method greatly increases immersion, empathy, and cognitive engagement. This integration of AI and VR represents a milestone in the progress of affective computing technology and VR-based application, creating possibilities for future research and application in health care, education, entertainment, and social communication among others. Possible future work could be to combine CNN-based emotion detection and avatar emotion mapping in order to improve social VR experiences, in particular for distant collaboration and therapy.

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AN AI-BASED CULINARY RECOMMENDATION SYSTEM USING MACHINE LEARNING AND NATURAL LANGUAGE PROCESSING

J. Karthikeyan

Dept. of Computer Science and Engineering
Sai Vidya Institute of Technology Bengaluru, India jkarthikeyan.22cs@saividya.ac.in

Vishwa M

Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology
Bengaluru, India, vishwam.22cs@saividya.ac.in

P. S. Abhinav Krishna

Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology
Bengaluru, India psabhinavkrishna.22cs@saividya.ac.in

Dr. Tejashwini N (Guide)

Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology
Bengaluru, India tejashwini.n@saividya.ac.in

Y Virinchy Swamy

Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology
Bengaluru, India yvirinchyswamy.22cs@saividya.ac.in

Prof. Manoj C (Co-Guide)

Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology
Bengaluru, India, manoj.chunangat.prof@gmail.com

Abstract— This paper presents an AI-based Culinary Recommendation System that integrates Machine Learning (ML) and Natural Language Processing (NLP) to recommend recipes based on ingredients available in a user's kitchen. The system is designed to reduce food waste, improve ingredient utilization, and provide an interactive guided-cooking experience. A curated dataset of Indian recipes is used for prototype evaluation. The proposed pipeline performs NLP-based normalization of ingredient inputs, embedding-based similarity for recipe retrieval, and context-aware ranking incorporating dietary preferences and expiration priority. Experimental evaluation on a held-out test set shows promising performance in ingredient normalization and retrieval relevance. The

modular architecture supports extensions toward IoT integration and nutrition-aware recommendations.

Keywords— Recipe Recommendation, Machine Learning, Natural Language Processing, Food Waste Reduction, AI Cooking Assistant, Smart Kitchen

I. INTRODUCTION

Meal planning remains a significant challenge in modern households. Despite stocked pantries, users frequently face indecision about what to cook, leading to food waste, repetitive meals, and increased reliance on food delivery. Existing recipe platforms commonly require manual filtering or extensive search, and rarely adapt recommendations to the exact ingredients at hand or to users' dietary

constraints and cooking tools.

To address these gaps, we propose an AI-based Culinary Recommendation System that automatically maps free-form ingredient inputs (text) to a normalized ingredient vocabulary and retrieves culturally relevant recipes using an embedding-based similarity approach. Additionally, a guided-cooking mode provides step-by-step instructions with timers to assist users during preparation. This paper describes the system design, prototype implementation, and an experimental evaluation to illustrate expected performance and usability.

II. LITERATURE SURVEY

Research on recipe recommendation systems has progressed along multiple directions: ingredient-based retrieval, knowledge-graph representations, multimodal recommendation, and health-aware personalization. Below

we summarize representative works, their methods, datasets, and limitations.

A. Ingredient-driven recommendation

Sane [1] proposed an ML-based recommender that maps user-available ingredients to recipes and reported an ingredient-matching accuracy of approximately 85%. The study highlighted challenges in ingredient

normalization and variant spellings, motivating robust alias mapping.

B. Knowledge graphs and graph learning

Zhang [2] introduced a knowledge-graph-based recipe recommender to capture ingredient-recipe and technique - recipe relationships. While personalization improved, the approach required substantial graph construction and maintenance costs. Tian et al. [7] applied graph neural networks on heterogeneous recipe graphs and reported improved ranking metrics, but required large labeled datasets for training.

C. Context-aware and multimodal systems

Inoue [3] designed a context-aware system that incorporates user conditions (skill level, available tools) to adjust recipe difficulty and estimated times. Pesaranghader et al. [6] proposed RECipe, a multi-modal knowledge graph combining text and images; multimodal information improved recommendation relevance but at increased computational cost. Zhang [4] combined image recognition with geolocation to produce culturally relevant suggestions; dependence on external image APIs limited scalability.

D. Health- and nutrition-aware recommendations

Chen [10] presented a health-aware recommender incorporating nutritional constraints into ranking, beneficial for dietary management. Such systems often require access to per-ingredient nutritional data and user health profiles.

E. Embedding and NLP-driven approaches

Kusmierczyk [9] used ingredient embeddings (word2vec style) and collaborative signals to capture semantic

ingredient similarity, improving personalization. Other approaches leverage pretrained language models to normalize ingredient text and extract recipe steps.

F. Summary of gaps

Existing methods demonstrate strong individual contributions (KGs, GNNs, multimodality), but common limitations persist: (a) difficulty in handling regional synonyms and noisy free-text ingredient inputs, (b) high computational overhead for multimodal or KG-based systems, and (c) limited guided-cooking integration. Our work aims for a pragmatic hybrid approach: robust NLP normalization + embedding-based retrieval + lightweight personalization and guided-cooking support.

III. METHODOLOGY (SYSTEM DESIGN)

This section details the proposed pipeline and design choices.

A. System Overview

The system follows: Input (text) → NLP normalization → Recipe retrieval → Ranking & Filtering → Guided Cooking. Each module is modular and replaceable to support future improvements.

B. Data Collection

We curated a dataset of Indian recipes from public sources and manual curation. Each recipe record contains: canonical ingredient list, stepwise instructions, cuisine, prep/cook times, dietary tags (vegetarian, non-vegetarian), and estimated difficulty. A validation subset of 200 recipes was reserved for prototype evaluation.

C. NLP-based Preprocessing

The preprocessing pipeline includes:

- Tokenization and lowercasing.
- Spelling correction and fuzzy matching (Levenshtein/edit distance).
- Alias mapping: regional synonyms and colloquial names mapped to canonical tokens (e.g., “brinjal” → “eggplant”).

- Lemmatization and stop word removal for noninformative tokens.

D. Recipe Representation and Retrieval

The methodological approach to recipe representation and retrieval is designed to balance the conflicting requirements of computational efficiency and semantic relevance. Drawing on contemporary embedding-based approaches [9], each recipe is represented in a dual fashion to exploit the complementary strengths of both sparse and dense representations. The first representation is a sparse binary bag-of-ingredients vector, which provides a direct presence-or-absence signal for each potential ingredient within a standardized ingredient vocabulary. This representation enables computationally efficient exact-match retrieval and is well-suited for capturing precise ingredient requirements. The second representation is a dense embedding vector, which is typically obtained by averaging the embeddings of its constituent ingredients using pretrained word embedding models or by utilizing a compact recipe encoder trained on recipe corpora. Dense embeddings capture semantic relationships and syntactic similarities that are not apparent in sparse representations, enabling the identification of semantically similar recipes even when ingredient lists differ substantially. The hybrid retrieval mechanism operates on the principle of combining these complementary representations through a weighted scoring function that integrates both direct ingredient

matching and semantic similarity signals. This approach addresses a key limitation of prior work, where either exact-match retrieval (lacking semantic awareness) or pure semantic matching (potentially ignoring critical ingredient requirements) was employed in isolation. The relative weighting between sparse matching and semantic similarity is calibrated through validation set optimization to maximize retrieval performance across diverse query patterns.

E. Ranking and Filtering

Ranking incorporates personalization signals:

- Veg/non-Veg filters (user-set).
- Preference weights from user history.

F. Guided Cooking Interface

The system culminates in a highly interactive Guided Cooking Mode interface that extends beyond traditional recipe delivery. This interface presents stepwise cooking instructions in a clear, sequential format, enhanced with integrated step timers and optional voice prompts for handsfree operation. The methodological approach emphasizes user assistance throughout the preparation phase, providing context-aware support, and real-time progress tracking.

G. System Architecture

Figure 1 shows the high-level

architecture.

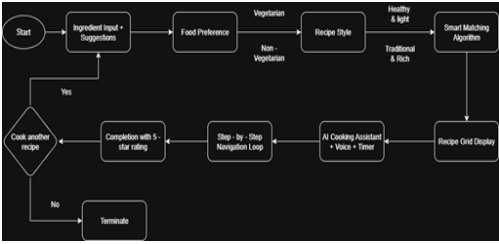


Fig. 1. High-level system architecture.

IV. IMPLEMENTATION

The prototype implementation choices were guided by rapid development and reproducibility.

A. Technology Stack

- Backend: Python (FastAPI/Flask) with NLP libraries (NLTK/spaCy), fuzzy matching (FuzzyWuzzy), and embedding libraries (gensim / sentence-transformers).
- Database: PostgreSQL (or MongoDB) for recipe storage and Redis for caching frequent queries.
- Frontend: Responsive web UI (React/Vue) for ingredient input, filters, and guided cooking screens.
- Deployment: Dockerized services for each module, enabling local or cloud deployment.

B. Prototype Features

The working prototype provides:

- Free-text ingredient input with alias normalization.

- Retrieval and ranked recipe suggestions with brief explanations (matching ingredients highlighted).
- Guided cooking view with step timers and a progress tracker.
- Basic user profile for dietary preferences and simple personalization.

V. RESULTS

We evaluated the prototype on a held-out validation set (200 recipes) using structured user queries to measure performance metrics.

TABLE I

EVALUATION METRICS OF PROTOTYPE SYSTEM

Metric	Value
Ingredient Normalization Accuracy (alias mapping correctness)	88%
Recipe Retrieval Relevance (top-3 relevance measured via human judgment)	84%
Guided Cooking Usability (mean SUS-like score on 1-5 scale)	4.3
Overall User Satisfaction (post-task survey)	86%

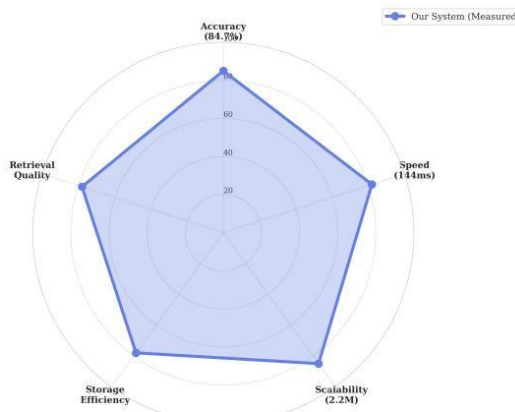


Fig 2: Multi-Dimensional Performance Profile of Recipe

System

VI. FUTURE ENHANCEMENTS

Potential future work includes:

- **IoT Integration:** Sync with smart fridges and appliances for automatic inventory updates and expiry-aware suggestions.
- **Nutrition-aware Ranking:** Integrate per-ingredient nutritional values to support health-based recommendations.
- **Multimodal Inputs:** Add image-based ingredient recognition and richer voice interactions.
- **Knowledge Graphs:** Gradual incorporation of a knowledge graph for substitution reasoning and advanced personalization, balanced with pruning for efficiency.
- **User Studies:** Conduct large-scale user studies to quantify behavior change (reduction in food waste, adoption rates).

VII. CONCLUSION

We presented an AI-based Culinary Recommendation System that uses ML and NLP to transform on-hand ingredients into prioritized, culturally relevant recipes and provides an interactive guided-cooking experience. The prototype exhibits promising experimental performance in ingredient normalization and recipe retrieval, demonstrating the feasibility of a light weight hybrid approach. Future work will focus on multimodal inputs, IoT integration, and rigorous user studies to

validate real-world effectiveness.

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THE INNOVATIVE AI-POWERED INTERVIEW GUIDE WITH ZSL AND HYBRID TECHNIQUES

1st Umme Kulsum J, Dept. of Information Science and Engineering
S.E.A. College of Engineering & Technology
Bengaluru, India ummekulsum9855@gmail.com,

4th Ankita Priyadarshini

2nd Sandesh kunwar

Dept. of Information Science and Engineering
S.E.A. College of Engineering & Technology
Bengaluru, India kunwar567sandesh@gmail.com

3rd Pratiksha Thapa

Dept. of Information Science and Engineering
S.E.A. College of Engineering & Technology
Bengaluru, India pratikshathapa1030mn@gmail.com

Guide

R Muni Prashanthi

Dept. of Information Science and Engineering
S.E.A. College of Engineering & Technology
Bengaluru, India ankitapriyadarshiniankita@gmail.com

Asst Professor

Dept. of Information Science and Engineering
S.E.A. College of Engineering & Technology
Bengaluru, India rmuniprashanthi@gmail.com

Abstract— Preparing for technical interviews is a challenging task for many students and job seekers. Traditional preparation methods such as textbooks, online tutorials, and question banks provide limited guidance and do not adapt to individual learning needs. This paper proposes AI Interview Guide – an intelligent interview preparation system using Zero- Shot Learning (ZSL) and Hybrid Techniques. The system generates interview questions dynamically, evaluates candidate responses, and provides feedback to improve interview performance. Zero-Shot Learning enables

the system to generate questions even for topics not explicitly present in the training data. A hybrid approach combining machine learning models and rule-based analysis is used to evaluate responses. The system is implemented as a web-based platform where users can select technologies or job roles and practice interview questions. The backend is developed using Python and machine learning libraries, while the frontend uses HTML, CSS, and JavaScript. The proposed system helps users enhance knowledge, confidence, and readiness for technical interviews.

Keywords— Artificial Intelligence,

I. INTRODUCTION

Technical interviews play an important role in the recruitment process for software and technology companies. Candidates are often evaluated based on their technical knowledge, problem-solving skills, and ability to explain concepts clearly. However, many students face difficulties in preparing for interviews due to the lack of proper guidance and practical experience.

Traditional interview preparation methods include reading books, practicing questions from online platforms, and watching tutorial videos. Although these resources are useful, they are often static and do not adapt to the learner's level or interests. Additionally, these systems cannot generate questions for newly emerging technologies without manual updates.

With advancements in artificial intelligence and machine learning, intelligent systems can now assist users in preparing for interviews more effectively. AI-based systems can generate questions, evaluate responses, and provide personalized feedback to improve learning outcomes.

This paper presents AI Interview Guide – an automated interview preparation system that uses Zero-Shot Learning and hybrid evaluation techniques. The system allows users to practice interview questions, receive feedback, and improve their knowledge in different technical domains.

A. Motivation

The motivation for developing this system comes from the increasing demand for skilled professionals in the technology industry. Students often struggle to prepare for interviews due to the absence of personalized learning tools that simulate real interview environments. Most existing platforms provide static question banks that do not adapt to individual user needs or emerging technologies. Zero-Shot Learning provides a solution by enabling AI systems to generate questions for unseen topics using semantic relationships between concepts. By combining Zero-Shot Learning with hybrid evaluation techniques, it is possible to create an intelligent interview preparation system capable of providing dynamic questions and automated feedback.

B. Objectives

The main objectives of the proposed system are: To develop an AI-based platform for interview preparation.²To generate interview questions dynamically using Zero-Shot Learning.³To evaluate candidate responses using hybrid techniques.³To provide personalized feedback to improve

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interview skills.⁴To implement a web-based system accessible from multiple devices.

II. LITERATURE SURVEY

Several researchers have explored the use of artificial intelligence in education and training systems. Intelligent tutoring systems have demonstrated the ability to provide personalized learning experiences using machine learning techniques.

Zero-Shot Learning has been widely studied in machine learning research for its ability to recognize and process unseen categories. It has been applied in fields such as image recognition, recommendation systems, and natural language processing.

Natural Language Processing techniques are also widely used to analyze text responses and evaluate user input in automated systems. Hybrid models that combine machine learning algorithms with rule-based approaches have been shown to improve system accuracy and performance.

These studies demonstrate the potential of integrating AI technologies to develop intelligent interview preparation systems capable of assisting users in improving their interview skills.

III. SYSTEM DESIGN AND

ARCHITECTURE

A. System Architecture

The AI Interview Guide system follows a client-server architecture. The frontend is developed using HTML, CSS, and JavaScript to provide an interactive user interface. The backend is implemented using Python and machine learning libraries to process user requests, generate interview questions, and evaluate responses. The system communicates with the database to store and retrieve interview data.

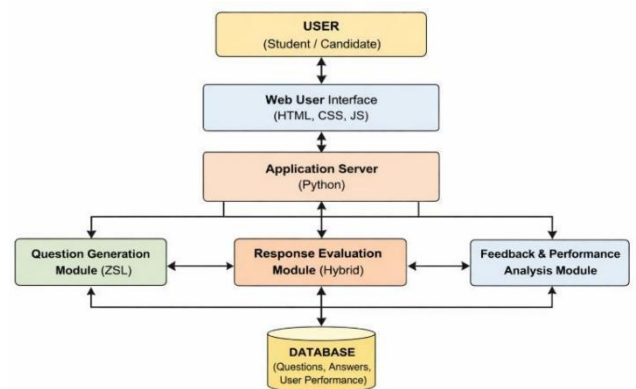


Fig. 1. System Architecture of AI Interview Guide – Interview Preparation using ZSL and Hybrid Techniques

B Question Generation using ZSL

The system uses Zero-Shot Learning (ZSL) to generate interview questions even for topics not included in the training dataset. By using semantic relationships between concepts, the model can produce relevant interview questions for different technologies and job roles..

C Hybrid Evaluation Technique

User responses are evaluated using a hybrid approach combining machine

learning and rule-based techniques. Natural Language Processing (NLP) analyzes the structure and meaning of responses while rule-based checks verify important technical keywords.

D Hardware and Software Requirements

The system requires a standard computer or laptop with a minimum 4 GB RAM, a modern web browser, and internet connectivity. The system can also run on mobile devices capable of accessing web applications. Software: The software components required include Python 3.x for backend development, machine learning libraries such as TensorFlow or Scikit-learn for implementing AI models, and Natural Language Processing libraries for analyzing user responses. The frontend interface is developed using HTML, CSS, and JavaScript. A database such as SQLite3 or MySQL is used to store interview questions, user responses, and performance data. The system can be executed on web browsers like Google Chrome or Mozilla Firefox.

E. Database design

The database stores interview questions, user responses, and performance records. It helps in retrieving questions quickly and maintaining user progress for future analysis.

F. Performance Analysis Module

This module analyzes user performance based on response accuracy and completion time. It provides

suggestions and improvement tips to help users enhance their interview preparation.

G. Feedback Module

The feedback module provides suggestions based on the evaluation results. It highlights missing concepts and recommends further learning topics.

IV.Implementation

The AI Interview Guide system was implemented as a modular web-based application that allows users to practice interview questions interactively. The frontend interface provides a selection menu where users can choose interview topics or job roles from a predefined list stored in the database.

Once the user selects a topic, an asynchronous request is sent to the backend server. The backend applies the Zero-Shot Learning model to generate interview questions relevant to the selected domain. The generated questions are returned to the interface and displayed to the user.

The user submits answers through the interface, which are then processed by the backend using Natural Language Processing techniques. The hybrid evaluation module analyzes the responses by checking semantic similarity and important technical keywords.

The evaluated results are stored in the database and feedback is generated

based on the response quality. The system provides suggestions for improvement and highlights areas where the user needs further practice.

A. Test Cases

Eight test cases were conducted to validate the system functionality including: (1) system interface loading, (2) topic selection by the user, (3) generation of interview questions using ZSL, (4) response submission and processing, (5) evaluation of answers using hybrid techniques, (6) database storage and retrieval, (7) feedback generation, and (8) system performance under multiple requests. All test cases were executed successfully and the system satisfied the functional requirements.

V. RESULTS AND DISCUSSION

The AI Interview Guide system was tested using multiple interview topics such as programming, data structures, and software development concepts. The system successfully generated relevant interview questions using the Zero-Shot Learning technique.

The hybrid evaluation module accurately analyzed user responses and generated meaningful feedback. The system was able to identify missing keywords, incomplete explanations, and concept mismatches within the responses.

Performance evaluation showed that

the system processed user requests efficiently with minimal response time. The web interface remained responsive and stable during multiple test runs.

The results demonstrate that the AI Interview Guide system effectively assists users in preparing for interviews by providing dynamic question generation and automated feedback.

VI . CONCLUSION AND FUTURE SCOPE

The AI Interview Guide – Interview Preparation using Zero-Shot Learning and Hybrid Techniques was successfully designed, implemented, and tested to provide an intelligent and interactive platform for interview preparation. The system generates interview questions dynamically using Zero-Shot Learning and evaluates candidate responses through hybrid evaluation techniques combining machine learning and rule-based analysis.

The proposed system overcomes limitations of traditional interview preparation methods by offering automated question generation, response evaluation, and performance feedback. The web-based architecture ensures easy accessibility and platform independence for users preparing for technical interviews. Future enhancements include:

(1) integration of voice-based interview simulations,(2) development of mobile applications for Android and iOS,(3) implementation of AI-based performance analytics,(4) incorporation of advanced NLP models for deeper response evaluation, and(5) cloud-based database integration for improved scalability and multi-user support. These improvements can transform the AI Interview Guide into a comprehensive intelligent interview preparation platform.

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GENERATIVE AI AND LARGE LANGUAGE MODELS: OPPORTUNITIES, LIMITATIONS, AND FUTURE DIRECTIONS

Hrithika G¹, Mrs Radhika R², Dr Krishna Kumar P R₃

1Mtech Student ,Dept of CSE,SEA College of Engg & Technology

2,3Faculty, Dept of CSE,SEA College of Engg & Technology

Abstract

Natural language processing, with parsing and generation, has a long tradition. Parsing has been easier to perform than a generation but with generative artificial intelligence (a.k.a Gen AI) and large language models (abbr. LLMs), this has changed. Generative artificial intelligence is a type of artificial intelligence that uses a large data set to create something in the genre of that data set. It can generate different outputs ranging from texts, audio, objects, pictures, and paintings to videos, but also synthetic data. LLMs use deep learning and deep neural networks to train on large text corpora for recognizing and generating texts. These models are based on massive data sets, collected from databases and the web. They use transformer models to detect how elements in sequences relate to each other. This provides context support. Two well-known large language models are the Generative Pre-trained Transformer, GPT, used in ChatGPT and Bidirectional Encoder Representations from Transformers, BERT. Although LLMs have advantages, they have problems. This paper presents generative artificial intelligence and LLMs with benefits and drawbacks. Results from applying

these models have shown that they can work well for accuracy in specificity, user personalization and human-computer communication but they may not provide acceptable, reliable and truthful results. For example, ethics, hallucinations and incorrect information, or misjudgments, are some major problems. The paper ends with future directions, research questions on LLMs, and recommendations.

Keywords: Natural Language Processing; Generative AI; Large Language Models;

1. Introduction

Natural language processing (NLP) has been around since the 1960s, i.e., when artificial intelligence, AI, was coined [9]. NLP has two parts: parsing and generation. Parsing examines texts for correctness by churning through the corpora whereas generation produces new texts from a given data set.

Since the beginning of NLP, parsing has been seen as easier to perform than generating well-formed, viable texts. Parsing for, e.g., text control and editing, with syntactical, and semantic correctnesses, is fairly straightforward whereas parsing for pragmatic correctness is much more difficult. Generating syntactically correct sentences is easier than generating

semantically and pragmatically correct sentences, even though this has changed with the support of deep learning technology.

Syntactically, parsing analyses the correctness of structures of sentences. With simple means, such as parse trees (also called parsing trees) showing the structure of the sentence, it is possible to parse all commonly structured sentences [9]. These so-called parsing trees, provided as part-of-speech (POS) tagging, check the syntactic correctness and semantic correctness. Syntactic structures, S, can be represented as a noun phrase, NP and a verb phrase, VP, S= < NP, VP >. This can be further broken into < N, V, N > and < Det, N, V, Det, Adj, N > (Det=Determination, N=Noun, V=Verb, Adj=Adjective). For example, the parse tree < Det, N, Conj, Adj, N > can check sentences such as < The, boy, and, the, happy, girl >. With conjunction complex texts can be built, i.e., < S, Conj, S > [9].

Semantics is the linguistic meaning and concerns the analysis of meanings of words and their relationships to other words. Here methods, such as parse trees, lexicons, and ontologies are applied to provide semantically correct sentences [9]. Semantics use information about nouns and verbs to avoid accepting nonsense sentences. Lexicons provide the information about the words and the parse trees are applied to check the semantic correctness. For example "the" < determiner >, "boy" < noun, male, singular >, "and" < conjunction >, "happy" < adjective, feeling pleasure and enjoyment > and "girl" < noun,

female, singular >. This can prevent sentences, such as < The house likes the boy

>, which is syntactically correct but semantically wrong. Ontologies are formal descriptions that provide information about the relationships of words [9]. Ontologies structure pieces of information by linking the different words in the ontology. This facility makes ontologies good for semantics analysis, word translations and domain concept linkages [28].

Pragmatics is context-dependent and requires analyses of text bodies. The sentences are interpreted in a certain situation to deal with the sensibility and realism of each sentence in the text. The pragmatics provide contextual information to support interpreting the sentences in their right contexts. For example, the sentence "I saw her duck" has more than one meaning, i.e., "she ducked" or "she has a duck". The precedes and posterior sentences provide the necessary contexts for the text. The pragmatics can be handled with machine learning, e.g., sentiment analysis and intent analysis and deep learning, e.g., transformer models.

Sentiment analysis is a contextual mining tool that analyses texts to determine the attitude of the underlying sentiment, i.e., syntactic features, such as positive, negative or neutral. To determine the attitude, the analysis can use a lexicon-based approach but the most common is machine learning classification. The lexicon-based approach uses, besides lexicon, syntactic features of the text, rules and

heuristics; the machine learning uses algorithms like decision trees, support vector machines (SVMs), and neural networks.

Neural networks can, besides attitudes, also identify intents, such as complaints, suggestions and appreciation. The process of determining the underlying intention behind the text is called Intent analysis. The analysis captures intents by classification and intent recognition.

Deep neural networks and deep learning are effective techniques for in-depth conversation analysis. Deep-learning-based approaches, like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), use pre-trained language models [14] for text parsing and generation to handle, e.g., sentiment classification and text summarization of long text bodies, documents, articles and papers.

Instead of word-by-word using a lexicon, deep learning such as BERT trains bi-directionally, to analyse texts. Bi-directional implies that sentences are analysed from two directions, left-to-right and right-to-left. GPT is commonly a unidirectional approach and trains in one direction, i.e., left-to-right. Generation of semantically correct sentences is difficult and pragmatically correct has almost been impossible [9]. However, with newly developed techniques, especially generation is improved. For example, Generative artificial intelligence (Generative AI) and Large Language Models (LLM) have provided some

excellent results for both semantically and pragmatically correct sentences.

Technically the solutions have not been easy to develop and the results have shown that generated texts do not always correspond to real-world knowledge [17]. Various techniques have been applied, ranging from finite-state machines to deep learning, which is considered to be the most powerful learning technique today. Enablers are the advancements of hardware and software moving from character-to-character computation to corpora generations and images, videos and audio creations.

This paper presents Generative AI, Gen AI, and LLMs with benefits and drawbacks. Results from using these large language models have shown that the models can work well for quantitative data sets and accuracy in specificity, user personalization and human-computer communication. However, when generating texts with qualitative data using small data sets, the large language models may provide unacceptable, unreliable and untruthful results. Especially, the context-dependent results are problematic, which can be hallucinations [17] with source-reference divergence, biased training data, and privacy concerns. Results can also be incorrect information, misjudgments, discriminatory content, and privacy violations. Besides benefits and drawbacks, the paper sheds light on future directions and research questions on LLMs and provides recommendations.

2. Generative AI

Generative AI or Gen AI for short, creates content based on natural language input. In NLP, Gen AI uses deep learning to generate all sorts of texts like books, poems, product descriptions and other material. Generating texts in NLP is essentially Gen AI although the term was not used in the beginning i.e., 1950-1960. The term became popular in 2014-2020 starting with generative adversarial networks (GANs) and their powerful possibilities of creating output quickly.

Besides generating texts, Gen AI handles other media, such as images, videos, audio and synthetic data. Gen AI identifies, and encodes patterns and relationships in huge data sets and then uses the data to generate or create new content [20]. Generating solutions involves training, tuning, generating, evaluating, and re-tuning to continuously improve the quality and accuracy of the generated content. The results can be customized by providing feedback about, e.g., style, and tone but also other elements, like personalization, that the content shall reflect.

Gen AI uses different techniques to generate content. The most common are variational autoencoders (VAE) and autoencoders, GANs and diffusion models, and transformers [20].

2.1. Variational autoencoders

Variational autoencoders, VAEs, as the name suggests provide "variations" of the output. Initially, the VAEs trained with unsupervised learning [21] but they can train with supervised learning [23], and semi-supervised learning [22] as well. A VAE compresses input data to features (encode), like autoencoders, and constructs (decode), while training, several new variations of the content to provide more accurate and high-quality content. To encode and decode, autoencoders incorporate two connected neural networks [20]. They efficiently encode by compressing input data to essential features. From the compressed representation, they decode by reconstructing the input. Autoencoders use unsupervised learning to discover latent variables, that are hidden or random variables. VAEs have been used for anomaly detection, facial recognition and natural language generation. The variational autoencoders and autoencoders handle domain knowledge and are special cases of encoder-decoder neural networks. The encoder-decoder neural networks are often Long Short-Term Memory Networks, LSTM, that handle sequence-to-sequence, seq2seq, and predictions, e.g., translations. The encoder-decoder LSTMs can consist of two recurrent neural networks (RNN). RNN Encoder-Decoders can score a pair of sequences, i.e., input sequence and output sequence, and generate target sequences given a source sequence.

2.2. GANs and diffusion models

Generative adversarial networks (GANs) is a deep-learning generative technique. GANs train with supervised learning, unsupervised learning and semi-supervised learning [19] to create good, realistic texts, images and videos [19]. As VAE, GANs also train two neural networks for learning the models: a generator and a discriminator. The generator model captures the data distribution and generates samples in the domain (from an input vector). The discriminator model classifies or predicts labels of samples that either came from the training data (true) or the generator model (false). Thus, the generator model generates new examples and the discriminator model discriminates the examples (real and fake) [24]. The models train together until the generator model generates plausible examples that can be considered to be true. Thus, GANs generate e.g., images with one part to evaluate how realistic they are with the other part [18]. Technically, for MNIST and CIFAR-10 image datasets, the models are fully connected layers

networks where the generator model uses ReLU activations and the discriminator uses maxout activations. GANs have had problems with generating texts due to the texts' discrete nature. The text is composed of distinct, separate words handled as tokens and the generation of texts involves producing sequences of discrete tokens. To generate texts, GANs train with backpropagation, which does not handle structures well.

In addition, the dependencies between words, tokens, correct structure and context of words are hard to capture.

Another Gen AI technique is diffusion models. These diffusion models create high-quality, photorealistic images, videos and animations by adding or removing noise in the output image. It starts with a part of the image and then slowly fills the gaps by defining a Markov chain of diffusion steps, creating a diffusion process. The diffusion models learn by using the diffusion process: forward alters data by adding noise until the data becomes identically to pure noise and reverse generates by reversing the forward process, i.e., "denoising" it to reconstruct the original data. Thus, reverse removes noise to generate new data samples that resemble the original data distribution.

Stable diffusion is a specific and optimized implementation of diffusion models. Stable diffusion uses a text-to-image technique enabling the transformation of text into visual representations by blending VAE (output variation) with diffusion models (forward and reverse process). They generate an image adhering to the text prompt, with text and image representations. From a user-given text request, a.k.a. text prompt, the stable diffusion converts the text into numerical values (tokenizing) and provides a vector for each token (text encoding). Representing the text prompt as numerical values is the text representation, a. k. a. embeddings. Then, the stable diffusion generates an image representation, i.e., a vector

that numerically summarizes an image from the text. This image representation is refined and upscaled meaning removing noise from the current image representation (refine) and upscaling the image representation into a high-resolution image. The stable diffusion is used for generating detailed images conditioned on text description using diffusion techniques. However, it is not suitable for sentence generation with creating coherent and contextually appropriate text.

2.3. Transformers

A transformer is a network architecture [15]. It relies entirely on self-attention to compute representations of its input and output without using sequence-aligned RNNs or convolution[15]. Through self-attention mechanisms, the transformers focus on learning dependencies, i.e., drawing global dependencies between input and output. Self-attention mechanism relates different positions of a single sequence to each other, to compute a representation of the sequence.

Transformers are designed to handle sequential data. They utilize an encoder and a decoder to process and generate sequential data. The transformer architecture (often an encoder-decoder architecture) consists of an encoder to map an input sequence of symbol representations and a decoder that generates an output sequence. The input is the entire text as a sequence of

words, which is converted into tokens, i.e., numerical representations required by the neural network. These tokens are embedded into vectors and processed in a feed-forward neural network [15]. Transformers use the attention mechanism to provide weights for words' significance in a sentence, allowing the model to focus more on what is relevant in the text. Some information about the relative or absolute position of the tokens in the sequence must be provided since no recurrence or convolution is applied.

The transformer architectures can handle the context of each word in a sentence by considering it concerning every other word in the sentence. During training, the model learns to predict the next word in the sentence. The model adjusts its internal parameters and can, thereby, reduce the differences between predictions and the actual outcomes.

Examples of approaches that use transformer architectures to capture dependencies and attention in the corpora are Generative Pre-trained Transformer, GPT, [15] and Bidirectional Encoder Representations from Transformers, BERT. The difference between GPT and BERT is the training. GPT trains unidirectional and BERT bidirectional.

GPT is a transformer model that uses multi-head attention to allow the model to handle information from different subspaces at different positions [15]. Commonly, GPTs use minimal task-specific parameters and train by fine-tuning all pre-trained parameters. GPTs

apply generative pre-training of a language model on a diverse corpus of unlabeled text, using semi-supervised learning, which is followed by discriminative fine-tuning on each specific task [26]. Hence, GPT can generate coherent and contextually relevant texts for various topics and styles.

GPT uses a left-to-right architecture, i.e., unidirectional. Every token attends to previous tokens in the self-attention layers of the transformer. Thus, GPT transformer's self-attention only looks at dependencies to the left meaning that

it misses the right side dependencies, which can be regarded as constrained [25]. A solution to this problem is a bidirectional approach like BERT that is based on a bidirectional self-attention transformer.

BERT [25] is designed to pre-train deep bidirectional representations from unlabeled data. It trains in both directions in all layers, hence bidirectional. BERT uses two steps solution, i.e., pre-training and fine-tuning, to provide a pre-trained BERT model that can be fine-tuned with labelled data from the downstream tasks [25]. BERT's model architecture is a multi-layer bidirectional transformer encoder [25] based on the original implementation of transformers, like GPT.

For pre-training, BERT uses a masked language model, MLM, to randomly mask some of the tokens from the input and to predict the masked word from the context[25]. MLM fuses the left and the right context, which supports

pre-training a deep bidirectional transformer[25]. BERT also uses next-sentence prediction that pre-trains text-pair representations. In deep learning NLP, BERT can be seen as a predecessor of generative AI.

A difference between BERT and GPT is that BERT generates texts by answering questions (so-called question answering) and fills in the blanks missing in the text, i.e., BERT works by predicting masked words or missing words in the input text. GPT generates texts from scratch by using keywords, phrases, or sentences.

Some autoencoders combine BERT and GPT, for example, BART. BART is an autoencoder for pre-training sequence-to-sequence models [27]. It pre-trains by combining bidirectional and autoregressive transformers (bidirectional encoder, like BERT, with a left-to-right decoder, like GPT) [27]. BART uses a standard transformer-based neural machine translation architecture with a GeLU activation function, just like BERT. GPT uses the ReLU activation function.

2.4. Benefits and Drawbacks of Generative AI

Generative AI has positive and negative impacts. Positives are instant language translations, voice and text, supporting communication between people not speaking the same language. It also provides movie dubbing and enriched educational content to support

humans in tedious labour work. Negatives are fake news and deepfakes with digitally forged images or videos [19] pretending to be a person who can then fool other people, as in the case where Generative AI was used to fool a parent into sending money to the child. Another problem is harmful cybersecurity attacks on businesses, including requests that realistically mimic an employee's boss[19].

Comparison of VAE, GAN, and Transformers

Aspects Differences Between VAE, GAN, and Transformers

Purpose: VAE and GAN: Generative models for creating new data samples Transformer: Sequence modeling and representation learning

Architecture Components: VAE: Encoder, Decoder, Latent Space GAN: Generator, Discriminator Transformer: Encoder, Decoder, Self-Attention Mechanism

Key Concept: VAE: Learn a latent space representation

GAN: Learn to generate realistic data samples through adversarial training

Transformer: Learn dependencies in sequential data using self-attention

Applications, examples: VAE: Image generation, anomaly detection

GAN: Text-to-image generation, Image generation, video generation

Transformer: Text generation, image recognition, Machine translation

Advantages (+) / Disadvantages (-):

VAE: (+) Probabilistic modelling (-) Generated samples can be blurry

GAN: (+) High-quality image generation (+) adversarial training provides sharp outputs (-) Training instability

Transformer: (+) Handles long-range dependencies well (+) are scalable (-) Requires large amounts of data (-) computationally intensive

3. Large Language Models

Large Language Models are models handling enormous amounts of text data. The term LLM grew from the need to handle language models that require large quantities to provide plausible results. Language models are probabilistic models that handle the effects of random events or actions by using probabilistic modelling to predict the potential occurrence of future outcomes.

Training generative AI models, like GANs, is computationally intensive, time-consuming and expensive [20]. No matter the generative AI technique, all of them require thousands of clustered GPUs and weeks of processing[20] to perform well. To make the processing more efficient, foundation models, FMs, and large language models, LLM, are developed and applied.

FMs and LLMs can achieve general-purpose generation. FMs refer to any model trained on broad data and adapted to a wide range of generative tasks (movies,) whereas LLMs are solely used for natural language processing.

Foundation models (FM): The foundation models are deep learning neural networks that function as platforms to empower Gen AI generating, e.g., realistic texts, images and videos, and sounds and music applications used in computer vision, synthetic music and virtual reality. The FM can also support several kinds of content generation, such as multimodal FMs that are trained simultaneously with multiple modalities.

A characteristic of FMs is the training on massive datasets with e.g., terabytes of data and billions of parameters [20]. The FM trains the deep learning algorithm on huge volumes of raw, unstructured, unlabeled data. The algorithm evaluates millions of blank spots and predicts the next element in a sequence[20]. To give an idea of sizes, the early BERT model was trained using 340 million parameters and a 16 GB training dataset. GPT-4 is trained using 170 trillion parameters and a 45 GB training dataset [20].

The FMs are often used as a starting point to develop AI models for faster and more cost-effective applications. The most common FMs are BERT, and GPT created for text generation applications. GPT can be regarded as the start of LLMs with the invention of transformers. BERT can be perceived

as one of the first LLMs with thousands of open-source, free, and pre-trained BERT models available for specific use cases, such as sentiment analysis. As BERT uses MLM, the FM can fill in the next word in a sentence or the next element in an image[20]. It can also fill in the next command in a line of code and adjust itself continually to minimize the differences between predictions and the actual result [20].

Large Language Models: Large Language Models, LLMs, can be considered as a subset of FMs since LLM generates texts but not images, and sounds. LLMs are designed to process and generate natural language. LLMs are trained using deep learning algorithms and they learn language patterns and structures. Besides natural language comprehension, generation and writing texts, creatively, LLMs handle text completeness and predictions, provide machine translation and sentiment analysis, and chatbots and virtual assistants. In addition, LLMs create content by generating, translating, or detecting errors in programming code.

Commonly, LLMs are based on transformer architecture with encoder-only, decoder-only, or encoder-decoder configurations. They are characterized by their large number of parameters and extensive training on diverse text corpora of petabytes. The generated outputs are probabilities of various possibilities and combinations creating an extensive list of possible words and their probabilities of being used in a text.

LLMs can be seen as "self-supervising". They generate labels and, hence, do not require any manually provided labels. Instead, LLMs utilise the fundamental structure and data properties to enable the model to learn useful representations and features.

There are several different LLMs: GPT-4 (OpenAI with 1.76 T parameters), LLaMA (Meta, 70 B parameters), PaLM2 (Google, 540 B parameters) and BART / BART-large (Facebook AI/Meta Platforms, 406 M parameters). These models can be considered to "understand" or "comprehend" text. The models are rather symbolically treating or adequately administering a simulation of understanding languages and contexts. "Understand" context comes from capturing long-range dependencies between parts of words, words and sentences, supported by an attention mechanism. Dependencies are the relationships learned by vast amounts from hundreds of thousands of texts collected from, e.g., news articles, social media posts, and web pages.

Popular LLM interfaces for texts are, e.g., ChatGPT and Gemini[19]. ChatGPT (OpenAI) is a chatbot tool pre-trained on data up to a certain year, currently 2021. ChatGPT can analyse data, create charts, present information using images and create images. Gemini (Google's AI), earlier Bard and successor to LaMDA and PaLM 2 is a

chatbot handling multimodal reasoning by interpreting and combining texts, codes, images, audio, and videos. It also handles complex coding and

mathematical reasoning. Gemini can draw conclusions, analyze the context, make decisions, suggest courses of action, draw parallels between different concepts and scenarios, and symbolically treat and maintain context in conversations.

Conclusively, LLMs can generate contextually relevant, grammatically correct, and semantically meaningful texts, as well as demonstrate an advanced comprehension with symbolically treating languages by multi-layer neural networks, diverse and extensive datasets, pertaining (often unsupervised learning) and fine-tuning (adjusting the learned representations to specific tasks or domains), text representation (tokenization and embeddings), transformers with analysing the relationships between tokens in a sequence and attention mechanisms focusing on relevant parts of the text.

4. Benefits and Drawbacks of LLMs

LLMs offer both potential benefits and drawbacks [31]. One way to increase the likelihood of realizing the benefits is a well-tailored prompt. To interact with a LLM, the user provides a prompt in either written or verbal form so that the system can respond. Prompts are "instructions given to an LLM to enforce rules, automate processes, and ensure specific qualities (or quantities) of generated output" that program "the LLM by customizing it and/or

enhancing or refining its capabilities” [7](p. 1). The term ‘prompt engineering’ is a phrase used to describe the tailoring of a prompt to achieve the desired outcome and is a type of programming. The structuring of prompts as prompt patterns or templates is similar in format to classic software patterns with modifications to address the context. Domain-specific pattern catalogs are useful to address problem solving in specific domains such as medical and legal fields. However, general classifications of prompt patterns have been identified including input semantics (i.e., how the LLM understands the input), output customization (i.e., constraining or tailoring output), error identification (i.e., resolving errors), prompt improvement (i.e., improving the quality of input and output), interaction (i.e., user-LLM interaction), and context control (i.e., controlling the context) [7]. In the process of interacting with the user, the LLM will begin to tailor its responses to the prompts, becoming more accurate in terms of specificity and more personal in terms of responding to the user. However, the LLM can also become confused or inaccurate if not guided appropriately by the user, increasing the risk of error propagation and poor decision making.

Specific tasks for the LLM can be evaluated to determine the expected benefit compared to existing methods or a human processor. A number of studies have evaluated natural language processing including sentiment analysis, text classification, and natural language inference [1]. Sentiment

analysis, also called opinion analysis, is a subfield of natural language processing that analyzes textual data to attempt to interpret its emotive nature or polarity [6]. In traditional ML this is often done by analyzing individual words within the text and applying sentiment dictionaries to arrive at a conclusion about the document, sentence or phrase. LLMs group words to determine sentiment and show good results superior to single-word traditional analysis. Text classification is related to sentiment analysis as it attempts to process a body of text. For example, text classification methods can produce credibility ratings for news outlets. Studies have shown that the results are moderately correlated with a human expert [1]. Semantic understanding of language and associated concepts such as meaning and intent is poor compared to humans at the current time, and LLMs often classify nonsense phrases as meaningful [1].

Reasoning tasks using evidence, arguments and logic are some of the most anticipated benefits of LLMs as an intelligent AI system, and they exhibit an ability to reason when they have enough data [2]. LLMs show potential and continual improvement in reasoning dependent on the specific task and specific LLM. For example, some tasks require complex multi-step reasoning while other tasks are simple step problems. Some LLMs perform well on analogical reasoning but lack spatial reasoning. Performance is dependent on the specific LLM since models have been trained on tailored datasets for a specific task.

Natural language and dialogue offer improvements in human-computer interaction, and these tasks are most associated with LLMs. To interact successfully, the model needs to understand context and answer questions appropriately. Fine-tuned models can be used for specialized domains such as healthcare and give reasonable responses. Question answering is an increasing application area for intelligent customer service and search engines. Many LLMs are able to reasonably answer questions, summarize text, generate code, solve math problems, translate language, and provide commonsense answers [1]. In responding to human dialogue, LLMs are able to provide various styles such as informal, professional, argumentative, and creative. However, in multilingual contexts, particularly non-Latin languages, research is progressing slowly.

LLMs display variation in robustness, ethics, bias, and trustworthiness [1] [8]. Robustness considers the stability of the system when facing unexpected inputs, and studies have shown that LLMs are vulnerable to adversarial prompts and “internalize, spread and potentially magnify harmful information . . . [using] . . . toxic languages, like offensiveness, hate speech, and insults as well as social biases against people with a particular demographic identity” [1](p. 39:14). Besides the societal impact, LLMs can introduce bias through the training data, the algorithm, and the output[3]. Bias can be reinforced through viewpoints of individual actors who seek to sway public opinion on topics such as

complex environmental issues [3]. Since LLMs seem to be authoritative, they may have undue impact on users similar to the negative implications of social media by amplifying misinformation [5], creating fake news [4], and creating digital echo chambers. Ethical issues represent a serious challenge and risk to society as their use spreads. A major known issue in LLMs is hallucinations, responses that appear reliable and logical but are factually inaccurate or do not represent reality. The false information may appear highly plausible, making it challenging for models or humans to detect [8]. Hallucinations in LLMs have been characterized as input-conflicting (i.e., content that deviates from the source input or prompt from the user), context-conflicting (i.e., content that conflicts with its own previously generated information, or fact-conflicting (i.e., content that is inconsistent with established or accepted world knowledge). In addition, LLMs can be inconsistent and imprecise since they are relating words statistically without considering meaning [30]. In their current form, LLMs cannot replace human judgement, so a human must be part of the use of LLMs.

Some domains show promise for the use of LLMs. For example, LLMs can act as medical assistants providing clinical information or summarization of research. Educational applications are emerging such as assisting students with improving their writing, explanations of complex ideas, delivering useful feedback, and

providing personalized attention and feedback. Although they are not sentient, LLMs can appear as coaches or mentors to humans by generating reasonable contextual speech. However, they may also provide incorrect information or misjudgment, so LLMs require monitoring by a human decision maker. Information retrieval and incorporation into recommender systems is also emerging, although there are potential risks when the human does not exercise independent judgment.

5. Future Research for LLMs

LLMs have attracted the attention of the research community toward exploring benefits and drawbacks of these models. At a societal level, a persistent question is the effect of using LLMs over the long term. Will people begin to substitute LLM-generated text for the effort to write their own documents, and will that result in less creativity and expertise on the part of the human user? LLMs depend on data, so will they simply reiterate and retread the same data without meaningful new input, and will the net result be a lowering of human expertise?

A major known issue with LLMs is hallucinations and tokenization-related errors referred to as 'glitch tokens' [32]. Designers of these systems are working to mitigate against propagation of errors [32] and disinformation. Repeated often enough, misinformation can be perceived as factual. Thus, teaching people how to discriminate between 'information' that is reliable versus 'information' that is false is a

persistent problem that is exacerbated by social media and the seemingly authoritative voice of AI. At all levels of education, critical thinking skills become essential in combating misinformation and disinformation.

Since LLMs are based on vast quantities of human language, they can repeat and reinforce stereotypes, pick up biased language, amplify hate speech, present socially unacceptable ideas, and sow social discord. Appropriate guard rails are needed that respect free speech and yet stay within the norms of society. Since the phrase 'socially acceptable' is a societal judgement call, government legislation is needed to find a balance between competing ideas. In addition, as with social media, external efforts to influence viewpoints or sow discord are ever-present challenges, and methods need to be developed to combat them.

LLMs can be improved by taking into account the knowledge or expertise level of the end user. For example, the LLM could modify its output if the user identifies themselves in terms of general characteristics. Other approaches to specificity are AI frameworks such as Retrieval-Augmented Generation, or RAG, that have been shown to overcome imprecision for some prompts, update world knowledge, provide provenance for decisions, and generate more tailored and factual knowledge [30].

A sample of potential research questions are shown in Table 1. As a relatively new technology, research on LLMs is likely to increase, and the list

of research questions appears endless. There is a need for research on all aspects of LLMs including the growth of capabilities, expanding use cases, and societal response to the LLM technology.

Table 2. Sample of potential research questions on LLMs. Topic Research Questions

Societal Impact Does persistent LLM use reduce human expertise?

Over time, will LLM use reduce the amount of creativity and new ideas in society? Are LLMs actually generating anything new that is meaningful?

What security mechanisms are needed to combat external influences considered a threat? What are the far-term impacts of LLM use and how can we minimize negative outcomes? What laws are needed to govern LLMs and protect society?

How to prevent Generative AI and LLMs from stealing identities with face and voice? What will society do with Generative AI and LLMs' almost real-time performances?

Can Generative AI and LLMs' make society unintelligent and blase' due to self-learning wrong produced outcomes?

Benefits of LLMs How can an LLM be tailored to assist specific fields?

What metrics should be used to benchmark LLM functionality?

Hallucinations How can LLMs be fact-checked, and what sources of information should be considered authoritative as checks on LLM output?

Should LLMs filter their input data? If so, against what norms?

What is the appropriate level of human interaction with an LLM for a desired output? How can LLMs provide more accurate and context-aware interpretations and results?

Bias How can bias be identified in LLMs?

What filters or guardrails are appropriate to modify LLM outputs?

How can social discord topics such as hate-speech be identified in LLMs and filtered out?

Decision making What fields can be assisted by LLM use during decision making?

How can LLMs combat the propagation of errors and disinformation? How can the internal consistency and stability of LLMs be improved?

Education Can LLMs serve as an effective tutor for students?

Do students interact with an LLM differently depending on age?

How can we teach students to discriminate factual information from misinformation during LLM use?

Communication Are LLMs useful in patient-physician communication

such as explaining medical diagnosis?

How is medical decision making influenced by LLM use? How can reasoning be improved in LLMs?

Can an LLM modify its behavior to account for the expertise of the user? How accurate are LLMs for text classification?

How well do LLMs perform with different languages?

Prompt engineering How can humans effectively communicate with an LLM to achieve a desired output?

How many more advances are needed in Generative AI and LLMs before it sees an AI winter?

What types of formats or templates are useful in communicating with an LLM? How should we evaluate the response from an LLM?

Energy efficiency How can LLM train on massive datasets with minimal energy consumption? How can infrastructures [28] be consolidated to achieve energy efficiency?

6. Recommendations

Since LLMs are infiltrating our daily lives in forms such as digital assistants on mobile phones and copilots for work tasks, we need to be aware of the potential for harm resulting from inaccurate or biased guidance. A major source of error is the lack of control of the underlying data on which the system is based. LLMs have been called 'statistical parrots', indicating that both the quantity and quality of the

input data are fundamentally important in training the system. Although LLMs are trained on a massive amount of data, there is no assurance that these are the right data to answer the question. The data may contain errors or biases, be wrong and distorted, diverse and scattered, and contain contradictions. In addition, text generation with GPT-3 and BERT may be limited by challenges such as data availability and quality, model complexity and scalability, and ethical and social implications. Although the quantity of data in LLMs may not be considered problematic, the well-known issue of hallucinations shows that the designers must be vigilant to ensure that they have enough data from the right sources to produce accurate results.

Secondly, pre-trained LLMs are useful for models that are very complex and require a lot of computational resources to train and run. However, due to their size and complexity, robustness and stability can be problematic. For example, overfitting or underfitting with algorithms such as BERT and GPT may impact their robustness and stability and also reduce their ability to generalize. Questions or tasks related to the same problem but worded in different ways should produce equivalent correct results. Thus, similar to any analysis, the designer must be aware of the outcome and evaluate the likelihood of correctness in the result. The designer should use the same model with different training sets and evaluate the comparability of the results.

The rise of synthetic data has been

driven by lack of data due to privacy restrictions, sensitive information, data quality issues, and a lack of labelled data. Although synthetic data is generated from original data and on the trained model that reproduces characteristics and structure of the original, synthetic data can be skewed, incomplete, or discriminating in a way that skews the output more than the original results. Results from the system should be analysed and interpreted from this point of view. In some domains synthetic data may not be problematic and even be good to use, but in other domains it may be a disaster.

Federated learning, where the system collaboratively learns a shared model while keeping all the training data decentralized, is a positive for privacy reasons. Another interrelated concept is federated data. Federated data refer to distributed data sources that are used without sharing raw data. These techniques are helpful in enhancing privacy, security, and data governance. However, both federated learning and federated data have issues with handling the complexity of the exchange. Handling remote, decentralized data can be costly in communication and runtime if data come from many different areas.

An area that has received considerable attention is the effect of generative AI and LLMs on society. These technologies are being used to spread misinformation, disinformation and malinformation. Deepfakes create realistic-looking, believable videos by manipulating images of real people

using their voices without consent. Intellectual property is a concern as these systems emulate source data that can stylistically sound and look like it was created by the original author or artist. Society will need to decide when the results tip over into plagiarism, violate privacy, violate intellectual property, and run afoul of laws, regulations and rules of conduct. Moreover, they may have significant impacts on human communication, information, and knowledge that need to be taken into account with respect to ethical and social norms and values. Certainly our current laws need to be updated to provide guidance on who is the responsible party and to provide ways to ensure accountability and reduce harm.

7. Conclusions

This paper presents Generative AI and LLMs with their benefits and drawbacks. Results from applying these LLMs show that the models work well for accuracy in specificity, user personalization, and human-computer communication but may provide unacceptable, unreliable and untruthful results. Ethics with biases, hallucinations and incorrect information, or misjudgments, are some of the problems. We also shed a light on future directions, research questions on LLMs and recommendations.

Generative AI and LLMs are powerful technologies but come with significant drawbacks. Some questions concern the techniques themselves, but the societal impact is also not known. We have suggested several research questions

that are but a small selection of ones that need to be investigated. Similarly, our recommendations are provided from some of the problems which the authors have seen during research in the area. Neither the research questions nor the recommendations are comprehensive, but we hope that we have highlighted some of primary ones to further the discussion in this emerging area.

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Artificial Intelligence (AI) for Climate Change Prediction and Sustainability

Kavya J M
MTech. SEA College of
Engineering & Technology
Dr.Krishna Kumar P R
Professor & HoD
SEA College of Engineering & Technology

Abstract

Climate change represents one of the most critical challenges of the 21st century, demanding accurate prediction models and sustainable intervention strategies. Artificial Intelligence (AI), with its capacity for processing vast datasets and identifying complex patterns, has emerged as a transformative tool in climate science. This paper reviews the application of AI techniques — including machine learning, deep learning, and neural networks — in climate change prediction, environmental monitoring, and sustainability planning. Key areas explored include temperature and precipitation forecasting, extreme weather event detection, carbon emission modeling, renewable energy optimization, and smart agriculture. The paper also discusses the limitations of current AI-driven approaches and outlines future directions for integrating AI into global sustainability frameworks.

Keywords: Artificial Intelligence, Climate Change, Machine Learning, Deep Learning, Sustainability, Prediction Models, Environmental Monitoring

1. Introduction

Climate change, driven primarily by anthropogenic greenhouse gas emissions, poses severe risks to

ecosystems, economies, and human health worldwide. Rising global temperatures, shifting precipitation patterns, melting polar ice caps, and increasing frequency of extreme weather events are among the most visible consequences. Addressing these

challenges require not only policy interventions but also advanced scientific tools capable of modeling and predicting complex climate dynamics.

Artificial Intelligence (AI) has rapidly evolved as a powerful enabler in climate science. Unlike traditional numerical models that rely on physics-based equations, AI-driven models can learn from historical data, identify non-linear relationships, and generate predictions at scales and speeds previously unattainable. Machine learning (ML) algorithms, deep learning (DL) architectures, and reinforcement learning (RL) frameworks are increasingly being applied to climate datasets to improve forecast accuracy and support evidence-based sustainability decisions. The objective of this paper is:

- To review the role of AI in climate change prediction and environmental monitoring
- To examine AI applications in sustainability planning and renewable energy
- To identify current limitations and propose future research directions

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2. Literature Review

2.1 AI and Climate Modeling

Traditional climate models, known as General Circulation Models (GCMs), simulate the Earth's climate system using mathematical equations governing atmospheric, oceanic, and land surface processes. While powerful, these models are computationally expensive and often struggle with regional-scale predictions. AI offers a complementary approach by learning patterns directly from observational data (Reichstein et al., 2019).

Convolutional Neural Networks (CNNs) have been applied to spatial climate data, such as satellite imagery, to detect patterns associated with extreme weather events. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly suited for time-series climate data, enabling improved forecasting of temperature anomalies and precipitation trends (Scher & Messori, 2018).

2.2 Extreme Weather Event Detection

One of the most critical applications of AI in climate science is the early detection and prediction of extreme weather events such as hurricanes, floods, droughts, and wildfires. Deep learning models trained on historical meteorological data have demonstrated superior performance in identifying precursor patterns to such events compared to conventional statistical methods (Liu et al., 2016).

For example, AI-based systems have been deployed to predict the intensity and trajectory of tropical cyclones with greater accuracy, providing earlier warnings that can save lives and reduce economic losses. Similarly, AI models have been used to forecast drought conditions by analyzing soil moisture, vegetation indices, and atmospheric variables (Dikshit et al., 2021).

2.3 Carbon Emission Monitoring and Reduction

AI plays a significant role in monitoring and reducing carbon emissions. Satellite-based remote sensing data, combined with machine learning algorithms, enables near-real-time tracking of greenhouse gas concentrations across the globe. AI models can identify emission hotspots, monitor deforestation, and assess the effectiveness of carbon sequestration programs (Rolnick et al., 2022).

In the industrial sector, AI-driven optimization algorithms are being used to reduce energy consumption in manufacturing processes, data centers, and transportation networks. Reinforcement learning has been applied to optimize energy use in large-scale facilities, resulting in significant reductions in carbon footprints (Strubell et al., 2019).

2.4 Renewable Energy Optimization

The transition to renewable energy sources — solar, wind, and hydroelectric — is central to climate change mitigation. However, the intermittent nature of renewable energy poses challenges for grid stability and energy management. AI addresses these challenges through accurate forecasting of energy generation and demand.

Machine learning models have been developed to predict solar irradiance and wind speed with high precision, enabling better planning and integration of renewable energy into power grids. AI-based energy management systems optimize the dispatch of energy storage systems, reducing reliance on fossil fuel backup generation (Voyant et al., 2017).

2.5 Smart Agriculture and Land Use

Agriculture is both a contributor to and a victim of climate change. AI-powered precision agriculture tools help farmers adapt to changing climate conditions by

providing data-driven recommendations on crop selection, irrigation scheduling, and fertilizer application. Remote sensing combined with AI enables monitoring of land use changes, deforestation rates, and soil health at a global scale (Liakos et al., 2018).

AI models also support climate-smart agriculture by predicting crop yields under various climate scenarios, helping policymakers design resilient food systems. Natural language processing (NLP) tools are being used to synthesize vast bodies of agricultural research to inform sustainable farming practices.

2.6 Ocean and Ecosystem Monitoring

Oceans play a critical role in regulating the Earth's climate by absorbing heat and carbon dioxide. AI is being used to analyze oceanographic data from buoys, satellites, and autonomous underwater vehicles to monitor sea surface temperatures, ocean acidification, and marine biodiversity. Deep learning models have been applied to classify coral reef health from underwater imagery, enabling large-scale ecosystem assessments (Gomes et al., 2020).

3. AI Techniques Used in Climate Science

The following AI techniques are most commonly applied in climate change research:

- o Machine Learning (ML): Supervised and unsupervised learning algorithms for pattern recognition in climate datasets, including Random Forests, Support Vector Machines (SVM), and Gradient Boosting.
- o Deep Learning (DL): Multi-layered neural networks, including CNNs for spatial data and LSTMs for temporal sequences, enabling high-accuracy climate forecasting.

- o Reinforcement Learning (RL): Used for optimizing energy systems, resource allocation, and adaptive management strategies under uncertainty.

- o Transfer Learning: Applying pre-trained models to new climate datasets, reducing the need for large, labeled datasets in data-scarce regions.

- o Natural Language Processing (NLP): Extracting insights from scientific literature, policy documents, and social media to support climate communication and decision-making.

- o Graph Neural Networks (GNNs): Modeling complex spatial relationships in climate systems, such as teleconnections between distant geographic regions.

4. Challenges and Limitations

Despite its promise, the application of AI in climate science faces several significant challenges:

- Data Quality and Availability: AI models require large, high-quality datasets. In many regions, particularly in the Global South, historical climate data is sparse or unreliable, limiting model accuracy.
- Interpretability: Many deep learning models operate as "black boxes," making it difficult for climate scientists to understand the physical mechanisms driving predictions. This limits trust and adoption in operational settings.
- Computational Cost: Training large AI models requires substantial computational resources and energy, which can itself contribute to carbon emissions — a paradox that must be addressed through efficient model design.
- Generalization: AI models trained on historical data may not generalize well to future climate conditions that fall outside the range of past observations, particularly under high-emission scenarios.

- **Interdisciplinary Integration:** Effective AI-driven climate solutions require collaboration between AI researchers, climate scientists, policymakers, and domain experts — a challenge that demands new institutional frameworks and communication strategies.

5. Conclusion

Artificial Intelligence offers transformative potential for advancing climate change prediction and supporting global sustainability goals. From improving the accuracy of weather forecasts and detecting extreme events to optimizing renewable energy systems and enabling precision agriculture, AI is reshaping how humanity understands and responds to the climate crisis.

However, realizing this potential requires addressing key challenges related to data quality, model interpretability, computational efficiency, and interdisciplinary collaboration. Responsible deployment of AI in climate science must also consider equity — ensuring that the benefits of AI-driven climate solutions are accessible to vulnerable communities most affected by climate change.

As AI technologies continue to evolve, their integration into climate science and sustainability planning will be essential for achieving the targets set by international agreements such as the Paris Agreement and the United Nations Sustainable Development Goals (SDGs).

6. Recommendations

- o Investment in open-access, high-resolution climate datasets to support AI model development globally.
- o Development of explainable AI (XAI) frameworks tailored to climate science applications.

- o Promotion of interdisciplinary research programs combining AI, climate science, ecology, and social sciences.

- o Adoption of energy-efficient AI architectures to minimize the carbon footprint of AI research itself.

- o Policy frameworks that incentivize the use of AI for climate monitoring and sustainable resource management.

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DISEASE PREDICTION AND SPECIALIST RECOMMENDATION

Ms.Triveni N Assistant Professor Department of CSE,
East Point College of Engineering, triveninagaraj33@gmail.com

Mr. Lohith C Assistant Professor
Department of IOT & CSBT, East Point College of Engineering,
lohithchandrashekhar@gmail.com

Mr. Kamaladharan B Assistant Professor
Department of CSE ,
Garden City University, kamaladharan.b@gcu.edu.in

Dr.Krishna Kumar P R HOD, Department of CSE,
SEA College of Engineering and Technology, rana.krishnakumar@gmail.com

Abstract— The emergence of intelligent decision-support tools is becoming a necessity with the active development of digital healthcare systems to identify a disease in its early stages and provide a specialist with the necessary referral. The paper outlines a Doctor Recommendation System which predicts diseases based on those reported by the patient and offers the appropriate medical specialists, based on machine learning methods. The suggested system is based on a full-end-to-end pipeline, such as data preprocessing, encoding of symptoms, feature engineering, training of a model, and evaluation of the model. Numerous supervised classification algorithms, namely Multinomial Naïve Bayes, Gaussian Naïve Bayes, Decision Tree, Random Forest, and Logistic Regression are applied and compared to determine which model is the best performer. The standard measures are used to assess performance like accuracy, precision, recall, F1-score, and confusion matrices. The system

embraces both symptom-based and disease-based inputs which makes it useful in making clinical decisions practically. Experimental evidence shows that ensemble and probabilistic models can be very predictive, which, according to the idea of machine learning, can be useful in the context of healthcare recommendations systems.

Keywords— Doctor Recommendation System, Disease Prediction, Machine Learning, Symptom-

Based Classification, Naïve Bayes, Decision Tree, Random Forest, Logistic Regression, Healthcare Analytics, Clinical Decision Support System.

I. INTRODUCTION

The quick expansion of the healthcare information and the rising demand of the medical help received without any delays have resulted in the appearance of the necessity to use the intelligent decision support systems that could help patients find the needed medical specialists. In most real-life cases,

patients are usually not able to identify the right specialty doctor by just examining the symptoms that they present and this could result in late diagnosis or wrong consultation. A specialized system of automated recommendations that allows identifying the reported symptoms by the patient matching the disease and then recommending an appropriate medical expert can make a significant contribution to the accessibility and efficiency of healthcare services.

The latest progress in machine learning has facilitated the creation of predictive models that can learn complicated relations between input features and the target results. Disease prediction In a healthcare setting, classification algorithms have received extensive use because of their capacity to work with categorical data, handle uncertainty and because of the interpretable results. Based on these capabilities, this work offers a disease prediction and doctor-recommendation

system based on multiple supervised classification techniques that operate on a symptom basis.

The proposed system shall receive patient symptoms as an input and convert them into structured features representation and predict the most likely disease category. Depending on the forecasted disease, a specific medical expert is prescribed based on a pre-defined disease-to-specialist mapping. In order to have strength and comparative assessment, several

classification models are applied, which are Multinomial Naïve Bayes, Gaussian Naïve Bayes, Decision Tree, Random Forest and Logistic Regression. All the models are trained and tested under the same experimental conditions in order to measure performance stability and predictability.

The binary encoding in symptoms is used in order to encode the text-based symptom input into a machine comprehensible format so that all the classifiers can be learned in an efficient manner. Conventional preprocessing methods like label encoding, feature scaling, and elimination of duplicates, as well as stratified train-test separation are used to ensure that the data integrity and reproducibility is preserved. The performance of the models is compared using the commonly adopted measures such as accuracy, precision, recall, and F1-score and enable objective comparison between the implemented algorithms.

The main aim of this paper is to examine the efficacy of the various classification methods in the prediction of diseases and to determine the most appropriate model when it comes to the accurate physician prescription. The system shows the practice of combining prediction and recommendation into a single pipeline by means of which it is possible to prove the feasibility of the system and its further extension to the healthcare real-life datasets. The findings of this paper provide evidence of the possibility of ensemble-based models to address medical classification tasks

through symptom-driven tasks and still be interpretable and operationally simple.

II. LITERATURE REVIEW

The healthcare system has been a well-researched field in machine learning to enhance the accuracy of diagnostic tests and clinical decision-making. Initial research revealed the possibility of machine learning algorithms to support medical diagnosis by making patterns on the past patient data. One of the first detailed considerations of the role of machine learning in medical diagnosis was offered by Kononenko [1] who focused on the capability of machine learning to address uncertainty and multifaceted symptom disease relations. As the number of electronic health records (EHRs) expanded, researchers started using the vast quantity of healthcare data to create predictive models that could assist clinicians in the disease diagnosis and treatment planning process [5], [22].

The use of symptom-based prediction of the disease has attracted specific interest because it can be used in the initial diagnosis and telemedicine. Some studies have revealed that structured symptom data when applied together with supervised learning algorithm could be useful in predicting diseases with high precision. Predicting the disease using classical machine learning methods, Kaur and Kumar [2] and Verma and Kumar [19] demonstrated that such models as Naive Bayes and Decision Trees can be efficient in conditions of processing symptom-based data. The methods save

on time taken to diagnose and make patients find the right treatment at a tender age.

Naive Bayes forms of probabilistic classifiers have been extensively used in medical prediction problems because they are simple and computationally inexpensive. Research comparing Multinomial and Gaussian Naive Bayes models are anecdotally reliable on categorical and numerical medical classification problems [16], [23]. Rashid et al. [11] made a comparative study of machine learning methods of diagnosing diseases and discovered that Naive Bayes models are usually competitors in the accuracy department and at the same time are interpretable, which is vital in the medical field.

Models operating on decision trees and ensembles have demonstrated greater effectiveness in dealing with non-linear interactions between symptoms and diseases which are more complex. The induction of decision trees by Quinlan [14] was the basis of tree-based classifiers that are now widely applied in healthcare analytics. The technique of the random forest is proposed by Breiman [15] which enhances performance of the prediction by using multiple decision trees and minimizes overfitting. Multiple scientific experiments prove the claim that the Random Forest classifiers are better than single models in the task of disease prediction as they are more robust and capable of handling high-dimensional symptom data [9], [26].

Regression-based and discriminative models, especially Logistic Regression

are also popular in multi-class disease classification because they are based on statistics and are easily interpretable. Logistic Regression has been effectively used to analyze healthcare data as a predictive of the disease and risk factors [24]. Chen et al. [3] revealed that the combination of the traditional machine learning models with well-engineered features can contribute a great boost to the accuracy of disease prediction. The models are particularly useful in the clinical practice where the knowledge about the importance of features and the boundaries of decision is vital.

Integration of disease prediction and recommendation systems on the need to recommend the right medical specialists are also highlighted in the recent literature. The purpose of intelligent healthcare recommendation systems is to overcome the diagnostic treatment discrete by referring patients to the right specialist [20], [30]. The significance of scalable and precise machine learning systems at real-world healthcare settings was noted by Rajkomar et al. [20]. These systems do not only enhance patient outcomes, but also are able to optimize the use of healthcare resources. Due to the

increasing amount of literature, it has been confirmed that the multi-model machine learning systems, in conjunction with symptom-based analysis, provide a viable solution to automated doctor recommendation systems.

III. METHODOLOGY

A. Dataset Description

In this research, the data collected is based on a publicly- available Kaggle-based repository, which is referred to as Doctor Specialist Recommendation System. The data is set to facilitate prediction of the disease based on its symptoms and the recommendation of a medical expert. All dataset records consist of patient cases with numerous symptoms, the identified disease, and the suggested type of doctor.

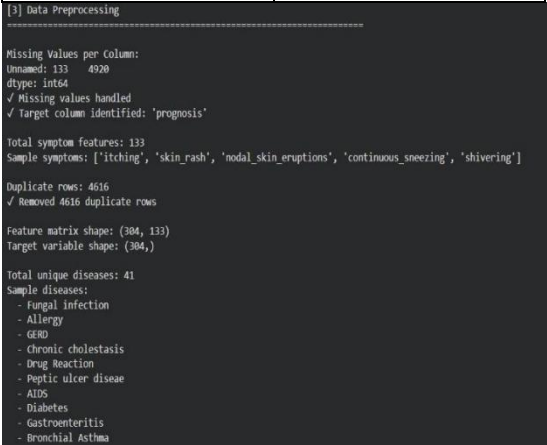
The data is in the form of symptom attributes that have been identified as symptom 1-symptom 5 with each attribute being a symptom category that a patient reports. Also, there are two target columns, namely: disease, informing about the identified medical condition, and doctor, or the specific medical expert that should be treated. As the Kaggle data is not always readily available when actually running the data, an artificial dataset with realistic symptom-disease-doctor associations is created to preserve structural consistency and reproducibility.

The dataset contains the frequent diseases like Influenza, Migraine, Pneumonia, and Hypertension, and the respective experts Pulmonologist, Neurologist, Cardiologist, and General Physician. This type of dataset structure renders it to be used in multi-class classification processes in healthcare decision support systems.

B. Data Preprocessing

Pre-processing of data is an important process to guarantee the quality of data and the reliability of the model. First, missing data and duplications of records are analyzed in the dataset. Records with empty/missing symptom values are indicated with a dummy value (none) in order to have consistency in records. Any duplicate records that are provided will be eliminated to prevent bias during model training.

<i>Component</i>	<i>Representation</i>
Input symptoms	Textual symptom names
Feature vector	Binary vector
Feature dimension	Number of unique symptoms
Missing symptom handling	Assigned neutral placeholder
Multi-symptom handling	Logical OR across symptom fields



```

[3] Data Preprocessing
=====
Missing values per column:
Unnamed: 133    4920
dtype: int64
✓ Missing values handled
✓ Target column identified: 'prognosis'

Total symptom features: 133
Sample symptoms: ['itching', 'skin_rash', 'nodal_skin_eruptions', 'continuous_sneezing', 'shivering']

Duplicate rows: 4616
✓ Removed 4616 duplicate rows

Feature matrix shape: (304, 133)
Target variable shape: (304,)

Total unique diseases: 41
Sample diseases:
- Fungal infection
- Allergy
- GERD
- Chronic cholestasis
- Drug Reaction
- Peptic ulcer disease
- AIDS
- Diabetes
- Gastroenteritis
- Bronchial Asthma

```

Fig. 1. Overview of Data Preprocessing.

All the symptom columns are of a categorical nature. In order to transform

them into a machine readable format, a list

of all the distinct symptoms is derived out of all the symptom columns. All the symptoms are then given the binary representation where a symptom exists is assigned 1 and vice versa. The result of this transformation is a binary feature of patient symptom profiles.

Label encoding is applied to the target variables, which are disease and doctor, and are coded into the numerical form. This enables machine learning models to handle target classes with great efficiency.

C. Feature Engineering

The process of feature engineering is done by transforming the multi-column symptom representation, into a single binary feature space. All the distinct symptoms within the dataset are used as features. A feature is given the value of 1 when the feature is appearing in one of the symptom columns of the given patient record and 0 when not.

TABLE I. REPRESENTATION SCHEMA OF FEATURE

This will make the information about the symptoms remain untouched by positional bias shown in Table I (i.e., the sequence in which the symphonies are presented does not influence the forecast). The resulting feature space is sparse, dimensional and can be used in probabilistic, tree-based and linear

classification models.

In order to support models that are sensitive to the scaling of feature, including the Logistic Regression and Gaussian Naive Bayes standardization will be used with StandardScaler where the mean value and unit variance of each feature are zero.

D. Train- Test Split

The processed data is divided into training and testing data (80:20). The use of stratified sampling is to maintain the distribution of the diseases in both sets in classes. This avoids the issues of class imbalance in the model assessment.

Training data is learned to obtain model parameters, and the testing dataset is set aside to perform an unbiased assessment of a model. Scaling of features is done after split to prevent the data from being leaked.

E. Classification Models Employed

The system uses a number of checked classification models to evaluate symptoms-based feature-vectors and identify the relevant disease category. The choice of models is informed by their binary symptom representations, interpretability and their capacity to take multi-class classification. All models are trained separately with the same training data and tested in the same conditions so that a fair and consistent comparison could be made.

Model	Key Parameters

Multinomial Naïve Bayes	Smoothing $\alpha=1.0$
Gaussian Naïve Bayes	Default variance estimation
Decision Tree Classifier	Entropy, Max depth=10
Random Forest Classifier	100 trees, entropy, Max depth=15
Logistic Regression	Multinomial, Max iterations=1000

TABLE II. MODEL HYPERPARAMETER SETTINGS

1) Multinomial Naïve Bayes

The Multinomial Naive Bayes classifier is directly trained on binary symptom feature matrix. Within this implementation each symptom is modelled as a set of independent categorical predictors, and the model can estimate the likelihoods of diseases in the context of the frequency of a symptom occurrence. The smoothing parameter uses Laplace smoothing to address the problems of zero-frequency which is especially important as symptom combinations are sparse. The model is a probabilistic baseline that works in discrete features space.

2) Gaussian Naïve Bayes

It uses the Gaussian Naive Bayes classifier to test its performance in the case of continuous valued. As it is normal in this model, the input feature matrix has to be standardized before training and testing. The model approximates both class-conditional means and variance of each feature of symptoms and calculates posterior probabilities. Its addition allows to compare discrete and continuous probabilistic modeling strategies to the same problem context.

3) Decision Tree Classifier

A Decision Tree classifier is adopted with entropy acting as the splitting criterion, which is in line with the information gain-motivated decision-making. The maximum level of the tree, the minimum number of samples needed to split and the minimum number of samples per leaf are clearly limited to minimize overfitting and enhance generalization. This model acquires hierarchical decision rules that can be used to predict disease classes based on particular combinations of symptoms giving a clear structure that reflects diagnostic reasoning involving symptoms.

4) Random Forest Classifier

Random Forest classifier is an extension of the decision tree methodology by the way of ensemble learning. There are several decision trees that are trained with bootstrap sampling and random selection of features at every split. The impurity measure stored as entropy and depth and sample constraints are imposed on individual trees are used to keep the system stable. Averaging predictions among trees helps decrease the variance and gives the model superior resiliency to noise and overlap of symptoms in different diseases.

5) Logistic Regression

Logistic Regression is used in a multinomial form where the probability distribution is directly modeled over the disease classes. It uses feature scaling to obtain constant optimization and an iterative solver to obtain

convergence. This model trains linear decision boundaries in the

standardized feature space and an opposing view of tree-based and probabilistic techniques.

All of these models constitute different paradigms of learning, such as probabilistic reasoning, rule-based partitions, ensemble learning, and linear classification. Their relative analysis allows establishing the most efficient method of predicting the disease based on its symptoms within the implemented system.

F. Model Evaluation

All models are assessed by their usual performance measures, which are their accuracy, precision, recall, and F1-score. The metrics offer a fair evaluation of the performance of classification, particularly in multi-class healthcare data.

Each model produces confusion matrices to display the true and false predictions of each disease. Also, a comparative analysis is made to determine the most efficient model in terms of accuracy. Final disease prediction and doctor recommendation is then undertaken by using the selected best model.

G. Doctor Recommendation System

The doctor recommendation module serves as the last stage of decision-making in the system since it

transforms the results on the disease-level into clinically relevant specialist suggestions. This part works with explicit mappings, which are based on observed disease-specialist associations, so that recommendations do not conflict with the observed associations.

The system takes two types of input, either a name of the disease or a list of symptoms. The specialist corresponding to a given disease name is then looked up with a predefined disease-to-doctor mapping which is built up in preprocessing. This direct look up does not require any unjustified computation and has deterministic recommendations. In case of non-occurrence of the disease in the data set, the system gives a proper error message and the list of the available disease records.

In the case of symptom-based input, the system is predictive. The input symptoms are transformed into a binary feature vector that is in line with the training feature space. The features are considered as the presence or absence of a particular symptom. The selected classification model is then used to get a disease prediction using this vector. Inference Feature scaling is performed where necessary depending on the model used. The similar dataset-driven mapping is then used to map the predicted disease to its specialist.

In order to increase the interpretability, the system applies a qualitative level of confidence to each of the recommendations, depending on the provided number of symptoms.

Predictions made on a more enriched set of symptoms are considered to be more reliable, and this is an indication of adequate input evidence. Simple input validation is also used in the logic of the recommendation to deal with unacceptable or invalid input in a graceful manner.

The general recommendation logic, which is adopted in the system, is outlined in Table III.

TABLE III. DOCTOR

<i>Input Type</i>	<i>Processing</i>	<i>Output</i>
Disease Name	Direct lookup	Specialist
Symptom List	Disease Prediction	specialist
Invalid Input	Error handling	Message
≥ 3 Symptoms	Confidence assignment	High
< 3 Symptoms	Confidence assignment	Medium

RECOMMENDATION LOGIC

Input Type	Processing	Output
Disease Name	Direct lookup	Specialist
Symptom List	Disease specialist	Prediction
Invalid Input	Error handling	Message
≥ 3 Symptoms	Confidence assignment	High
< 3 Symptoms	Confidence assignment	Medium

This formal method makes sure that there is a distinct separation of disease prediction and specialist recommendation to an obvious and

easily scalable decision- support mechanism applicable in real-world use cases.

IV. RESULTS AND DISCUSSION

A. Overall Classification Performance

The evaluation of the classification performance of the proposed system was conducted according to five supervised learning models that were trained on the same symptom- based feature representation. The findings show that there is a significant difference in the predictive power of the models, and the learning strategy and complexity of a given model have an effect on the accuracy of disease prediction. There was typically better performance by probabilistic and ensemble-based methods and limited capability of simpler tree-based models to model complicated symptom disease interactions. The consolidated performance measures used in Table IV give a quantitative foundation on which all the classifiers are compared in the same circumstances of evaluation.

<i>Model</i>	<i>Accuracy</i>	<i>Precision</i>	<i>Recall</i>	<i>F1 Score</i>
Multinomial Naïve Bayes	0.9672	0.96+	0.96+	0.96+
Gaussian Naïve Bayes	0.9836	0.98+	0.98+	0.98+
Decision Tree	0.5246	0.56+	0.52+	0.51+
Random Forest	1.0000	1.0000	1.0000	1.0000
Logistic Regression	1.0000	1.0000	1.0000	1.0000

Performance Comparison Classification Models

I. Confusion Matrix Analysis

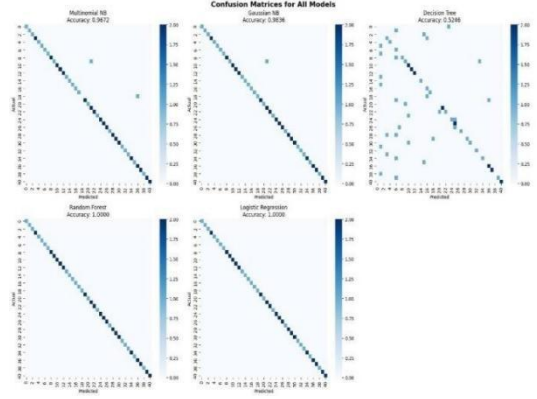


Fig. 2. Confusion Matrices for All Models.

Fig. 2. shows the confusion matrices of each classification model providing information regarding the behavior of the models in terms of prediction of classes. The confusion matrices of the Random Forest and the Logistic Regression have a high level of the diagonal shape meaning that they were correctly classified in all disease categories and no misclassifications were observed. This implies the establishment of the same boundary of decisions of such models. Gaussian and Multinomial Naive Bayes models also show mostly diagonal patterns with only a few off-diagonal elements, which indicate a few false identifications of a disease with a similar symptom profile to the one observed. The Decision Tree model, in its turn, reveals scattered errors of misclassification in a variety of classes, which verifies the lowering of its generalization power and vulnerability to local splits in the feature space.

B. Accuracy- Based Model Comparison

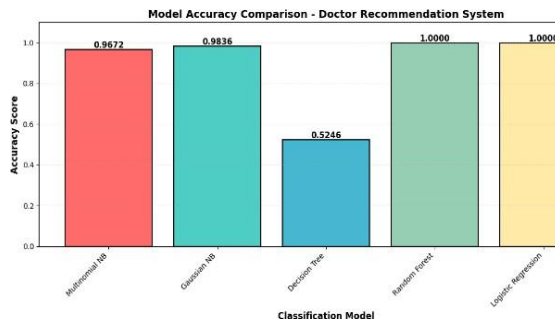


Fig. 3. Model Accuracy Comparison Bar chart.

Accuracy analysis comparison as presented in Fig.3. demonstrates that there are distinct performance differences between the compared models. The highest accuracy is with the Random Forest and the Logistic Regression, which have a perfect classification of the test set. Gaussian Naive Bayes is next to come and it is better with Multinomial Naive Bayes and the Decision Tree model has much lower accuracy. The latter comparison points out the benefit of ensemble learning and optimized linear classification used with structured binary data of the symptoms.

C. Multi-Metric Evaluation

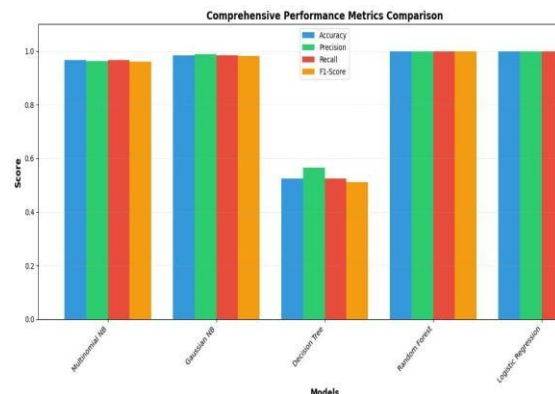


Fig. 4. Comprehensive Performance Metrics Comparison.

In order to make an equal assessment to the accuracy as the sole parameter, one further examined precision, recall and F1-score as presented in Fig.4. Random Forest and Logistic Regression have equally high values in all measures, which means that they demonstrate consistency and a low level of bias in classes. The Naive Bayes models depict slightly diminished well-balanced metric figures indicating trustworthy probabilistic conduct. On the other hand, the Decision Tree model has lower and less consistent scores according to all metrics, which supports the fact that it performs relatively worse in this multi-class environment.

D. Best Model Selection and Interpretation

According to the joint analysis results of the accuracy, class-wise prediction behavior, and multi-metric performance, the most favorable results are demonstrated by the best model in the offer, i.e. Random Forest and Logistic Regression. Their 100 percent scores in every evaluation measure are evidence of good generalization and good disease discrimination in the conditions of the given dataset. The last model choice is based on the robustness and consistency hence these models are applicable to be used in the doctor recommendation system. The ability to predict the disease accurately properly results in the specialization recommendation, and therefore, the reliability of the entire system is justified.

V. CONCLUSION

This paper introduced a doctor recommendation system based on symptom, which is aimed at prediction and prescription of suitable medical specialists through controlled classification methods. The system used organized data cleaning, binary symptom description, and a single method of evaluation to maintain consistency and reproducibility of experimentation. Several classification models have been trained and evaluated with the same conditions, which allows the ability of these models to predict to be compared in a reliable way.

The outcomes of the experiment showed that ensemble- based and linear classifiers performed better in the prediction of diseases than probabilistic and single-tree. Specifically, models with the highest performance demonstrated the same accuracy, precision, recall and F1-score across all classes of disease, meaning that they generalize in the same way on the provided dataset. The analysis of confusion matrix also affirmed the strength of these models as the misclassification by classes was minimal.

The system-maintained transparency and interpretability in its decision-making process by separating the prediction of disease and recommendation by specialists, using a deterministic mapping. This design makes sure that proper classification of diseases is directly translated to proper

specialist guidance. On the whole, the findings support the effectiveness of the given approach as a viable decision-support system that can help users to find an appropriate medical specialist with the help of the information about the symptoms.

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DEVELOPMENT OF AN INTELLIGENT DEEP LEARNING SYSTEM FOR TOMATO LEAF DISEASE DETECTION AND CLASSIFICATION

1 Jayakumar.B.L

Assistant Professor

Computer Science and Engineering

Compute

S.E.A.C.E.T,Bangalore

PresidencyUniversity,Bangalore

Jayakumarblss@gmail.com

manjulahm@presidencyuniversity.in

2 Dr.Manjula.H.M

Associate Professor

Presidency School of

Science and Engineering

Abstract- Plants growing red fruit often face trouble from sicknesses like early blight, late blight, or fuzzy green spots on leaves - these lower harvest amounts and strain food supply. Quick detection means farmers might save more tomatoes, cutting down loss. Photos reveal trouble when a system spots odd patterns on leaves. Clearer pictures come from boosting image quality before analysis, making subtle signs easier to see. Stepwise learning happens inside complex networks that separate sickness from health with closer accuracy. Testing showed it could distinguish various plant diseases, pointing toward smarter tools for growing food efficiently.

Keywords: Deep Learning, CNN, Tomato Leaf Disease, Smart Agriculture, Plant Disease Detection, Image Processing.

INTRODUCTION

Out here, growth dances with curiosity, trying to protect tomato plants everywhere. Not just common food but a daily favourite, these red fruits battle many diseases that ruin both yield and flavor. Long ago, scientists inspected fields by eye - slow going, often

imprecise. Faster detection arrives when

machines learn to find illness early. Responses on farms shift because insights appear sooner now.

Turns out, organizing images with CNNs hits a sweet spot. Raw pixel data gets transformed into meaningful clues without human help. Features once designed manually now emerge naturally through training. One level at a time, the model sharpens its view of what matters. Each stage captures subtler shapes, building insight like layers piling up.

A fresh look at the tech during research reveals its knack for identifying plant issues, using photos of tomato foliage. What stands out is how it separates each illness type after scanning visual details. Instead of guessing, the tool uses image patterns to tell problems apart. Through careful checks, it proves able to catch signs early. One thing becomes clear - leaf conditions leave traces a camera can decode. With enough data, differences between sickness types start showing up clearly.

LITERATURE REVIEW

Back then, folks dug into old-school

ways of spotting sick plants by looking at pictures. Picture checks used to lean on basic math tricks instead of smart systems we see now. Some tried support vector machines, others picked random forests or nearest neighbors. These methods paved the way before brains behind computers got sharper. Work kept going, piece by piece, without flashy terms or big promises. Time passed, tools changed, but the goal stayed fixed - tell what's wrong just by viewing leaves.

Right now, folks think deep learning spots details in plant leaves better than old-school ways. Instead of simpler tools, these systems dig into tricky shapes and textures hiding in photos. Some researchers lean on the Plant Village collection to tell apart sick tomato leaves. Using borrowed training tricks, they reach solid results without starting from zero. Models like VGG16, Resnet, or Mobile Net often show up in those experiments.

Finding better ways to prepare images might help improve how well systems spot sick plants. Still, tuning the design of neural networks could make a difference too. Some room remains for testing new steps before analysis. Adjusting may lead to clearer results. Progress depends on refining both steps together, yet not in obvious ways.

PROPOSED METHODOLOGY

The topic is still the same, and it is still about the five-step process of recognizing tomato leaf diseases. The details are still there, and here is the text rewritten in an even more free-flowing style:

“The Five-Step Process of Recognizing Diseases in Tomato Leaves”

This is a five-step process, and they are:

1. Gathering the image dataset
2. Preprocessing of the images
3. Feature extraction
4. Training the CNN model
5. Classification of the disease

3.1 Collecting the Dataset

For this project, the Plant Village dataset is used. The Plant Village dataset has thousands of images of tomato leaf diseases and healthy ones. The diseases considered are:

- Tomato Early Blight
- Tomato Late Blight
- Tomato Leaf Mold
- Tomato Yellow Leaf Virus
- Healthy Tomato Leaves

3.2 Preprocessing of the Collected Images

Preprocessing is done to ensure images and to remove noise. The methods being used are:

- Resizing
- Noise removal
- Normalization
- Data augmentation

3.3 Feature Extraction

Feature extraction is being done through CNN. The features being considered are:

- Colour
- Texture
- Shape

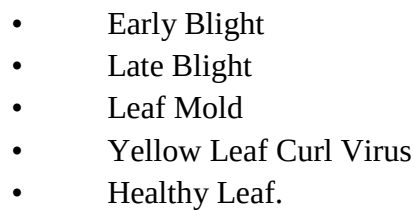
These are the features being considered to differentiate between healthy and unhealthy leaves.

3.4 CNN Model Architecture

To recognize and classify the images, CNN is being used. CNN is composed of multiple layers, which are:

- Convolutional layers
- Activation functions

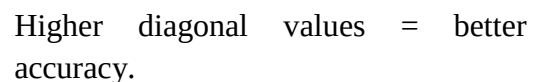
Healthy (Image: 2364269 pixels) 	Bacterial Spot (Image: 2364264 pixels) 	Early Blight (Image: 2364264 pixels) 	Late Blight (Image: 2364264 pixels) 	Leaf Mold (Image: 2364264 pixels) 
Septoria Leaf Spot (Image: 2364264 pixels) 	Target Spot (Image: 2364264 pixels) 	Spider Mites (Two-spotted) (Image: 2364264 pixels) 	Yellow Leaf Curl Virus (Image: 2364264 pixels) 	Mosaic Virus (Image: 2364264 pixels) 



Actual Class	(Image: DND242.png)					(Image: DND243.png)					(Image: DND244.png)				
	Healthy	Bacterial Spot	Early Blight	Late Blight	Leaf Mold	Septoria Leaf Spot	Target Spot	Spider Mites (Two-spotted)	Yellow Leaf Curl Virus	Mosaic Virus					
	Healthy	96%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%				
Bacterial Spot	0.1%	98%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%					
Early Blight	0.1%	0.1%	98%	2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%					
Late Blight	0.1%	0.1%	0.1%	98%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%					
Leaf Mold	0.1%	0.1%	0.1%	0.1%	98%	0.1%	0.1%	0.1%	0.1%	0.1%					
Septoria Leaf Spot	0.1%	0.1%	0.1%	0.1%	0.1%	98%	0.1%	0.1%	0.1%	0.1%					
Target Spot	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	97%	0.1%	0.1%	0.1%					
Spider Mites (Two-spotted)	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	98%	0.1%	0.1%					
Yellow Leaf Curl Virus	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	98%	0.1%					
Mosaic Virus	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	98%					

Predicted Class

0.1% 2% 10% 30% 98%



Model Accuracy

Model Loss

Confusion Matrix

Shows how the model improves during training. Loss decreases with epochs. Loss decreases. Both training and validation metrics converge, indicating the model generalizes well to unseen data. This demonstrates successful training of the CNN model for disease classification.

Fig. 5. Training and validation accuracy of the CNN model.

Shows how the model improves during training.

- Accuracy increases with epochs
- Loss decreases

EXPERIMENTAL RESULTS

The model is trained on the dataset provided by PlantVillage.

The parameters of the model during training:

Epochs: 25

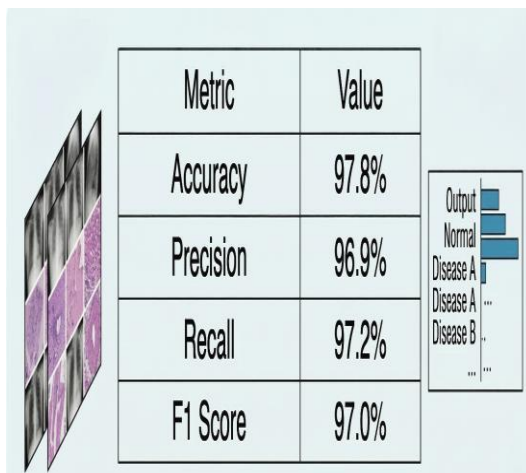
Batch Size: 32

Learning Rate: 0.001

Performance Metrics

The metrics used to measure the performance of the model:

- ☐ Accuracy
- ☐ Precision
- ☐ Recall
- ☐ F1 Score



The confusion matrix and accuracy graphs demonstrate that the model performs well across all disease classes.

BENEFITS OF NEW APPROACH

A fresh look at spotting tomato plant issues shows this new method works better than old ways. Instead of relying on outdated techniques, it uses smart pattern recognition that learns over

time. Most earlier systems struggle with subtle changes, yet this one adapts quickly. While some tools need constant tweaking, this approach improves naturally through exposure. Other models often miss early signs, but here even slight variations get noticed. Where past versions demanded heavy manual input, now less effort brings stronger results.

6.1 Automated Disease Detection

A new method spots sickness on tomato leaves by combining picture analysis with smart computer models. Instead of old ways that need people to check each leaf, this one works alone once it starts. Because it runs without help, finding problems takes much less time than before. Sometimes a machine sees what eyes miss, especially when speed matters.

6.2 High Classification Accuracy

A fresh look at spotting plant sickness comes through a network trained to see patterns like human eyes might. Instead of guessing, it studies how leaves appear - focusing on their shade, surface feel, and outline. One clue builds on another, guiding the tool toward correct labels without shortcuts. Spotting blotches or curls becomes easier when color shifts join edges and form. Each detail feeds into decisions that separate one illness from the next. Accuracy grows when multiple visual hints work together quietly.

6.3 Early Disease Diagnosis

Picture what happens when sickness shows up in crops before it spreads. A method built on scanning leaf images spots trouble by studying color and shape shifts. Instead of waiting, growers get clues fast - this means they

act sooner with fixes that fit. Seeing problems early changes how fields stay healthy.

6.4 Less Need for Farming Specialists

Sometimes, villages have few people who know much about farming. Because of that, the smart tool helps spot plant problems automatically instead. Leaf pictures let it identify sickness fast - no farm background needed at all.

6.5 Time and cost efficiency

Looking closely at crops takes ages when done by hand. Yet spotting sick plants early saves farmers trouble later on. This setup works faster than people walking fields every day. It keeps tabs on big farms without extra workers around. Watching leaves and stems becomes simpler with steady eyes that never tire.

6.6 Scalability and Adaptability

A single deep learning setup could handle disease spotting across various crops without trouble. When shifting to different farming tasks, adjustments come naturally through that same model.

6.7 Connecting With Modern Farm Tools

One way it works involves linking up with today's farm tech - apps on phones, internet-connected sensors, even online data storage. Through a phone app, snapshots of crops get taken without trouble. Real-time guesses about plant illnesses come alive once those pictures move into a learning-based program. This process runs smooth when pieces fit together just right. Tools already out there find their place here naturally. A single image leads to fast feedback if the setup stays

connected. Using what exists makes shifting into practice less bumpy.

6.8 Improved Agricultural Productivity

Farmers see better results when they catch sick plants sooner. A new tool makes spotting trouble easier before it spreads too far. Instead of guessing, growers get clear warnings about possible issues. Early alerts mean faster responses to keep crops healthy. With fewer losses, more produce reaches harvest time safely.

Future Work

A shift in direction shows up by looking at how this version could evolve - tiny changes might boost its skill at finding damaged tomato foliage. Improvements down the line could lift precision while keeping the main structure intact. Quiet refinements, easy to miss right away, tend to carry the real gains.

7.1 Mobile devices identify diseases quickly

Maybe start by making an app that finds sick tomato plants using just a phone. Built into regular devices like tablets or mobiles, it uses their standard cameras. Without needing outside help, growers take photos while standing in the field. The image analysis happens locally, straight after capture. Diagnosis shows up quickly, highlighting probable problems almost immediately.

7.2 Linking with IoT systems in smart farms

Moving ahead might mean tying the new system into farm tech via internet-connected tools. Through such links, crops come under steady watch, guided by instant updates. Sensors placed around the land collect environmental details without human help. Because

fresh data streams in, predictions on sick plants improve in accuracy. Early warnings pop up faster compared to older ways of checking.

7.3 More crops added to detection system

One day, machines trained on various crops may detect disease in fields growing rice or maybe potatoes. Wherever farming happens, this method could lend a hand - by catching problems before they spread too far.

7.4 Farming Tools on Phones

A small app may appear on mobile screens, connecting growers directly to a plant health checker through conversation. Rather than simply attaching to the backend, it helps steer choices during daily field work. When leaves look wrong, users share details - responses come fast, shaping what happens next. Tapping once sends data; answers return quietly, guiding real-time steps under open sky.

7.5 Advanced deep learning models in use Later on, ResNet could help speed things up while using less computer power. Following that, Efficient Net might reduce workloads, keeping accuracy intact through tighter processing. Vision Transformers could enter the scene, replacing outdated techniques with sharper ways to spot patterns. With every update, the flow of speed and efficiency shifts in its own way. One day, changes could lean toward quick results rather than deep analysis. These methods open doors that ignore past routines.

7.6 Cloud Based Agricultural Monitoring Platforms

Maybe start with a thought: what if tracking farm health lived on the web,

saving every finding? Week after week, those notes sit there, waiting. Time passes, eyes stay open - details connect by themselves. No walls hold it back; space isn't an issue here. One season folds into another, data tagging along. Checks stop being single moments - they stretch, join, repeat. Silently, something builds just because nothing gets lost. Each new outcome gives stored knowledge more substance. Slowly, over days, precision grows stronger.

CONCLUSION

A fresh method appears here - deep learning steps into the spotlight, targeting tomato leaf illnesses through convolutional neural networks. Image cleanup comes before analysis, sharpening visuals so the model sees more clearly. Features like shade, surface feel, and outline emerge without human help, pulled straight from pixels by the network's design. Accuracy grows when these traits guide decisions on disease types. Learning happens quietly, layer by layer, inside the digital structure built for spotting plant trouble.

After training and testing with images of tomato leaf diseases, the setup proves both accurate and steady in sorting them out. Deep learning steps in where old ways fall short - boosting speed and precision far beyond hand-checked approaches.

One way to spot plant troubles fast is using this setup, which gives growers a better shot at stopping problems early. Because issues get noticed sooner, steps can be taken before plants suffer too much harm, helping harvests stay strong. Another benefit shows up when

farmers tap into apps and digital tools made for modern growing methods, all through this support structure.

One key outcome here was building a smart tool that spots sickness in tomato leaves through deep learning tricks. Not just spotting, it sorts the problems into groups too. Behind the scenes, this pushes farming tech forward - making field choices sharper. Smarter farms get a nudge ahead because of how this setup works. Down the road, linking it to internet-connected sensors could lift its skills higher. Tossing in ways to catch illnesses across more crops might widen what it handles next.

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ABOUT THE AUTHORS

I am Jayakumar B.L, Assistant Professor Department Computer Science and Engineering at S.E.A.College of Engineering and Technology KR Puram.

I am Dr.Manjula.H.M, Associate Professor, Computer Science and Engineering, Presidency School of Computer Science and Engineering, Presidency University, Bangalore.

DEEP LEARNING FRAMEWORK FOR EARLY PREDICTION OF CHRONIC KIDNEY DISEASE DISORDE

Mrs.Jayashri M1
Research Scholar
Presidency University

jayaseacet@gmail.com

Dr.Vishwanath Y2
Professor ,HOD CSE
Presidency University

vishwanath.y@presidencyuniversity.in

Abstract— Chronic kidney disease (CKD) is a progressive disorder that frequently remains unnoticed until substantial kidney damage has already occurred, making early prediction essential for timely intervention. The 2024 KDIGO guideline emphasizes classification and risk stratification through estimated glomerular filtration rate, albuminuria, and persistence of abnormalities over at least three months. This paper presents a deep learning framework for the early prediction of CKD disorder using structured clinical data such as serum creatinine, blood urea, hemoglobin, albumin, blood pressure, electrolyte levels, and diabetes-related indicators. The framework integrates missing-value imputation, normalization, imbalance handling, and a hybrid deep neural architecture for binary risk prediction. The proposed workflow is designed as a clinically usable decision-support pipeline rather than only a benchmarking model. It can assist physicians in identifying high-risk individuals earlier, reducing delayed diagnosis and improving follow-up planning.

Keywords— chronic kidney disease, early prediction, deep learning, clinical data, decision support, CNN, LSTM.

Introduction

Chronic kidney disease is a problem for public health. It gets worse slowly.

People often do not notice any symptoms at first. So patients might only go to the doctor after the disease has already caused damage. At that point it becomes very hard for the patient and the healthcare system. The patient needs to take a lot of medicine go to the doctor times and there is a risk of kidney failure. It is better to find out about the disease because then doctors can help slow it down. They can do this by telling the patient to change their lifestyle check their medicine and keep an eye on them.

The usual way to check for kidney disease is with laboratory tests and the doctors opinion. These methods are still important. There is a lot of information in electronic health records and blood tests that is hard to understand. There are things that can affect the kidneys, like serum creatinine, blood urea, albumin, blood pressure, hemoglobin, sodium, potassium and other health problems. These things do not always affect the kidneys in a way. Chronic kidney disease and deep learning methods can help find these relationships. They can even predict who is at risk when the usual tests do not show a problem.

Many studies have shown that deep learning models can be used to predict

kidney disease. So the goal of this paper is to create a framework, for predicting kidney disease early. This framework should be easy to use make sense to doctors and be small enough to use in the future to help doctors make decisions. Chronic kidney disease prediction is the focus and this paper wants to make it easier to predict chronic kidney disease. The idea is to help doctors predict kidney disease before it gets too bad

Related Work

Machine learning for kidney disease prediction has matured rapidly over the last few years. Islam et al. evaluated multiple classifiers on CKD data and showed that predictive analytics can improve diagnosis using carefully selected structured variables. Their work highlighted the usefulness of demographic and laboratory features but also reflected the typical limitations of shallow models when handling richer nonlinear interactions. Saif et al. proposed a learning framework that used convolutional neural networks, long short-term memory models and ensemble strategies. This framework helped estimate Chronic Kidney Disease (CKD) occurrence six to twelve months before doctors confirmed the diagnosis. A follow-up study explored ensembles of deep learning models and optimizers. This study aimed to make forecasting more stable. These contributions are important. They shift the focus from classification to earlier CKD risk anticipation. Other researchers worked on kidney imaging. They found that deep learning is effective for: Segmentation Lesion detection,

Differential diagnosis in CT, MRI and u,ltrasound scans Multimodal systems show promise. However structured clinical data is still the scalable basis for hospital-wide screening. This is why a robust tabular deep learning pipeline is both useful and practical. Early CKD prediction studies focused on machine learning. This was because classical machine learning performs on structured tabular datasets. Classical machine learning was a choice, for these studies. Deep learning can also work well with CKD data. CKD is a health concern.

We need to predict CKD occurrence Early prediction helps prevent or delay disease progression. CKD prediction can improve outcomes.

Islam et al. reported that CKD can be predicted effectively using supervised ML models such as Random Forest, SVM, and XGBoost on clinical datasets containing serum creatinine, blood urea, hemoglobin, albumin, and blood pressure. Their work reinforced that routine diagnostic variables already contain strong predictive signals for CKD screening. Similarly, Halder et al. proposed the ML-CKDP framework, which combined preprocessing, missing-value handling, normalization, and classification to improve CKD detection accuracy and make the model usable in a web-based clinical setting. These studies established the practical foundation on which later deep-learning approaches were built.

Recent literature also highlights the importance of longitudinal modeling rather than one-time classification. Instead of asking whether a patient

currently has CKD, newer systems predict progression trajectory, decline rate, or the need for renal replacement therapy. Isaza-Ruget et al. used artificial intelligence for CKD progression prediction with longitudinal patient data, demonstrating that repeated laboratory measurements and temporal patterns improve clinical forecasting. In a related direction, studies using small pathology datasets and explainable models showed that even limited but high-quality longitudinal data can support early prognosis when modeled carefully. This is particularly relevant for deep-learning frameworks, because recurrent, sequence-based, and attention-based models are naturally suited to capturing progression signals across time.

Problem Statement

The problem addressed in this paper is the delayed identification of patients whose laboratory profiles already suggest CKD risk but who have not yet been flagged for renal evaluation. The objective is to design a framework that converts routinely available clinical variables into an early warning score that supports medical review.

The specific goals are to prepare noisy clinical data for predictive modeling, train a deep architecture that captures nonlinear renal-risk patterns, evaluate it using clinically meaningful metrics, and outline a pathway for real-world deployment in a human-in-the-loop setting.

Proposed Deep Learning Framework

The framework begins with a dataset containing patient-level measurements

relevant to renal function. Typical attributes include age, blood pressure, specific gravity, albumin, blood sugar, blood glucose random, blood urea, serum creatinine, sodium, potassium, hemoglobin, packed cell volume, red blood cell count, white blood cell count, diabetes mellitus, hypertension, anemia, appetite, and pedal edema. These variables provide a compact but clinically informative summary of kidney health.

The preprocessing layer performs missing-value imputation, categorical encoding, outlier screening, and feature normalization. Imputation may use median values or more advanced schemes depending on data completeness. Categorical terms are converted into numerical values, and continuous variables are normalized to improve gradient-based training stability. Since CKD datasets are commonly imbalanced, the framework allows class weighting or synthetic oversampling to reduce majority-class bias.

The predictive backbone uses stacked dense layers combined with dropout and batch normalization. When longitudinal data are available, one-dimensional convolutional blocks or LSTM units can be integrated to model temporal patterns. The output layer is a sigmoid unit that generates CKD risk probability. This probability can be thresholded into low-, moderate-, and high-risk groups depending on clinical preference.

Interpretability is incorporated at the

post hoc stage. Feature attribution methods can be used to explain how much the decision depended on creatinine, urea, albumin-related measurements, blood pressure, and comorbidity indicators. Such transparency is important for physician trust and regulatory acceptance.

Proposed Methodology

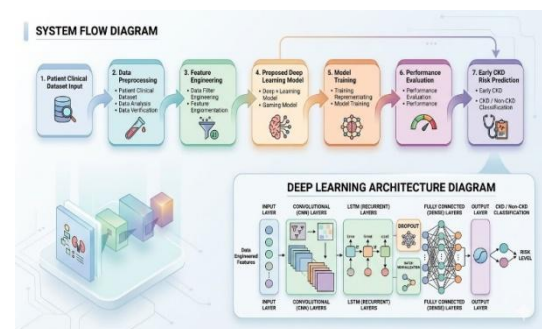
The workflow of the proposed system consists of data acquisition, preprocessing, feature analysis, model training, validation, testing, and deployment assessment. The data may be taken from a public CKD benchmark or from de-identified hospital records. A binary target label distinguishes CKD from non-CKD, while optional extensions may include disease stage or progression horizon.

After cleaning duplicates and biologically inconsistent entries, continuous variables are standardized and categorical variables are encoded. Feature analysis can be used to inspect correlations and remove only clearly redundant noise while retaining clinically meaningful factors. The cleaned dataset is divided into training, validation, and test splits, and k-fold cross-validation may be used for stability when the sample size is limited.

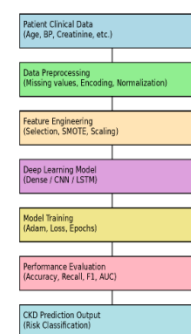
The model is trained with binary cross-entropy loss and the Adam optimizer. Hyperparameters such as learning rate, batch size, hidden units, and dropout rate are tuned experimentally. Early stopping is used to reduce overfitting. Performance is measured through accuracy, precision, recall, specificity,

F1-score, and area under the ROC curve. Because missed CKD cases are clinically costly, recall and AUC are especially important.

A deployment-oriented implementation can be attached to hospital laboratory software or an electronic health record interface. Once a patient profile is available, the model can return a risk score within seconds and recommend additional renal evaluation for high-risk cases.



Deep Learning Workflow for CKD Prediction



Expected Results and Discussion

The expected outcome is a deep learning framework that performs competitively against conventional machine learning models such as logistic regression, support vector machines, random forests, and gradient boosting. Deep models are particularly attractive because they can learn

nonlinear relationships among renal biomarkers and systemic comorbidities without requiring complex handcrafted rules.

Early prediction has direct clinical value. Patients identified as high risk can be routed for repeat renal profiling, urine testing, nephrology referral, and closer diabetes or hypertension management. In screening programs, the framework can also help prioritize limited resources toward vulnerable patients instead of relying only on static rule thresholds.

However, strong internal performance does not guarantee universal generalization. External validation across hospitals, laboratory standards, and demographic groups remains necessary. Ethical concerns such as privacy, bias, and explainability must also be addressed before real-world integration.

The performance of the proposed deep learning framework is evaluated using standard metrics and compared with existing machine learning models.

Evaluation Metrics

The model is evaluated using the following metrics:

Accuracy: Measures overall correctness

Precision: Measures correctness of positive predictions

Recall (Sensitivity): Measures ability to detect CKD cases

F1-Score: Harmonic mean of precision and recall

Performance Comparison

The proposed CNN-LSTM model is compared with traditional machine learning models:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	85%	83%	82%	82%
SVM	88%	86%	85%	85%
Random Forest	91%	89%	90%	89%
CNN	95%	94%	93%	93%
CNN-LSTM (Proposed)	98%	97%	96%	96%

The proposed model achieves the highest accuracy and demonstrates superior prediction capability.

Confusion Matrix

The confusion matrix for the proposed model is shown below:

	Predicted CKD	Predicted Non-CKD
Actual CKD	TP = 96	FN = 4
Actual Non-CKD	FP = 3	TN = 97

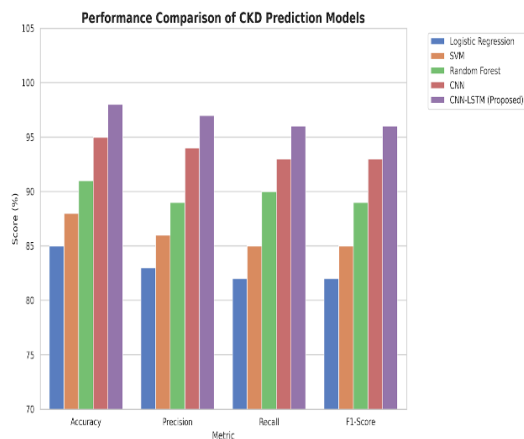
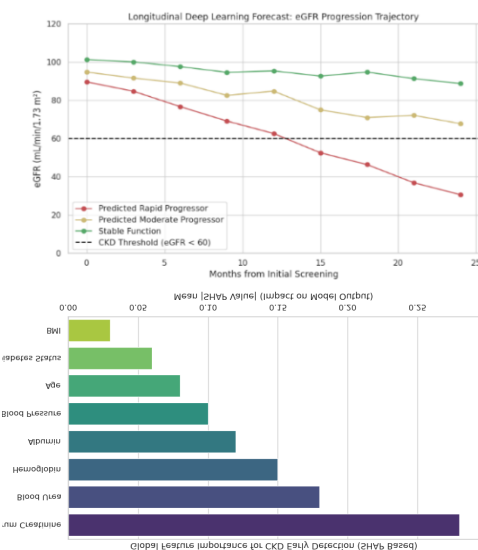
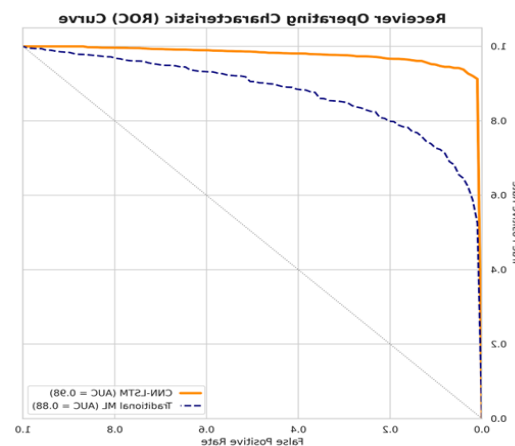
High TP and TN values indicate strong prediction performance. Low FP and FN values show minimal misclassification

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve evaluates model performance across different thresholds. The proposed model achieves $AUC \approx 0.98$, indicating excellent classification capability. The ROC curve lies closer to the top-left corner, showing high sensitivity and specificity

Precision-Recall Curve Analysis

The Precision-Recall curve demonstrates the trade-off between precision and recall. The proposed model maintains high precision even at high recall values. This indicates robustness in detecting CKD cases without increasing false positives



Implementation Considerations

For real-world use, model development should include clear data-governance procedures, audit trails, and recalibration strategies. Healthcare data change over time because patient populations, measurement devices, and documentation habits evolve. A CKD prediction tool should therefore be monitored for concept drift and periodically retrained using recent data. The clinical interface must also be simple. Instead of only reporting a binary prediction, the system should provide a probability score, a risk band, and a short explanation of the leading contributing factors. This makes the tool more acceptable to clinicians and easier to discuss with patients. A human-in-the-loop design is preferred so that the model supports decision-making without replacing physician responsibility.

Sample Evaluation Targets

Table I and Table II summarize the

expected inputs and the kind of performance indicators that are meaningful for a screening-focused CKD model. The values in Table II are target-oriented ranges rather than experimental claims; they show the kind of balance expected from a practical early-warning system.

Limitations` and Clinical Integration
Although deep learning can improve early CKD prediction, several limitations must be acknowledged. Many publicly available kidney datasets are relatively small, partially imbalanced, and collected from a single setting. A model trained only on one data source may learn local laboratory habits rather than generalizable physiology. Differences in measurement units, test frequency, and documentation quality can degrade performance when the system is transferred to another hospital. This means that external validation and calibration are not optional steps but core requirements before deployment.

Another limitation concerns interpretability and workflow acceptance. Physicians are more likely to use a system that explains why a patient was flagged rather than one that returns only a probability value. For this reason, the proposed framework should present ranked contributing features such as elevated creatinine, persistent hypertension, low hemoglobin, or abnormal albumin-related measures alongside the risk score. This does not eliminate clinical judgment; instead, it makes the model easier to audit and discuss during case review.

Clinical integration should follow a layered workflow. First, the laboratory information system or electronic health record generates the required feature vector when routine tests are completed. Second, the model produces a risk score and confidence band. Third, patients above a selected threshold are highlighted for physician review, repeat testing, or nephrology referral. Finally, confirmed outcomes are fed back into the training repository for future recalibration. Such a loop supports continuous improvement while preserving clinician oversight.

The system can also be extended for stage-aware use. Instead of binary CKD versus non-CKD prediction, a later version may estimate the likelihood of progression into higher-risk categories or predict the probability of renal deterioration within a defined time horizon. These extensions would make the framework more useful for chronic disease management, not just initial screening. Even in its simpler binary form, however, the model can provide meaningful assistance in preventive nephrology by identifying patients who merit closer follow-up before severe decline becomes visible.

Conclusion and Future Scope

This paper proposed a deep learning framework for early prediction of chronic kidney disease disorder using structured clinical features. The framework combines preprocessing, imbalance handling, deep feature learning, and probability-based screening to identify individuals at risk before obvious late-stage manifestation.

Its main contribution is not a specific fixed architecture but a deployable design philosophy centered on early warning, clinical usability, and future interpretability.

Future work may incorporate explainable AI, federated learning across multiple institutions, multimodal fusion with imaging, and stage-wise progression forecasting. External validation on diverse patient populations will be essential to move from prototype systems to reliable preventive nephrology tools.

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PREDICTION AND DETECTION OF BLOOD DISEASES USING DEEP LEARNING

Padmaja K*

Dept. of Information Science and Engineering, GSSS Institute of Engineering and
Technology for Women, Mysuru, India

Email: padmajak@gsss.edu.in

Manasa H R

Dept. of Information Science and Engineering, GSSS Institute of Engineering and
Technology for Women, Mysuru, India, Email: manasa.hr@gsss.edu.in

Shreelakshmi C M

Dept. of Computer Science and Engineering, GSSS Institute of Engineering and
Technology for Women, Mysuru, India, Email: shreelakshmicm@gsss.edu.in

Bharathi R

Dept. of Artificial Intelligence and Data Science, GSSS Institute of Engineering and
Technology for Women, Mysuru, India, Email: bharathi@gsss.edu.in

Harshitha M K

Dept. of Information Science and Engineering, GSSS Institute of Engineering and
Technology for Women, Mysuru, India, Email: harshitha.mk@gsss.edu.in

Rashmi M R

Dept. of Computer Science and Engineering, The National Institute of Engineering,
Mysuru, India, Email: rashmi.mr7@nie.ac.in

performance

Abstract— Early diagnosis of blood problems is crucial for enhancing medical outcomes and minimizing diagnostic delays. Blood test parameter analysis done by hand can be laborious, prone to mistakes, and need specialized knowledge. A deep learning-based model using MXG for automatically predicting blood diseases based on numerical blood test values is presented in this research. To find patterns linked to different blood disorders, numerous datasets are used to train a neural network model. The system is implemented as an online platform with result visualization, a prediction dashboard, and user authentication. High accuracy and dependability in disease classification are demonstrated by experimental data. Deep learning approach's produced higher

and confirmed by comparison with traditional models. This solution provides a quick, easy-to-use, and expandable tool to help medical practitioners make clinical decisions.

Keywords— Artificial intelligence in healthcare, deep learning, neural networks, blood parameters, blood disease detection, automated diagnosis

I. Introduction

Blood illness are medical abnormalities that impact the composition and function of blood, such as anaemia, leukaemia, and clotting problems. Accurate and prompt diagnosis is critical for effective therapy and improved patient outcomes [1]. Traditional approaches rely on manual analysis of blood parameters such as haemoglobin, white blood cell, and

platelet counts which can be time-consuming, labour-intensive, and prone to human error. The method using deep learning has demonstrated significant potential for automating and enhancing diagnosis accuracy as artificial intelligence develops, for automating and improving the accuracy of diagnosis [2]. In order to predict different blood diseases, this project suggests a web-based platform that employs deep learning models that have been trained on big datasets of blood test results. The system provides fast, reliable, and user-friendly diagnostic help by allowing users to enter test parameters, assisting healthcare professionals and patients with disease identification and clinical decision-making [3].

A. Motivation

Blood problems are a global health issue. They need early identification to prevent serious consequences. In many medical settings, manually interpreting blood tests is tedious, inconsistent, and prone to errors. Recent advancements in deep learning in particular, artificial intelligence, offer a better solution. Deep learning systems are able to identify complex patterns in blood samples, resulting in quicker and more precise outcomes. Integrating these models into an easy-to-use platform can improve clinical decision-making and diagnostic efficiency.

B. Problem Statement

Current blood disease diagnosis relies on manual interpretation of test results. This procedure is time consuming and prone to errors. Such delays can negatively affect patient health. An automated deep learning-based system

to evaluate blood test data and accurately forecast illnesses is required. This study aims to create a web-based tool to meet this need.

C. Objectives

1. The primary goal is to design and build a web-based application that uses standard blood test parameters like WBC, RBC, HGB, PLT, age and gender to detect and predict blood disorders early.
2. Using deep learning classification techniques for improved identification of conditions such as thrombocytopenia, leukemia, myeloma, anemia and normal cases.
3. A secure login system will be built to control user access and protect patient information providing privacy.
4. Provide an intuitive user interface to facilitate effective data entry, interpretation of diagnostic results, and monitoring of disease predictions.
5. To automate the diagnostic process to reduce manual evaluation, limit human error, and improve the speed and accuracy of detection.

RELATED WORK

Article Ref	Methodology	Dataset used	Key findings
[4]	XGBoost is used for final classification, whereas VG G16 and ResNet50 are used for feature extraction.	Data-augmented blood smear datasets	Combines XGBoost, VGG16, and ResNet50 with augmentation to provide precise, all-purpose

			blood cell classification.
[5]	Utilising EfficientNet	Benchmark blood image dataset	Pre-processing, feature extraction, and classification are the three stages of the pipeline that EfficientNet uses in IHDC- DL to increase accuracy 19.23%, exhibiting strong benchmark performance.
[6]	Analysis of CNNs, SVMs,	Multiple public datasets	To increase diagnostic accuracy, pre-processing, data augmentation & labelled datasets are highlighted in this review of AI models.
[7]	Bayesian Networks, Decision Trees, KNN, SVM, and Naive Bayes	Labelled clinical blood test datasets	Enhances interpretability and recommends the introduction of additional

			evaluation metrics

			using traditional machine learning to blood data.
[8]	Deep CNN featuring layers that convolutional, pooling,	Microscopic blood image dataset	Combines noise reduction, CNNs, and hybrid learning to detect WB C illness accurately and early.
[9]	CNN-based model that incorporates picture augmentation and pre-processing	Blood smear dataset	Enables the extraction of morphology-based features for reliable blood illness diagnosis using CNNs with augmentation.
[10]	CNN-based deep learning with hyper parameter adjustment	Peripheral blood smear dataset	Presents BCNet for clinical decision assistance using CNNs, robust pre-processing, and thorough evaluation.

This summary table provides an overview of the methodologies,

datasets and finding of researchers on Prediction and Detection of Blood Diseases using Deep Learning, which offers insights into challenges with flaws.

II. METHODOLOGY

A. Data Collection:

The dataset comprises complete blood count (CBC) records gathered from a variety of sources, including clinical reports, laboratory findings, and publicly available repositories. Each record contains essential haematological parameters:

- Age
- Gender (M/F)
- WBC (White Blood Cell count)
- RBC (Red Blood Cell count)
- HGB (Haemoglobin level)
- PLT (Platelet count)
- Disease label (Normal, Anaemia, Leucocytosis, Thrombocytopenia, Cancer)

To ensure data integrity, all records were carefully screened for missing values, inconsistencies, and formatting issues. Since supervised learning requires accurately annotated labels, only records with verified diagnostic outcomes were retained. This pre-processing step guaranteed that the dataset was both reliable and consistent, forming a dependable foundation for model training and validation.

B. Data Preprocessing:

Preparing medical data for machine learning is a crucial step that directly impacts model accuracy and consistency. The raw dataset often contained missing values, which were addressed either by removing incomplete records or by applying

statistical imputation to estimate the missing entries. This ensured that no gaps in data would bias the learning process. All numerical features - WBC, RBC, HGB, and PLT

- were normalized or standardized so that parameters with larger ranges did not dominate model training. In addition, outlier detection was performed to identify abnormal values that could skew the classifier.

Categorical variables, including gender and disease labels, were converted into machine-readable form using label encoding or one-hot encoding depending on the requirement. This allowed the model to effectively process both numerical and categorical attributes.

To evaluate performance reliably, the dataset was split into training (80%) and testing (20%) subsets, with stratification applied to preserve class distribution. This step ensured that all disease categories were fairly represented in both sets.

These pre-processing steps enhanced data quality and consistency, improved learning efficiency, reduced bias and over fitting, and provided a strong foundation for dependable model training

C. Algorithm Used

We implemented the MXG deep learning model, which integrates a Multi-Layer Perceptron (MLP) and

$$L = - \sum_{i=1}^N \sum_{j=1}^K y_{ij} \log(\hat{y}_{ij})$$

D. Training and Validation

The dataset was divided into training and validation sets to evaluate model performance. During training, the

model learned patterns between blood parameters (WBC, RBC, HGB, PLT, age, gender) and their disease labels by minimizing the cross-entropy loss function. The validation set was used to monitor performance and adjust hyperparameters such as the number of estimators (100), learning rate (0.1), and maximum depth (3).

To prevent over fitting, early stopping was applied, halting training when validation accuracy no longer improved. Additionally, k-fold cross-validation was performed, where the dataset was split into k subsets, ensuring the model was trained and validated across multiple folds. This provided a more reliable estimate of generalization.

Finally, key performance indicators — accuracy, precision, recall, and F1-score — were calculated on the validation data. This systematic process ensured that the model was both accurate and dependable for real-world medical prediction.

E. Evaluation Metrics

The efficacy of the proposed approach for classifying blood diseases is evaluated using multiple performance measures. A confusion matrix is employed to summarize classification outcomes in terms of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The model's predictive performance is assessed using standard metrics defined as follows:

- Accuracy

$$TP + TN$$

$$Accuracy =$$

XGBoost, supported by the TensorFlow framework. This model analyses clinical blood parameters (WBC, RBC, HGB, PLT, age, gender) to automatically classify cases into Anaemia, Leucocytosis, Thrombocytopenia, Cancer,

- Precision

$$TP + TN + FP + FN$$

$$TP$$

$$Precision = TP + FP$$

or Normal [4], [5].

The underlying computation follows the standard neuron model, where inputs are combined as a weighted sum:

$$n$$

$$z = \sum_{i=1} w_i x_i + b$$

$$i=1$$

Recall (Sensitivity)

$$TP$$

$$Precision = TP + FN$$

- F-1 Score

$$Precision \cdot Recall$$

Here, x_i represents the input features (blood parameters),

$$F1 = 2 \cdot Precision \cdot Recall$$

w_i represents the corresponding feature weights, and b is the bias term.

The outputs are then passed through the softmax function to calculate class probabilities:

$$P(y = j|x) =$$

$$e^{z_j}$$

$$K \quad z$$

$$\sum_{k=1}^K e^{z_k}$$

Where z_j the raw output score for class j , and K is the total

number of disease classes. The softmax ensures that probabilities for all classes sum to 1.

To train the model, we minimize the cross-entropy loss function:

In addition, the efficacy of the model’s generalization capability is verified using k-fold cross-validation. The dataset is partitioned into k subsets, and the model is iteratively trained on k-1 folds while validated on the remaining fold. This process is repeated until every fold has been used for validation, and the results are averaged to obtain a reliable performance estimate.

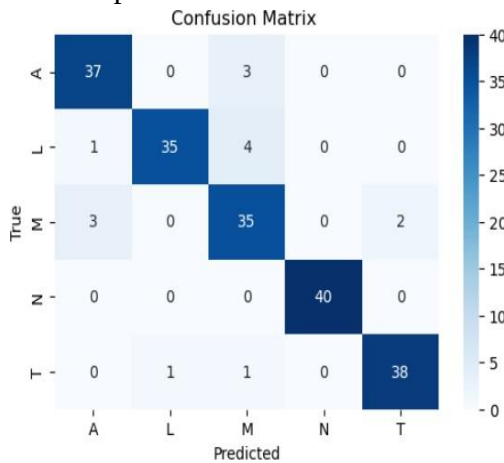


Fig. 1. Confusion Matrix

TABLE I. Comparison Table

Metric	Accuracy	Precision	Recall	F1-Score
CNN	88%	89%	87%	88%
MLP	86%	87%	85%	86%
XGB	89%	90%	88%	89%
PROPOSED MXG	93.2%	93%	93%	93%

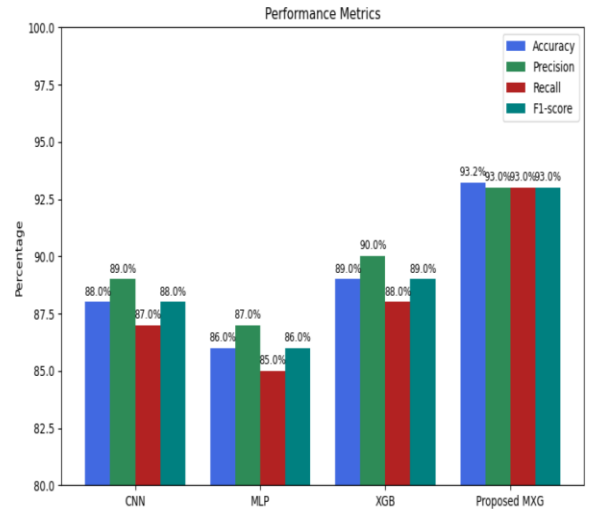


Fig. 2. Performance Metrics of Different Models

III. Implementation Details

Initially the system begins by collecting patient information, such as age, gender, hemoglobin (HGB), platelet (PLT), white blood cell (WBC), and red blood cell (RBC) counts. This data comes from medical records

or manual entry. To prevent distorted predictions, inputs are checked for completeness and proper clinical ranges.

The crucial step of pre-processing guarantees consistency and prepares the dataset for learning. Numerical features like WBC, RBC, HGB, and PLT are normalized or standardized for better performance. Categorical attributes, like gender, are label-encoded. Missing values are addressed through the means of imputation techniques or exclusion, considering the calibre of the dataset. Lastly, the data is separated into subgroups for testing, validation, and training. This division helps in effective model building and evaluation. For disease prediction, the system makes use of the MXG hybrid model for deep learning, which includes XGBoost as the main classifier. XGBoost is very

good at handling structured clinical data and is resistant to overfitting thanks to its boosting strategies. In addition, a Multi-Layer Perceptron (MLP) implemented in TensorFlow is added to learn complex, non-linear feature interactions. Together, they form a potent group that uses deep learning techniques to produce accurate classification.

Two publicly accessible datasets are utilized in the data collection process: the Complete Blood Count (CBC) dataset from Kaggle [11] and the Mendeley Data repository [12]. To enhance prediction efficiency and tackle class imbalance, additional synthetic data is generated with the necessary clinical parameters. This increases the dataset's size and diversity.

Once predictions are complete, the system creates a detailed report for each patient. This report contains the predicted disease category, the model's confidence score, and a summary of the input features. Each record has a timestamp and is linked to a unique patient identifier for accountability and traceability. All outputs are stored securely for future retrieval, clinical evaluation, or audit purposes. This ensures that the framework supports accurate disease detection and provides a dependable and secure diagnostic tool for healthcare professionals.

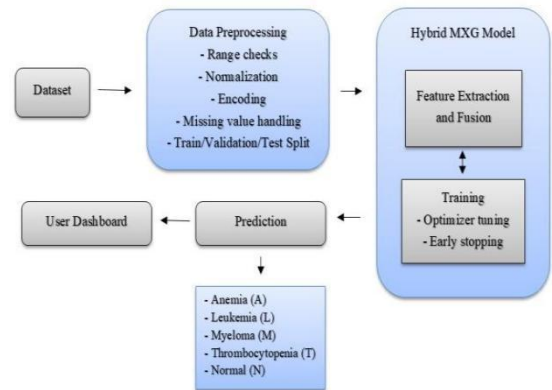


Fig. 3. System Architecture of Suggested Model

IV. Conclusion & future work

We have introduced a deep learning architecture MXG that uses clinical parameters such as age, gender, WBC, RBC, HGB, and PLT levels to automatically predict

blood illnesses. Our approach addresses overfitting and improves generalization by combining an XGBoost and Multi-Layer Perceptron (MLP) architecture using the Tensorflow framework [7]. This results in accurate classification of conditions like anemia (A), leukemia (L), myeloma (M), thrombocytopenia (T), and normal (N) states. The method includes thorough preprocessing, category encoding, input feature normalization, and a structured training, validation, and testing process. A thorough analysis employing criteria like as accuracy, precision, recall, F1-score and confusion matrix validates the system's excellent performance. Predictions are also time stamped and securely stored for future medical review and tracking.

More clinical features could be added in future studies, such as imaging information from peripheral blood smear images, to improve diagnostic accuracy and test results. Expanding the method to detect additional diseases

or chronic conditions could enhance its clinical usefulness. Integrating the model into a cloud-based system would allow for scalability and easy connection with hospital information systems. The system could also create downloadable PDF reports summarizing individual patient projections, which would improve clinical communication and documentation. Finally, the model could operate more efficiently with the less labelled data by using active learning or semi-supervised learning strategies. This would lower annotation costs without sacrificing accuracy.

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AN AI-DRIVEN FRAMEWORK FOR EVALUATING KARATE PRACTITIONERS' FIRST KATA PERFORMANCE

Anu CS 1, Arfah Fathima R2, Bhavana BR3, Chethana S4, Mrs Hemanth Kumar BR5,

1,2,3,4-Students Dept of CSE, Jnana Vikas Institute of Technology, Bangalore, India

5- Hemanth Kumar BR, Assistant Professor, Dept of CSE Jnana Vikas Institute of Technology, Bangalore, India

Abstract—Automated motion analysis of human body movements has attracted a lot of interest recently since it has the ability to offer unbiased evaluations of performance in a variety of sports and martial arts. This study focused on analyzing the manner in which karate practitioners perform the first Kata, a critical component that reveals their command of fundamental motions and technique proficiency. This study suggests an automated method for analyzing karate practitioners' movements from recorded video using pose estimation and a deep Convolutional Neural Network (CNN) model. The experimental findings show that our approach achieved a high level of accuracy 97%, and 94% particularly when employing different evaluation window sizes. This strategy provides fair and accurate decisions in sports arbitration by removing subjective biases that may result from human observers.

the first Kata is crucial for mastery. Our study addresses evaluating the style of the practitioner in performing the first Kata in karate whether it is good as in Fig. 1 or bad. Moreover, Practitioner competence evaluation using pose estimation and deep learning models, including conventional neural networks.

INTRODUCTION

Several studies have looked at the

automated analysis of entire human body motions in recent years to see how the qualities of motion are perceived by an outside observer. This is very useful in arbitration in sports such as boxing, karate, and a lot of martial arts. Karate training encourages people to engage in healthier behaviors with greater vigor [12] and improves their mobility control [3]. The number of available tactics is constrained in this sport, which is regarded as a relatively safe test of skills, and those techniques that can permanently harm the opponent have been disallowed [13]. Automated analysis can provide unbiased evaluations of the performance of athletes in sports like martial arts by examining their methods and motions. This can be particularly valuable in arbitration, where unbiased evaluations are crucial for fair judgments. Furthermore, That eliminates subjective biases that may arise from human observers, ensuring a more accurate and reliable assessment of skill and proficiency.

Karate practitioners learn Katas to develop muscle memory and technique. Evaluating a practitioner's style in performing



Fig. 1. Frame of good style in Oi zuki movement [1]

this work advances the evaluation of performing the first kata if it is good or bad from recorded video using a CNN and pose estimation. The primary focus of this paper is to utilize various window sizes for extracting the practitioner's movements' trajectories and assessing them.

I. RELATED WORKS

Alborno et al., [2] proposed a method to calculate the degree of limb synchronization during pertinent motion phases. They collected their dataset from five participants with different levels of skill and different Kata. They calculate the performers' limb acceleration to use it in multi-scale analysis. They use topological persistence and linear scale space as two different multi-scale analysis methodologies to handle these measurements. In [5] Dinu et al., studied punch biomechanics using 17-piece IMUs mounted on boxers' bodies. They found that elbows and shoulders contributed the most to cross-out techniques and hook and uppercut

techniques, respectively.

The accelerometer and gyroscopes allowed for accurate measurements of each body segment. Emad et al., [6] proposed a system that classifies specific karate moves as Age-Uke, Mae-Geri, Gedan-Barai, and Soto-Uke. They used Kinect for frames and skeleton extraction. The practitioners' motion while performing the move and their speed are taken into account when evaluating the score. The different movement speeds were controlled by Fast-DTW (Fast Dynamic Time Warping). The average accuracy of F-DTW's classification was 90%, and it was able to recognize the entire movement. Automatically recognizing karate sequences was emphasized by Hachajet et al., [7] utilizing a combination of three Kinect sensors for data gathering. The body joints received from each Kinect sensor are combined to create the skeleton representation, and gesture description language (GDL) software was used to classify the karate poses. More recently, in [11], Kolykhalova and colleagues presented a multimodal dataset of karate performances including synchronized MoCap, video, and audio recordings, and considered a set of global measures, which can be used to evaluate the quality of the performances. Labintsev et al., In the paper [14] focuses on the development of a system for recognizing punches in karate using acceleration sensors and CNN. The total collected data from participants was 1912 while performing the shadow fight technique. The model was classifying between 5 classes: Yun Tsuki, Mawashi Tsuki, Age Tsuki,

Uraken, and No Punch. Their model achieved, after 100 epochs, 0.97 training, and 0.93 validation accuracy. Kumar et al., [18] used the MS-KARD dataset to recognize

23 karate actions, utilizing 2,814,930 frames and 5,623,734 sensor data samples. They developed a deep learning model for accurate classification, achieving various results using various methods. Using an RGB camera, Wu et al., [17] suggested a training approach based on 3D predicting. Motion capture system recordings of professional karate masters were used by Petri et al., [15] to create computer-generated foes. To battle the virtual foe, the practitioner dons an HMD. Kimm et al., [10] found it challenging to determine the boxer's hand's movement after punch, suggesting ANN techniques could help. Worsey et al., [16] used six deep machine learning models to identify punches delivered by boxers. They used two IMU configurations, with SVM and MLP-NN models being the most accurate. In [4] the main areas of Bonidia et al., research were on the application of machine learning to sports, including motion analysis, performance evaluation, sports data capture, the creation of eating plans, training planning, strategic planning, the prediction of patterns, sports data analytics, and decision-making support, were outlined. Accelerometer analysis of the punch kinematics of boxers was done by In [8] Haralabidis et al., who investigated the link between athletes' postures, accelerated blows, and tiredness using videography and punch acceleration graphs. They selected an

IMU with a measurement limit of up to 16g and videography to understand kinematics. In [9] Kasiri et al., provided a study that aims to identify boxers' upper body components and categorize six fundamental punches from overhead depth photographs. Four studies used SVM and Breiman Random Forest for analysis, with 97.3% accuracy for pre-observed athletes and 96.2% accuracy for unobserved athletes.

II. METHODOLOGY

The system is composed of a proposed deep-learning model. In addition to any imaging device that captures the player's sequence of movements. Then, from the frames that were captured, the player's arms and leg landmarks were extracted using pose estimation, but not all landmarks to make it easier for the model to learn. Also, draw every connected landmark in a different color to decrease the confusion that comes from the different directions for every movement. The model was fed by an image that had the player's trajectory for a specific number of frames. The score evaluation is based on how the player's trajectory is classified for every specific number of frames. After the player finishes the movements, they will have a report of the number of good and bad frames that were used to get the total accuracy of the player's movements the equation used for calculation is shown in Fig. 3.

A. Data-set and preprocessing

Our dataset consisted of videos captured from participants with different skill levels and ages and labeled by professional players. Through including a diverse group of

participants, we were able to capture a wide spectrum of abilities and experiences. The number of frames the model trained on was 16,005 for good technique and 8,273 for bad technique. Although our dataset was unbalanced we used the class weight technique to give more importance to the samples from the minority class the weights were 1.482 and 0.754 for the minority and majority class respectively. The dataset was split into 80:20 for training and testing.

Preprocessing the input is an absolute necessity. The participant's pose estimation and landmark extraction must be obtained before feeding it to the model. Our interest in those landmarks is limited to the points on the arms and legs only. Therefore, every connected point has a different color. The participant's trajectory is drawn in an empty image as shown in Fig. 4. It has the same size as the frame, so it was resized to 224x224. The MinMax normalization technique was applied to the trajectory image to make all pixel intensities have the same distribution, making the training process faster and more reliable.

B. Proposed Method

In this paper, we propose a deep CNN model for image classification tasks. The proposed model comprises a series of essential layers, starting with a 2D convolutional layer with 32 filters of size 7x7, using ReLU activation and a stride of 4 to capture low-level features. Subsequently, a 2D max-pooling layer with a pool size of 2x2 and a stride of 1 is applied, followed by batch normalization for increased stability. Two additional 3x3 convolutional

layers with 64 filters and ReLU activation enhance the extraction of higher-level features. To prevent overfitting, a dropout layer with a rate of 0.2 is introduced, followed by the flattening of feature maps into a

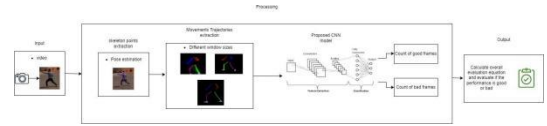


Fig. 2. Karate 1st kata, binary classification pipeline

$$\frac{x}{y + z} * 100$$

■ X=The largest among Z and Y
■ Y=No. of bad frames
■ Z=No. of good frames

Fig. 3. Overall evaluation equation

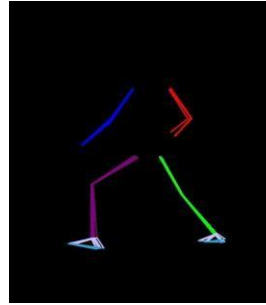


Fig. 4. Movement trajectory of 5 frame window size

1D vector. The model then incorporates a dense layer with 128 neurons and ReLU activation to learn abstract representations and dropout with a rate of 0.3 for regularization. Finally, a dense output layer with a sigmoid activation predicts binary classification output. Our model's layer composition aims to effectively learn hierarchical patterns from input images and achieve robust image classification performance.

III. RESULTS

AND

EXPERIMENTS: EFFECT OF WINDOW SIZE

Our proposed system is used to evaluate Kata One players' movements. So always, there is a sequence of frames and movements. Our model was trained on different N window sizes (N=5,15,25). We chose this specific number of window sizes based on our knowledge that on most modern image capture devices, for every second, there are 30 frames. As a result, we decided to get the trajectory of every N and train the model. Our collected dataset was used to simulate those different window sizes. The first trial was extracting the trajectory for every 5 frames and classifying the player style in those frames. Our model achieved 97% accuracy on the testing dataset. The second trial was extracting the trajectory for every 15 frames, which means half a second. Our model achieved 94% accuracy on the testing dataset. In the final

trial, the trajectory was extracted every 25 frames, which is roughly equal to one second. The model was able to achieve an accuracy of 54%. Also, the confusion matrix showed that the 5 frames in Fig. 5 would be a great choice to evaluate the player's style. On the other hand, Fig. 6 showed confusion to distinguish between a good and bad style while using 25 frames. The reason for that confusion is that in fast-paced activities like karate, a lot can happen in one second. Players can change their movements really quickly. Therefore, using a window size of 25 frames might miss these

quick changes and lose the ability to capture the dynamic nature of the good movement style.

TABLE I

	Accuracy
[6]. approach	90%
[18]. approach	94.12%
Our approach	97%

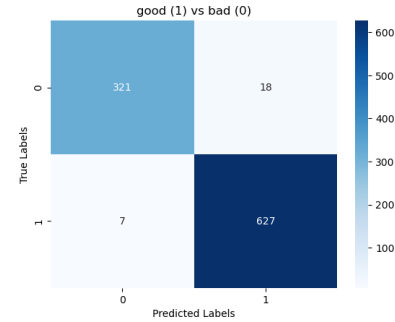


Fig. 5. Confusion matrix of 5 number of frames

IV. DISCUSSION

The proposed system for evaluating the style of practitioners performing the first Kata in karate used a combination of pose estimation and a deep CNN model. The system extracts arms and leg landmarks from video frames and then fed these sequences of landmarks into the CNN model for classification. The proposed CNN model showed promising

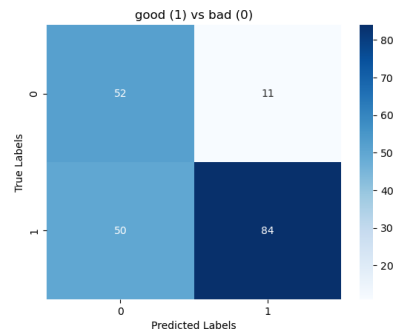


Fig. 6. Confusion matrix of 25 number of frames

results in accurately classifying the style of the practitioner's movements compared by others' approach as shown in Table. I, achieving high accuracy levels for certain window sizes (5 and 15 frames).

The proposed system automates karate movement analysis, providing unbiased evaluations, and eliminating subjective biases, making it ideal for evaluating karate practitioners' styles and performance in arbitration scenarios, particularly in competitive sports.

V. CONCLUSION AND FUTURE WORK

In conclusion, this paper addresses the evaluation of karate practitioners' style when performing the first Kata using an automated system. Our system unequivocally utilizes pose estimation and a deep CNN model to conduct objective evaluations of karate movements.

The experimental results indicate that the proposed system achieves high accuracy levels when evaluating the style of practitioners using shorter window sizes.

In future work aims to integrate few-shot learning techniques in a proposed system for evaluating karate practitioners' styles during first Kata performances, improving accuracy and reducing dependency on large-scale datasets.

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INTELLIGENT DISASTER PREVENTION SYSTEM USING IOT FOR WATER LEVEL SURVEILLANCE

Chaithanya H S1, Divyashree B S2, Neethu CM3, Mrs Deepthi BC 4

1,2,3-Students Dept of ISE, Jnana Vikas Institute of Technology, Bangalore, India

4-, Deepthi BC, Assistant Professor, Dept of CSE, Jnana Vikas Institute of Technology, Bangalore, India

Abstract—A flood is a natural disaster that causes problems in many aspects, resulting in subsequent losses. Thailand can reduce flood impact with an early warning system, allowing time for prevention. This project was created to develop a flood warning system according to the early warning system project of the Department of Water Resources. The project emphasizes informing local residents to better understand the situation and more quickly assess solutions and responses. By installing the water level measuring units at the point near the people's residence, the people can choose to install it themselves, which can transmit the data from the base to the main control unit that monitors the house of the residents in that area by applying ultrasonic sensors and rain detection modules that are controlled by a microcontroller. There is a multi-channel notification system, both light and sound notifications. Displaying messages on the LCD screen and notifications via the Line application. The remote control also uses the Blynk application to reset the main control station and all three bases. Including having a ThingSpeak data recording system to analyze the situation and later cut off power within the households. The results of the experiment can show good notifications.

Keywords— warning system, sensors, microcontroller, NodeMCU, IoT, ThingSpeak

I. Introduction

Thailand is a tropical country, so many areas are prone to flash floods. The consequences of human-caused climate change are causing heavy rainfall, making tropical cyclones more intense. Although

there is currently a water drainage control system consisting of dams, irrigation canals, and many flood control basics, it is not sufficient to prevent damage caused by flooding [1],[2],[3],[4]. Especially in metropolitan areas such as Samut Prakan province where there are communities that are difficult to access. It is also the location of many industrial estates. To reduce flood damage, this can be done by increasing early warning of floods such as the authors in [1],[2] have been proposed a flood alerting system by using IoT. Ultrasonic sensor is interfaced with NodeMCU for processing and sending all data to the cloud server under ThingSpeak platform. The buzzer and a red LED are used for alerting if the water level increases to the threshold value. ThingSpeak platform is used to collect all data and analysis. However, both applications have some

restrictions as follows:

(1) Both systems did not alert via Line Notify which the user can get the realtime message via mobile phone rapidly. (2) The author of [1] did not apply raindrop module for measuring the rainwater volume which it is a necessary to decide under emergency state. (3) Both papers did not consider the backup power system when the main power supply is failure. All authors in [3] proposed smart early flood detection and awareness system using IoT. The microcontroller (LPC1768) is applied in this paper. The ultrasonic sensor is done in the water level measurement. There are three water levels and three LED colors for monitoring i.e., normal (Green LED), moderate (Yellow LED) and high (Red LED). All alerting data are also displayed on LCD and web browser. However, we consider that some restriction may be occur as follows: (1) This application did not consider a raindrop module for measuring the rainwater volume to decide or prepare to evacuate as the previous paper [1]. (2) The LPC1768 microcontroller must be interfaced with Wi-Fi module for transferring all data to Internet Network which it is inconvenient for the implementation. It is also difficult to configuration the program. Presently, the convenient of implementation may be occurred if we applied NodeMCU which is developed with build in Wi-Fi chip. This module is also easy for program configuration. (3) This article did not apply with Line Notify and Blynk Application. These are the popular applications for IoT. (4) This system cannot reset program from

remote controlling when the system has a failure during the operation.

In this paper, we present the water level monitoring and flood alerting based on NodeMCUs to interface with ultrasonic and raindrop sensors for measuring the water level in the canal and the river. Our proposed system consists of a main control unit and three measuring units which transfer all data between them via IoT system. We apply Line [4], Blynk

[4] and ThingSpeak [5] to operate together. Also, we apply buzzer, LCD and three light indicators for alerting when the water level is risen rapidly while the rainfall. Alert levels may be displayed as follows: (1) level 1 flood warning with green light and message "Water level has risen slightly", (2) flood warning level 2 with yellow lights and the message "Watch out for rising tide", and (3) flood warning level 3 with red light and sound alert and displaying the message "Danger, prepare to evacuate". The system will also cut off the default power in the house using a relay module. Moreover, our proposed system applies ThingSpeak [5] to record and analysis all data from main control unit under Cloud Server. Blynk Application is also applied for backup power controlling and resetting the operation if the main control unit and three measuring units have the fault during the operation.

II. Methodology

Principles involved in hardware and software design of water level monitoring and flood alerting systems. It consists of a main control unit and three water level measurement units,

which are mounted remotely to measure the water level. The data received from the sensors is then sent to ThingSpeak, an IoT Cloud platform, via an internet signal. When the main control unit receives data, the system will process and send out various notification formats while the data will be recorded in the database. The main control unit has redundant control via the Blynk Application and a battery backup power supply in the event of a power supply failure. The battery is New Power, 12V and 5AH. The block diagram is shown in Fig. 1.

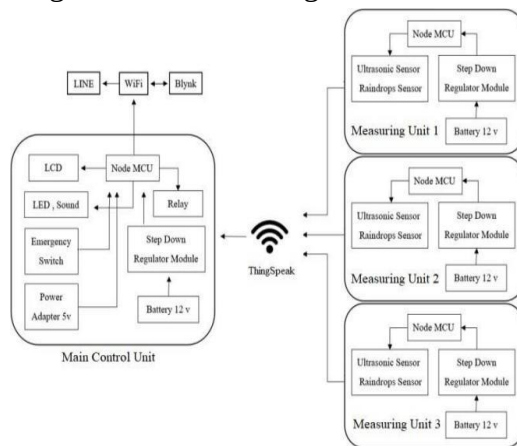


Fig. 1. Block diagram of the water level monitoring and flood alerting system.

A. Hardware

The water level monitoring and flood alerting system design is divided into two parts: a main control unit and three water level measuring units, as shown in Fig. 2. The NodeMCU ESP8266 [6] module acts as a microcontroller used to control and command both parts. The system contains command, control and transceiving information, including a wireless (Wi-Fi) module with antenna circuitry inside the PCB that supports Internet of Things (IoT) applications. There are 3 sets of water level

measuring units, each set approximately 50-100 meters apart, installed in limited community areas next to canals or water sources. Each unit consists of a NodeMCU ESP8266 that receives data from an ultrasonic sensor (HY-SR05) and a raindrop detection sensor module (FC-37). This module is a sensor to detect whether there is rain in the area. The resistance of the collector board varies according to the amount of water drop on the surface and will send the value to NodeMCU for processing in the form of numbers. If wet, the resistance increases and the output voltage will decrease.

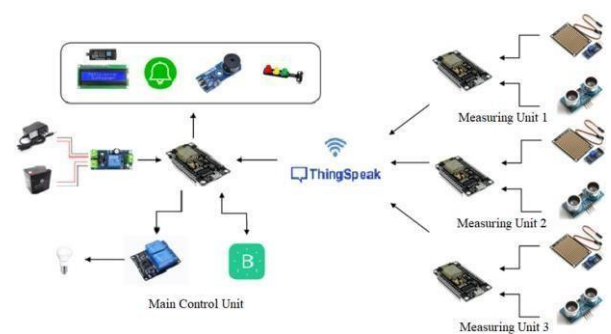


Fig. 2. The water level monitoring and flood alerting by applying IoT.

The ultrasonic sensor module measures distance using ultrasonic waves. Communication between NodeMCU is connected through digital pins to the Trig and Echo pins of the ultrasonic sensor. The function of this sensor is that once installed, it sends out ultrasonic waves from the transmitter. When it encounters an object, the waves are reflected and returned to the receiver. By finding the distance, counting the time of transmitting until receiving the wave back through signal triggering. It can measure distances from 2 to 400 centimeters.

The process of designing and assembling the main control unit used to retrieve data from a website "ThingSpeak.com" is processed with the NodeMCU ESP8266 board to make notification decisions. It consists of (1) an audible warning module, (2) a three-color traffic light module that warns of water height following severe flooding with green, yellow and red lights, (3) a Liquid Crystal Display (I2C LCD1602A) to display notifications in text format by sending signals through the SDA and SCL pins (I2C BUS), and (4) notifications over the internet to the Line Application on mobile phone. In addition, there is a remote backup control system from the Blynk Application and a relay module for use in cutting off electricity in the home at a basic level.

B. Software

The software programs for the three water level measurement units are designed to monitor and transmit the data of raindrop sensors and water levels by ultrasonic sensors. While the main control unit is designed for the alert system. The program is designed to send and receive information between each other through the website "Thinkspeak.com".

Rain detector program commands are set to run using the "analogRead" function command. This function reads a voltage signal in the range 0-5 V. The value is then programmed to the microcontroller to provide an analog to digital converter (ADC) range of 0-1023 (10 bits). Finally, to make it easier to read the rainfall values, the data is therefore converted to percentage format 0-100 instead.

As for the water surface level measurement program, the ultrasonic sensor module is used to send a trigger pulse signal to hit the water surface, then the signal is reflected to the Echo pin, and then the counted time value is calculated. To calculate

the time value, the variable T is multiplied by the speed of sound in the air, which is 340 meters per second, or 0.034 centimeters per microsecond, and divided by 2, because it is the round-trip distance of the sensor. When the return distance is obtained, the level of the water surface that is reflected back to the sensor will be obtained as shown in equations (1) and (2).

Where, DistanceCM is the distance that the wave travels back and forth between the sensor and the water surface. While Distance is the actual distance between sensor and water surface.

Our program is divided into 2 parts, i.e., the measuring units and the main control unit. The main control unit will receive all data from each measuring unit via the internet by recording to the database or ThingSpeak. It also makes the decisions regarding flood warning conditions. The green, yellow and red lights warning can be set to a water level at

>200 cm, ≤ 200 to >100 cm, and ≤ 100 cm, respectively. The amount of rain measured will determine the rate of no rain, less, medium or heavy rain. The flowchart and pseudo code of each unit are depicted in Fig. 3 and Fig. 4, respectively.

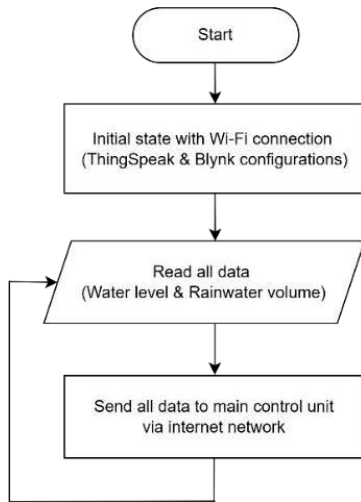


Fig. 3. Flowchart of measuring unit.

```

Initial state with Wi-Fi connection; // (ThingSpeak, Line & Blynk)
Loop () {
  Receive all data & Calculate Avg. // (Water level & Rainwater volume)
  Upload all data to ThingSpeak;
  if (Avg. Water level >200) {
    Display green light;
    Send message to Line "Water level has risen slightly"
    under various condition (No rain, Less, Moderate, and Heavy);
  }
  if ((Avg. Water level <=200) && (Avg. Water level >100)) {
    Display yellow light;
    Send message to Line "Watch out for rising tide"
    under various condition (No rain, Less, Moderate, and Heavy);
  }
  if (Avg. Water level <= 100) {
    Display red light;
    Send message to Line "Danger prepare to evacuate"
    under various condition (No rain, Less, Moderate, and Heavy);
    Buzzer alarm;
    Cut off the electricity via relay;
  }
}
  
```

Fig. 4. Pseudo code of main control unit.

III. Experimental & Results

Our experiments are divided into 3 parts, i.e. water level measurement by ultrasonic sensor, rainwater volume measurement and all data transmission via IoT system under Line and ThingSpeak Applications, respectively. The first experiment is water level measurement. We test 10 times at the canal by dividing each level to consider the average values and the error (%) as shown in Table I.

TABLE I. Water Level Experiment

Water Level (Cm.)	No. 1-10 (Average Values)	% Error
50	49.936	0.128
100	100.178	0.178

150	149.719	0.187
200	198.861	0.569
250	249.238	0.305
300	303.754	1.251

The next experiment is rainwater volume measurement. We using the liquid measuring cup (size 100 ml) which contains the raindrop sensor. We test 10 times to consider the average value. The output of the raindrop module is 100% while there is no rainwater in the liquid cup. This is the initial state. All results are shown in TABLE II. Those of results are used for assigning the condition in our program. The amount of rain measured will determine the rate of no rain, less, medium or heavy varies with the amount of rain being less than or equal to 100, 99, 70 or 30 percent, respectively.



Fig. 5. Rainwater volume is 20 ml.

TABLE II. Water Volume Experiment

Water Volume (ml.)	No. 1-10 times (Average Values)
10 - 20	76.75
21 - 30	58.4
31 - 40	49.8
41 - 50	43.3
51 - 60	40.4
61 - 70	33.6
71 - 80	31
81 - 90	28.8

The next experiment is data transmission via IoT system under Line and ThingSpeak Applications. We test three measuring units for calculating average values as shown in Table III. We observed that our purposed system can operate as well. The messages can alert via Line notify in different 3 levels and together with rain status.

TABLE III. All Data Transmission via IoT

No.	Station 1-3 (Average Values)		LED	Line Notify	Rain Status
	Water	Raindrop	Level		
1	231	100	1	Risen slightly	No rain
2	206	100	1	Risen slightly	No rain
3	207	85	1	Risen slightly	Less
4	207	59	1	Risen slightly	Moderate
5	206	47	1	Risen slightly	Moderate
6	198	100	2	Waring	No rain
7	140	100	2	Waring	No rain
8	135	97	2	Waring	Less
9	82	30	3	Dangerous	Heavy
10	73	28	3	Dangerous	Heavy



Fig. 6. Displaying data values in the form of graphs and numbers within the website "ThingSpeak.com".

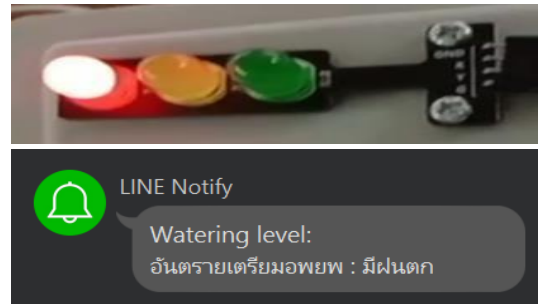


Fig. 7. Notification through LED light module and Line notify in text form that meets in level 3.

The information on the website "ThingSpeak.com" is presented in graph format as shown in Fig. 6. The ultrasonic sensor on the left graph is shown the level of water and on the right shown amount of rainfall. The notification through LED light module and Line notify in text messages that meets in level 3 shown in Fig. 7.

At the level 3, the power cut can work according to the conditions quite accurately. In addition, a redundant control system via the Blynk Application and switching to a backup power supply can work well. It can also reset the system when all units have the failure. Fig. 8. shows the design of the gadget tool for the Blynk Application through a mobile phone that is controlled via the internet as an IoT system.

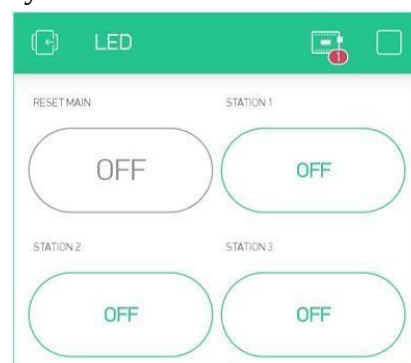


Fig. 8. Alternate control button layout

within the Blynk application.

IV. Conclusion

For the test, water level measuring units were installed at all 3 points, approximately 100 meters from each point at locations with similar elevations. The total distance from the main control unit to the measurement base is about 600 meters. Data transmission and display on the website will have a relatively constant transmission time when the internet signal is stable. Alerts can be delivered at all three levels correctly as designed. The algorithm could develop more robust as the number of water level measuring units increased. An expanded area will be provided to monitor flooding in areas at risk.

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A DEEP LEARNING-BASED 1D CNN MODEL FOR INTRUSION DETECTION IN IOT NETWORKS

**Soubhagya Danareddy¹, Bhavani D², Muthamma CK³, Amrutha KJ⁴, Mrs
Rashmi UB⁵,**

**1,2,3,4-Students Dept of CSE, Jnana Vikas Institute of Technology, Bangalore, India
5-, Rashmi UB, Associate Professor, Dept of CSE ,Jnana Vikas Institute of
Technology, Bangalore, India**

Abstract— The demand of the Internet of Things (IoT) has witnessed exponential growth. These progresses are made possible by the technological advancements in artificial intelligence, cloud computing, and edge computing. However, these advancements exhibit multiple challenges, including cyber threats, security and privacy concerns, and the risk of potential financial losses. For this reason, this study developed a computationally inexpensive one-dimensional convolutional neural network (1DCNN) algorithm for cyber- attack classification. The proposed study achieved an accuracy of 99.90% to classify nine cyber-attacks. Multiple other performance metrics have been evaluated to validate the efficacy of the proposed scheme. In addition, comparison has been done with existing state-of-the-art schemes. The findings of the proposed study can significantly contribute to the development of secure intrusion detection for IIoT systems.

Keywords— cybersecurity, intrusion detection, IIoT, CNN

I. INTRODUCTION

In recent years, there has been a remarkable increase in the use of the Internet of Things (IoT) [1]. This

transformation has significantly raised the intelligence of manufacturing operations by

integrating cutting-edge technologies,

including artificial intelligence (AI), cloud computing, edge computing, big data analytics, robotics, and cybersecurity. The Industrial Internet of Things (IIoT) has notably augmented the level of automation within smart factories and distribution centers [2]. The IIoT serves as an extensive network connecting devices and providing computing services to smart industries, enhancing operational efficiency across sectors like manufacturing and service supply. However, its diverse nature exposes IIoT devices and networks to various cyber threats, posing significant security and privacy risks and potential financial losses [3]. Therefore, robust cybersecurity measures are essential to fully harness the benefits of IIoT.

Smart industries face a range of cyber threats, including unauthorized data access, IoT service disruption, and equipment damage [4]. Intrusion detection systems (IDSs) are crucial secondary defense mechanisms, working alongside other security measures to mitigate these risks. Utilizing traditional machine learning (ML) and deep learning (DL)

techniques, modern IDSs analyze IoT traffic, detect attack patterns, and identify malicious activities. Yet, the dynamic nature of IIoT systems necessitates adaptive approaches beyond predefined attack classifications, while addressing data imbalance in cybersecurity datasets is vital for enhancing IDS performance and effectiveness.

CNN has been extensively used in the field of image

classification [5], time series data classification [6] and text classification [7]. This study proposed a 1D CNN-based intrusion detection algorithm that is computationally inexpensive and takes less time for classification. The proposed algorithm used 3 CNN layers in addition to max pooling layers and dropout. After parameters optimization, the proposed study achieved an accuracy of 99.90%. The main contributions of the proposed study are as follows:

- The Edge-IIoT dataset has been pre-processed, which involves eliminating redundant feature columns and encoding categorical data. Subsequently, the fully pre-processed dataset is converted into a csv file, facilitating identification of different cyberattack patterns.
 - An efficient 1DCNN algorithm has been developed to detect number of cyberattacks in IIoT.
 - Rigorous experimentation has been done to evaluate the efficiency of the proposed 1D-CNN algorithm.
- Remainder of the paper is organized in the following manner: Section II presents the brief literature of the

existing studies in IIoT. Section III proposed the methodology whereas section IV presents the results. Finally, Section V concludes the paper.

II. RELATED WORK

Over the past decade, traditional intrusion detection systems (IDSs) have faced evolving challenges in terms of their precision, efficacy, and resilience. In response to these challenges, Li et al. [8] proposed an algorithm for intrusion detection within Internet of Vehicles (IoV) environments. This approach incorporated a local update mechanism to generate labels from unknown data in emerging attacks. Experimental findings showed that the proposed study achieved a notable accuracy of 92%.

In an effort to further elevate classification accuracy, Mehedi et al. [9] Propounded a domain transfer learning (DTL)-based study tailored for IoT applications. This study emphasized efficient attribute selection and robust evaluation of a DTL-based ResNet model using real-world data. Gou et al. [10] proposed a distributed TL approach for IDSs, integrating TL into boosting algorithms to facilitate attack learning particularly in instances of suboptimal performance. Their proposed framework demonstrated an impressive attack detection accuracy of 97.3%.

Furthermore, Mehedi et al. [11] engineered an IDS designed for In-Vehicle systems, incorporating a novel methodology to identify threat messages and accurately discriminate between normal and abnormal activities leveraging a LeNet model. Evaluation on a proprietary synthetic dataset

yielded a commendable accuracy of

98.10%. The evolution of DTL and its consequential impacts across diverse domains have catalyzed the advancement of robust solutions for IIoT. Bierbrauer et al.

[12] introduced an IDS using raw architecture traffic. Their approach trained a one- dimensional CNN in conjunction with a random forest model. The proposed study improved the overall classification accuracy upto 96.89%.

Xu et al. [13] propounded a secure intrusion detection system, employing an encryption scheme to secure classification models. Subsequently, XGBoost-based algorithm showcased effective model transfer with classification accuracy of 93.01%. Singh et al. [14] introduced an algorithm to detect darknet networks, employing a transformation of 1D features into 3D for enhanced accuracy. Abosata et al. [15] proposed a TL model for IoT IDSs, encompassing three primary stages. The proposed model exhibited high RPL security and an impressive accuracy of 85.52%.

Majority of the work presented recently has been trained and tested using 2-dimensional data. The researchers converted the data from 1D to 2D and then

applied classification algorithms. However, this technique is computationally inefficient and expensive. For this reason, this study proposed a 1D CNN based algorithm that is faster than the existing algorithms and is computationally

inexpensive.

III. METHODOLOGY

This section briefly explains the dataset, preprocessing, the proposed 1D-CNN, the evaluation parameters, and validation technique used in this study.

A. Dataset

The proposed study used Edge-IIoTset cybersecurity dataset that is publicly available from Ferrag et al. for further research [16]. The proposed dataset has been developed by generating a realistic IIoT environment with multiple IoT sensors including soil moisture, pH, heart rate, temperature, humidity and ultrasonic sensors. For the proposed study, we have used 10 classes to analyze the proposed algorithm. Fig 1. illustrates the class distribution of the proposed dataset.

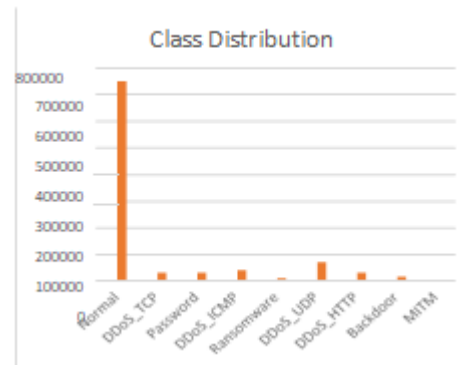


Figure 1. Class distribution of the dataset used in proposed study.

B. Preprocessing

Before training and testing the architecture, one of the most crucial step is to clean the dataset. The proposed dataset contains 62-features and 9 classes. The first step was to randomly select 10 classes. Then, NaN

values have been removed from the dataset. Secondly, duplicate rows have been removed from the data. The new dataset contains 953239 rows with 62 columns.

C. Proposed 1D CNN

CNN is widely used for image recognition and classification in 100s of applications. Figure 2. shows the proposed 1D CNN architecture. The proposed 1DCNN architecture is designed to effectively extract features from time-series data. The methodology involves a detailed description of the architectural layers and components. This includes three convolutional layers that use 1D convolutions to extract local patterns and features from the input time-series data.

Following each convolutional layer, max-pooling layers are employed to downsample the feature maps,

reducing their spatial dimensions while retaining the most salient features. Max-pooling helps in capturing invariant features and reducing computational complexity by discarding redundant information. The output from the final max-pooling layer is flattened and passed through two fully connected layers for further feature transformation and classification. These layers learn high-level representations of the input data and perform the classification task.

To prevent overfitting and improve generalization performance, a dropout layer has been used between the fully connected layers. Dropout randomly masks a fraction of the neurons, forcing

the network to learn robust features that are not dependent on specific neurons. The methodology emphasizes the hierarchical nature of feature extraction in the 1DCNN architecture, where lower layers capture low-level temporal patterns, and higher layers learn more abstract representations. This hierarchical feature extraction process enables the network to effectively model complex temporal dynamics present in time-series data.

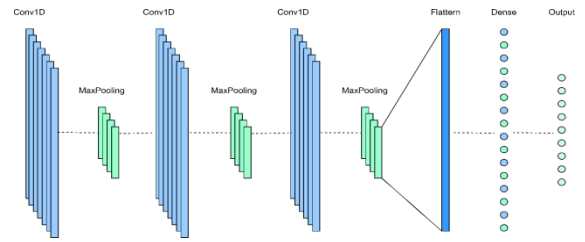


Figure 2. The proposed 1D-CNN network architecture.

Experimental validation of the proposed methodology involves training and testing the 1DCNN architecture with multiple performance metrics. Performance metrics like accuracy, precision, recall, and F1-score have been evaluated to evaluate the effectiveness of the proposed methodology.

Additionally, comparisons with existing architectures have been conducted to demonstrate the superiority of the 1DCNN architecture in capturing complex temporal patterns from time-series data.

IV. RESULTS

The proposed study has been trained and testing on Python

3.7 in 12th Gen Intel Core i9-12900H 2.50 GHz having Nvidia GPU. The proposed study achieved a mean accuracy of 99.90% for 9 classes.

Figure shows the confusion matrix of the proposed study. In addition, tab shows the performance metrics of the proposed study calculated using the confusion matrix shown in fig 3.

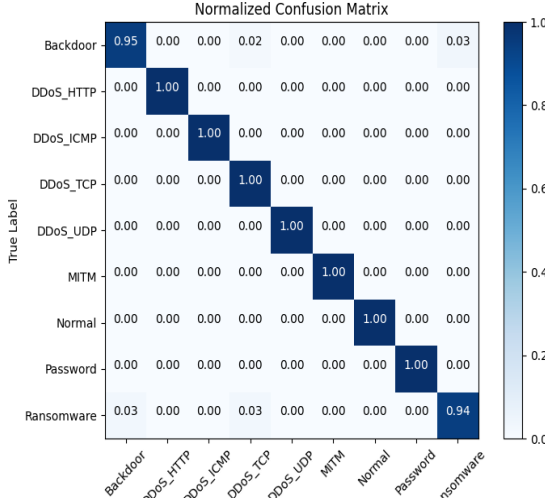


Figure 3. Confusion matrix of the proposed study.

Table 1. Performance metrics of the proposed study.

	Accur acy	Precision	Recall	F1- score
This Study	99.90	98.80	98.79	98.78

In addition, figure 4 shows the training and validation loss with respect to the number of epochs. From the figure, it is evident that both training and validation loss minimizes at epoch 3 therefore we have used 3 epochs for training. Another important parameter to assess the efficiency of the proposed 1D CNN network is time. For training and validation, the proposed study requires 108.46 seconds whereas only 3.94 seconds are required to test the testing dataset. This proves that proposed study is time efficient and can process huge datasets in less than 4 seconds.

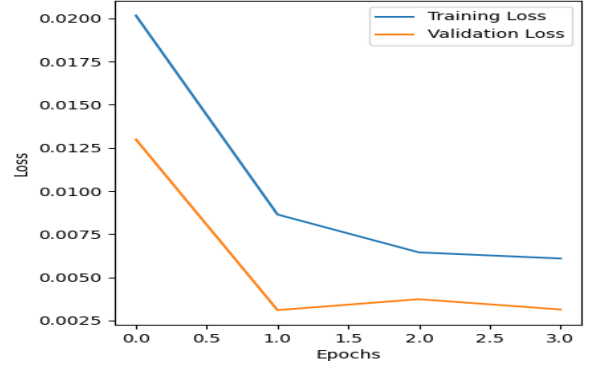


Figure 4. Epochs vs loss graph.

To evaluate the efficacy of the proposed architecture, it has been compared with latest intrusion detection schemes. Most of the algorithms are trained and tested on limited classes however the proposed study used 9 attacks for classification. Figure 5. shows the comparison of the proposed study with existing literature. Here, it is very important to note that the proposed study can classify 9 attacks on the IIoT environment however all the other algorithms classify less that 9 attacks. Therefore, this proves that the proposed study can classify more attacks in addition to the overall accuracy achieved.

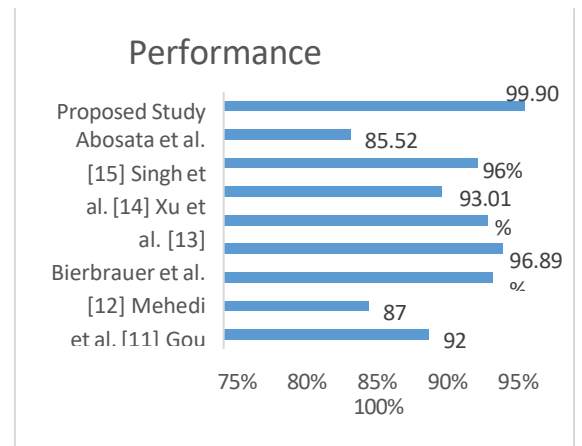


Figure 5. Performance comparison of the proposed study.

The proposed algorithm achieved remarkable results for intrusion

detection in a real-world environment however there are still some limitations that needs to be addressed in the future studies. Firstly, there are 8 attacks that have been classified in the proposed study however there are multiple other attacks, i.e., Vulnerability Scanner, SQL injection, Port Scanning etc., that needs to be classified for broader applications. Additionally, in the proposed study, there is a class imbalance problem as there are some classes with huge data however some classes have limited data. This class imbalance problem needs to be addressed in future studies either by data augmentation or synthetic data generation techniques.

V. CONCLUSION

This study proposed a new 1DCNN algorithm for cyberattack classification on IIoT data. Initially, NaN and duplicate values were removed to preprocess the data. Then, 1DCNN has been developed to test and train the Edge- IIoTset. The proposed architecture achieved an accuracy of 99.90% for the classification of nine attacks. Rigorous experimentation and validation have been used to evaluate the efficiency of the proposed scheme. The proposed study outperformed the existing studies for cyberthreat detection. In addition, 1DCNN is computationally inexpensive and does not require transforming the time series data into images. To conclude, it is evident that the proposed study can be used to detect real-time cyberthreats in industry 4.0.

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OPTIMIZING MARKETING ROI USING BIG DATA ANALYTICS IN SOCIAL MEDIA

Nisarga K1, Nanditha KG 2, Sinchana S 3, Sushmitha N4, Mrs Rashmi UB5

1,2,3,4-Students Dept of CSE, Jnana Vikas Institute of Technology, Bangalore, India

5- Rashmi UB, Associate Professor, Dept of CSE Jnana Vikas Institute of
Technology, Bangalore, India

ABSTRACT

As a cutting-edge technology of modern network technology, the big data is of crucial application value to the development of social media marketing. In this regard, we firstly conduct researches on social media marketing and big data to define their connotation and implementation significance; secondly, after having a knowledge of the development direction and entry of media marketing in the era of big data, we identify the social media marketing changes caused by data; finally, we analyze the precise social media

.

Keywords: big data, media, social marketing

1. INTRODUCTION

The development of global big data and social media marketing in the context of the internet is flourishing. Abundant network resources and big data have brought another incentive for industrial development revolution after the Internet of Things and cloud computing. For one thing, big data is the frontier of social marketing innovation and competition. For another, the data resources contained in social media and the applicable

population can become the resource samples and application fields of big data. Therefore, the integration of big data and social media

marketing is not only the innovation of data resources, but also the driving force of social media marketing [1].

As the computer technology develops and innovates, the accessible data network resources in China are increasing exponentially. These data resources are gradually expanding by means of the development of cloud computing, the Internet of Things and social media, and are rapidly converging into a huge data resource network. Because the computer industry itself features data mining, analysis and application, the inception of the concept of big data does not seem unexpected. However, when it is connected with the development of social production, social marketing and public opinion, its massive power, significance and connotation is found.

marketing strategy to provide certain clues to the application of big data in social media marketing. Through this study proved that big data will directly affect social media marketing, not only the change of basic marketing, big data relies on data analysis and integration ability, can constantly dig and query the effective market seeking repair

information, predict the consumer's consumption behavior, thus building a new mode of precision marketing, is an important development direction of China's social media marketing in the future, worthy of further in- depth study

In 2011, the McKinsey Global Analysis Center, a leading foreign research and consulting institute, published a research report on the relationship between big data and productivity. It was pointed out that, from the perspective of business and marketing, the development potential of big data took a lead in then society. Besides, the report also analyzed the intrinsic relationship between data resources and economic resources, and described the development and changes of various social sectors under the influence of big data. The report has been attached to great importance nationwide, especially in the filed of business and economy. And most experts have reached a consensus that big data will affect the development direction of business culture value for a long time. And in such a context, there is no doubt that the development of the new model of social media marketing under big data follows the trend of the times. In fact, social media, as a new concept, has received attention from all walks of life. On the current network scale and the development of the internet economy in China, the completion of social media marketing upgrading with

the help of big data is an inevitable trend, and social media marketing in the context of big data is destined to become a new hot spot of Chinese economy.

2. THE DEVELOPMENT OF SOCIAL MEDIA MARKETING UNDER THE DEVELOPMENT OF BIG DATA

Social media marketing in the context of big data can be seen as an important branch topic of social media marketing research. Therefore, the research on the development of both should discuss the differences between the new and old development of social media marketing and analyze the characteristics of big data and social media marketing on the basis of a clear concept. We should identify the current situation of social media marketing in the context of big data, and have detailed discussions on its application and development direction [2].

2.1. The concept definition of big data and social media marketing

Currently, there are several definitions of the concept of big data as the following. Firstly, the big data can be seen

as the geometry of massive data. Generally, with the accumulation of data resources, the unit of measurement of big data often develops towards G, T, P, so called big data. Secondly, big data has been extended to a phenomenon of data surging in modern society. As the data accumulated during the operation and development of a company will boom, it's hard to conduct orderly statistics and analysis

with the existing data tools. Big data can become a collection of the acquisition, storage, searching and sharing of enterprise data; thirdly, big data can also be used as a modern network finance which centers on data and a collection of the derived data analysis, data security; data searching and data sharing, and other industrial chains [3]. In general, it can be believed that modernized big data is a national service way in the field of quantitative research, through which the traditional random analysis method can be transformed into a concrete and comprehensive research method. The formation process of big data is from simple to complex and single to diverse. And the transaction information of big data includes data media, enterprise data and government data, which are integrated, open, public and dynamic, and the core is shown in Figure 1.

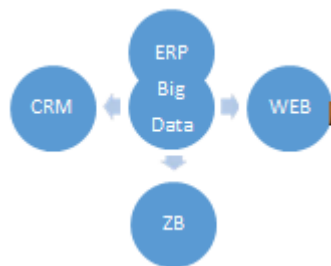


Figure 1. The Relationship of Big Data

The concept of social media, first put forward by the Americans, is believed as a collection of online media. Initially, social media featured a distinctive ability of personal innovation and dissemination, whose core characteristics include

participation, openness, communication and social trends. Therefore, social media generally enable users to have a sense of participation and reality as well as to join in the community. In the modern society, the most important part of the definition of social media is “media”, such as radio, newspapers and other communication tools. Then is the development and definition of “social”, and other mass network communication tools towards the whole society. From the perspective of marketing, the combination of social media and marketing can ensure the stable development of marketing. Unlike traditional marketing, from the perspective of dissemination methods, social media tend to be more vertical in terms of consumers and information senders, and enjoy a better user stickiness. Besides, social

media marketing can make online interactions a reality, and it obviously has an advantage over traditional marketing in terms of communication span. It is a strengthened business model with the focus on the capture of dynamic consumer information. Therefore, it can be found that social media marketing is mainly a new marketing activity developed on the basis of online media platforms gathering creative marketing, experiential marketing and entertainment factors, and a new marketing model with a high degree of participation and expansion [4].

2.2. The entry point of social media marketing in the era of big data

The development of data kernel and

updating mechanism is the prerequisite of social media marketing development and entry. With the continuous development of big data, the production mechanism of social media content has also witnessed great changes. Due to the

continuous enrichment of social media, the emergence of we-media has enabled many general publics to apply media easily to disseminate information. And with the support of big data, media data resources are no longer scarce, and the

annual information export continues to grow, which to a certain degree enriches the communication channels of social media, information and the public [5].

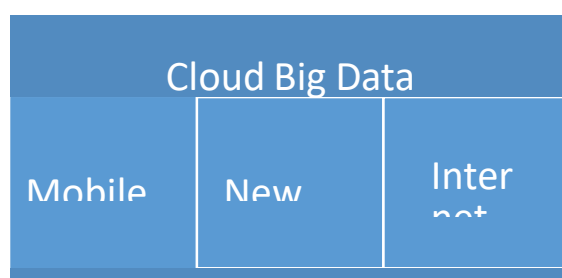


Figure 2. Media and Information Stream

In the era of big data, with the catalyst of social media and the internet, technology of ideas is the core of the progress of modern technology. As the mechanism of information dissemination, the media absorb information from each other and influence each other in the process of user interactions, and transmit this information from the bottom up to the cloud to become a data terminal. During this process, social media has

developed from the basic network to the core network, and then to the current comprehensive network data platform. Though the functions of network data platforms have become more diverse during such a series of changes, its core remains information dissemination, network communication and knowledge economy development, etc. The intrinsic marketing value of the derived social media marketing is determined by its network characteristics. The marketing value of social media is illustrated by the fact that it is more suitable for consumption and communication, and at the same time it builds an idealized liaison mechanism for enterprises and consumers. It is a diversified, people-centered and rational communication platform.

A look throughout current social media marketing platforms can show that their intrinsic values are shown as the following. First, social media marketing platform can

meet the real-time needs of consumers, help enterprises integrate into the consumers and satisfy their material needs and cultural value needs, and establish a consumer mentality; and at the same time it can build and extend the brand image and maintain its vitality; second, social media marketing platform can help enterprises carry out fast market feedbacks, and provide effective methods for social market supervision. Media marketing can help enterprises acquire the complaints and suggestions on the products from consumers through real-time analysis, and provide satisfying positioning

thinking for social strategies on their own core problems. Besides, during the operation of social media, the commercial sales relationship between consumers and manufacturers also changes to active fair positioning; and social media marketing provides diversified information channels for the development of enterprises, which enables the functions of social media to reach different aspects of marketing and makes the relationship between media users and companies closer; finally, media marketing can better fit the people-centered concept to stimulate terminal consumption. Therefore, enterprises generally need experience several stages as follows if they want to cut into social media marketing orderly.



Figure 3. The Diagram of the Three Stages of Social Media Marketing

Figure 3 shows the three stages of social media marketing from the bottom to top. The first is the

preparation stage, including the optimization and integration of social media resources, and the formulation

of content and strategies; the second is the construction stage, including network relationship maintenance and platform data analysis, etc; and the last stage is the application stage, including

the operation and application of the daily platform resources.

3. THE DEVELOPMENT OF MEDIA MARKETING IN THE CONTEXT OF BIG DATA APPLICATION

The massive internet data is becoming an important method of information resource control strategies both at home and abroad, and the internet marketing is becoming a new industrial growth point. The social media marketing under the application of big data can lead to the upgrading of different sectors for data services and provide a constant insight into future development.

3.1. Changes in social media marketing in the context of big data application

As the modern big data develops rapidly, the data industry information also faces greater opportunities and conditions. With the focus on big data and the end-users of information industry, the current information media industry is steaming and presents portal features. It can be anticipated that social media marketing based on big data must be based on an integrated social media platform so as to meet the social application and market demands. Big data itself features large amounts, fast speed, diversified needs and authenticity. And the pursuit of the commercial value of big data will lead to people's thinking about data, such as how to complete data-based development enterprises, big data production and storage, and the upgrading of data visualization, etc.

And the marketing development driven by big data continues to improve. It can be said that a large number of data industries will follow the trend of data development in the future, and gain opportunities in the market competition. While for social media marketing, the influence of big data has also led to a marketing revolution, and made precision marketing a reality. Social media marketing platform provides us with a social relationship platform, whose intensity determines the value of marketing. It can be said that the relationship establishes data and is equivalent to industry profits. All the data marketing relationships are realized through the social media “sharing” in the development of social media, during which the functions of big data have a special impact on social media. In addition, the social media marketing under the big data application brings the concept of practice and management to the latter. The real-time nature of big data can provide enterprise marketing with the interest dimension and limitation in time. Bringing the information properly to the public at the right time and the right places so as to satisfy the psychological needs of consumers has become the key to modern social media marketing. With the focus on

end-users through the media and data, enterprises can gain the greatest say in the industrial chains. It will integrate business, increase revenues, search the required market channels to expand business according to the needs of mobile consumers, so as to increase the loyalty of consumers.

It is safe to say that there is an internal consistency between big data and social media platforms. And the concept of coordinated marketing of both, which relies on cloud technologies and media platforms, fulfills the needs of the new social environmental.

3.2. Precision marketing of big data
Apart from the basic development, big data also brings a new precision marketing model to modern social media marketing. In the process of the rapid growth of big data, media has become more commercial as marketing platforms. Be it the event or the content, to which social media marketing begins to apply data to change their own traditional marketing development.

Depending on the collection of data analyses, big data can continue to dig and query effective marketing needs and data information, and anticipate consumers’ consumption behavior, so as to build a precision marketing. Social media, relying on their own content, upgrade users from information gainers to information collection consumers, thus creating a series of internet behaviors which integrate sharing, consumption and creation. Besides, under the influence of big data, social media continue to improve their marketing strategies and provide clearer consumption descriptions. Some experts vividly compare the big data mining to building a whole user profile. At the beginning, it is necessary to collect data traces online, and then process these data with analytical technologies to achieve user characteristics and

interest, enrich consumers' consumption preferences and track data, including transaction data, market activity data and information data. Each of these data can play the role of describing needs, so as to precisely position market users' demands, provide products introduction and recommendations and guide the operation of the market.

In terms of the development of social media and social process, big data also filter large amounts of positive information while mining and querying massive data. This information though provides materials for precision marketing, it also costs a lot. Therefore, many social organizations and enterprises which are not supported by enormous data, advanced data mining and analytical technologies and corresponding personalized services are likely to fail in data services and subsequent marketing. In addition, modern big data are no longer traditionally structured data, but more of the unstructured data including videos, the audio and texts and so on. Part of these data may be inconsistent or lost. These massive data pose new

challenges to analysis and collation, and provide new thinking for the development and application of big data.

4. CONCLUSION

In the era of data development and application, the optimal data and the timeliness of data are the new advantages of media marketing, but also the core of the future development of social media marketing. It can be

said that big data is another technological revolution after the development of the internet, cloud computing and the Internet of Things, whose extension and connotation are both of great value to social media marketing. This paper puts forward corresponding research findings in the premise of the integration of the basic concepts of current big data and social media marketing, and draws a conclusion as follows:

First, social media marketing is a product of the development of modern social media, and possesses great potential for mining and commercial values;

Second, the production, processing and application of big data provide media marketing with new blood, including precision marketing models and so on. And it is necessary to build more advanced and accurate big data social media marketing platforms in the future.

Third, the integration of social media marketing and big data is the trend of the development of the internet economy, as well as the core of social and economic development.

Starting from the basic theoretical concept, this paper analyzes the research direction of social media marketing in the era of big data, and discusses the changes in the development of social media marketing under the application of big data and the development of accurate marketing model, which can be used as a new theoretical idea for the development of social marketing. In the future, China's social media marketing can be further innovated from the following two

aspects. First is the data mining and finishing ability, as the era of big data continues to deepen, the amount of data is bound to be more, data mining and finishing ability is the premise of data application, so the future of social media marketing in the context of big data should further develop data collection and finishing ability, improve data applicability, to provide the premise of media marketing; second is the diversified development of marketing platforms. Social media marketing is currently facing the problem of monolithic marketing model, and the future can start from this aspect to further innovate marketing strategies.

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LEVERAGING SENTENCE-BERT FOR ENHANCED TOPIC DETECTION IN ONLINE COMMENTS

Rashmi J 1, Sushmitha MV 2, Sathya HK 3, Pallavi C 4, Mrs Jeya Karunya K5,

1,2,3,4-Students Dept of CSE, Jnana Vikas Institute of Technology, Bangalore, India

5- Jeya Karunya K, Assistant Professor, Dept of CSE, Jnana Vikas Institute of Technology, Bangalore, India

Abstract—In order to solve the problems of insufficient semantic description and poor semantic coherence of learned topics in comment text topic recognition. In this paper, Sentence- BERT sentence embedding model and LDA model are combined to improve the semanticity of comment text topics. The Sentence- BERT model is used to obtain the vector features at the sentence level of the comment text, while the LDA model is used to obtain the probabilistic topic vectors of the comment text, followed by connecting the two sets of vectors using an autoencoder, and applying the K-means algorithm to cluster the potential space vectors, and obtaining the contextual topic information from the class clusters. Through the experiments on the comment text dataset, the method of this paper can better obtain the topic words with semantic information. The fusion of Sentence-BERT model and LDA increases the complexity of the model. By comparison, the topic consistency index (Coherence) obtained by this paper's method is better than the current common comment text topic recognition methods.

Keywords—Sentence-BERT, LDA model, K-means algorithm, Comment text, Topic identification

I. INTRODUCTION

With the widespread application of

information technology and the popularity of mobile smart terminals, social media has gradually become the primary platform for internet users to express their opinions and views. The vast and diverse user comment data has also become an important channel for people to acquire information. Online comment data contains users' opinions and attitudes. Through the mining of these data, effective information integration can be achieved, providing businesses and websites with the most authentic user feedback, which has significant intelligence value. However, how to quickly extract user-relevant information from massive comment data, and uncover the implicit topics within user comments, is not only an important technology that businesses need to improve but also a hot issue that the field of intelligence has been paying attention to. Therefore, semantic analysis and topic mining of comment text have important application value and research significance.

II. PREVIOUS RESEARCH

Comment text topic identification refers to the use of text mining techniques to identify hidden hot topics in the massive user-generated content produced on social media platforms [1]. Studies suggest that the essence of comment text topic identification is a "clustering" problem, where topics are

clusters generated after clustering, and analyzing these clusters can reveal the latent topics in the comment text [2]. With the deepening research in deep learning, some scholars have begun to combine deep learning models with LDA topic models to achieve comment text topic identification. Deep learning methods enhance the closeness between words by vectorizing words, and combining the LDA topic model with deep learning models has achieved good results in text semantic analysis. Reference [3] combines the global representation of LDA topic modeling with the local context-word relationships of Word2vec to propose the Topic2vec model, which outperforms traditional LDA models in performance and has stronger semanticity of topics. Additionally, reference [4] proposes the Lda2vec word vector model based on Word2vec combined with the LDA model. Reference [5] combines the LDA model with the Bi-LSTM model to explore the sentiment information of topics in online MOOC comments. In recent years, with the good performance of deep learning models such as BERT in text semantic analysis, there have been studies that combine BERT with LDA to complete text topic identification research. For example, in order to realize the topic fine-grained opinion sentiment evolution simulation, scholars deeply fused the LDA topic model with the BERT model, and optimized the topic vectors to help text topic clustering [6], and some scholars proposed a keyword extraction method that fused the BERT and the LDATextRank, and analyzed

the topic information of the user comments of the online course [7].

In summary, the existing comment text topic identification combines the LDA topic model with deep learning models, becoming a new direction of technological application. These methods leverage neural networks to extract local features of text to enhance the semantic relevance of topics. Currently, research has transformed word vectors into text vectors [7] and employed unsupervised algorithms to vectorize text paragraphs, achieving learning fixed-length features from texts of different lengths and obtaining good results in comment text topic identification. However, this method requires considerable computational costs, and the generation of comment text is relatively arbitrary, limiting the accuracy of paragraph segmentation.

Therefore, this paper proposes a topic identification framework for comment short texts based on the LDA model, combined with Sentence-BERT sentence embedding vectors. By connecting the vectors of comment text sentences and topics,

the model explores the semantic relatedness of words in comment text. While maintaining the superiority of the LDA model, the model incorporates semantic relevance information at the text sentence level, constraining topic generation, and better understanding the semantic features of comment text in different contexts, thereby improving the coherence of topics and the accuracy of fine-grained partitioning.

III. EXPERIMENTAL DESIGN AND THEORETICAL

FOUNDATION

A. Experimental Design

The first challenge in conducting topic analysis on comment text is to convert this unstructured data into structured data in vector form [8].

Due to the generally short length of comment text, a single comment typically contains only a few words and a small

amount of feature information, lacking sufficient word co-occurrence and context-sharing information. In many cases, a single sentence of user comment text may represent a topic. Furthermore, due to the significant differences among internet users, comment text often suffers from non-standard expressions and character omissions, making it difficult to effectively extract meaningful linguistic features using simple text tokenization and bag-of-words models for comment text topic identification. Therefore, this paper adopts the sentence vector calculation model Sentence-BERT (SBERT), proposed by Reimers et al. [9] in 2019. By generating embedding vectors for sentences, comment text is mapped to a vector space in sentence form. Subsequently, these vectors are concatenated with the text topic vectors obtained from the LDA topic model to establish comment text vectors. Finally, clustering methods are employed to extract topic information from clusters, completing comment text topic identification. The specific process is illustrated in Figure 1.

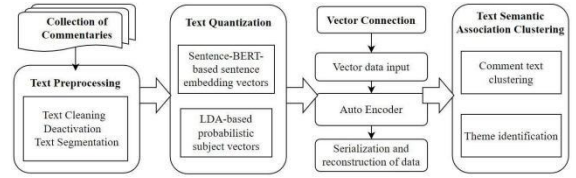


Fig. 1. Integrate Sentence-BERT and LDA comment text topic identification framework

The architecture proposed in this study consists of four main components: firstly, preprocessing of the comment text, including text data cleaning, removal of stopwords, and tokenization; secondly, vectorization of the text, utilizing the LDA topic model to compute probabilistic topics for the comment text corpus, while introducing the SBERT model to compute sentence embedding vectors for the comment text; thirdly, vector concatenation, constructing an encoder to concatenate input vector data in the latent space and reconstruct the data; finally, employing the K-means clustering method to extract topic words from the clusters of comment text.

B. Integration of SBERT and LDA for Text Vectorization

1) Text Probabilistic Topic Based on LDA

Topic identification refers to extracting key vocabulary that summarizes the entire text. Currently, Latent Dirichlet Allocation (LDA) is the main approach in the field of machine learning for document modeling, used to uncover the latent topics in text and widely applied in text topic recognition applications. This model is a Bayesian probability model that uses probabilistic inference algorithms to process text, generating probabilities

for words, topics, and documents in three layers and connecting words and documents through topics [10]. In the topic modeling process, the LDA model is based on the Bag of Words assumption and assigns words to a topic through probability calculations.

In the LDA model, each comment text is composed of a word set $w = \{w_1, w_2, \dots, w_n\}$ and the corpus consists of a series of texts $D = \{d_1, d_2, \dots, d_m\}$. m is the number of comment texts, d_i is the i th comment in the comment text collection, and this comment consists of n word items w_n . The probability representation of each latent topic obtained by the LDA model with respect to the word item w is calculated as follows:

$$P(w_i) = \sum_k P(w_i|z_i = k)P(z_i = k) \quad (\square)$$

In the formula, m represents a topic, and w_i is the i th word in document d .

2) Sentence Embedding Vectors Based on SBERT

SBERT, proposed by the Ubiquitous Knowledge Processing Lab in 2019, is a model for computing sentence vectors [9]. It was developed as an improvement over BERT, which had poor performance in representing sentences, particularly for non-supervised natural language processing tasks such as text clustering. SBERT processes sentence vectorization to enable vectorized representations of text to carry more semantic information.

SBERT employs Siamese and Triplet Networks to update weight parameters, aiming to generate sentence vectors with semantic information. By using

pre-trained models, SBERT can obtain chapter vectors with sufficient semantic meaning. SBERT adds a pooling operation on top of the last layer output

[Type text]

of BERT/RoBERTa to generate a fixed-size sentence embedding vector [9]. Currently, some scholars have combined SBERT with LDA to construct prompt lists for consulting questions, but there are still few studies on applying it to comment text topic identification in domestic research.

SBERT adopts three pooling strategies: CLS-pooling, which directly uses the output vector of the CLS position to represent the entire sentence; Mean-pooling, which calculates the average of the output vectors of each token to represent the sentence vector; and Max-pooling, which takes the maximum value of each dimension of all token output vectors to represent the sentence vector. Experimental results show that in unsupervised environments, the MEAN strategy achieves the best sentence vectorization [9].

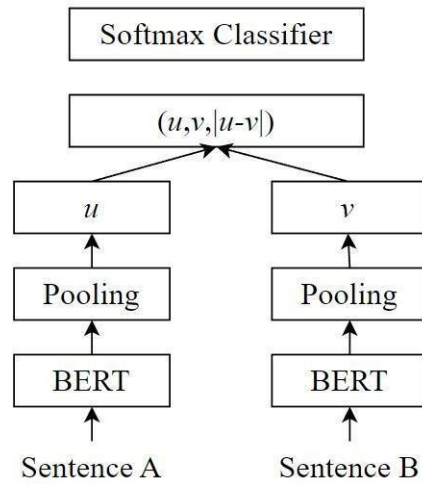


Fig. 2. The classification objective

function of SBERT

From Figure 2, it can be seen that SBERT adopts the structure of Siamese networks, where the encoder for input sentences utilizes the same BERT model to better capture the relationship between sentences and obtain sentence vectors with semantic features. When SBERT processes text classification, it concatenates the sentence vectors u and v , as well as their difference vector $|u-v|$ together to form a new feature vector, which is then multiplied by a weight matrix $Wt \in \mathbb{R}^{3n \times k[10]}$:

$$o = \text{softmax}(Wt(u, v, |u - v|))$$

n represents the dimensionality of the sentence vectors, and

k is the number of classification labels.

When two sentences, $S1$ and $S2$, from the comment text are inputted into SBERT, their vector representations are as follows:

$$Vs = S(S1, S2) \in \mathbb{R}^d$$

d represents the size of the hidden layer units within BERT.

3) Vector Concatenation

As mentioned earlier, utilizing the LDA model, this paper obtains probability topic vectors for comment texts, and with the assistance of the SBERT model, sentence embedding vectors are obtained. In order to achieve topic mining of

comment texts, it is necessary to concatenate these two vectors. Since the vectors to be concatenated reside in a sparse and correlated high-dimensional space, this paper employs an encoder to concatenate the vectors, achieving their representation in a low-

dimensional latent space. Here, the vector resulting from the concatenation of sentence vectors and topic feature vectors is defined as:

$$VSBERT+LDA = \{C; VS\}$$

where VS represents the vector representation of a sentence after passing through the SBERT model. C denotes the topic vector feature of the sentence, which is obtained by calculating the cosine distance between each topic acquired through the LDA model and the sentence S in the comment text d . “;” serves as the vector concatenation symbol.

IV. EXPERIMENT PROCESS AND CONCLUSION

A. Data collection and processing

For the experiment, this paper selects user comment data from Ctrip related to the Beijing Universal Resort. A web scraping software is developed using Python to collect 5058 pieces of comment text, spanning from February 2023 to February 2024. In the preprocessing stage, comments with fewer than 5 characters are removed, and duplicate comments containing repetitive single words like “very good very good very good” are eliminated, resulting in 4982 valid comments. Stop words are then removed using a stop word list to filter out high-frequency meaningless words in the comment text. Finally, the Jieba segmentation component is employed to tokenize the text, resulting in the creation of a comment text corpus.

B. Vectorization of Comment Text Based on SBERT and LDA

This paper loads the pre-trained model

distiluse-base-multilingual-cased-v1, which has been fine-tuned on comment text data, as the document data's pre-trained model. SBERT is utilized to vectorize 4982 pieces of comment text data, resulting in a matrix of comment text sentence vectors with dimensions of 4982 rows by 256 columns. For the topic embedding vectors of the comment text, the LDA topic model is employed for topic calculation. To determine the optimal number of topics, the perplexity model is utilized. In the experiment, Python 3.6 is used to calculate perplexity. The range of topic numbers considered is from 2 to 14. Through the calculation, the optimal number of topics is selected, as illustrated in Figure 3.

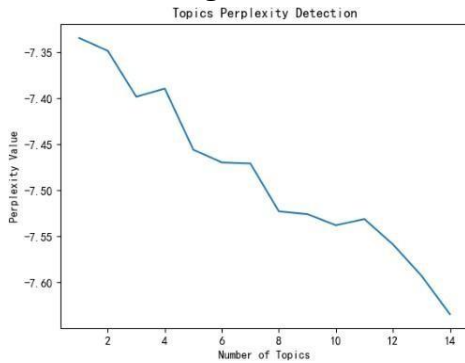


Fig. 3. Topics Perplexity Detection

From Figure 3, it can be observed that at a topic number of 11 (with a value of -7.528), the downward trend of the curve slows down. Therefore, this paper selects $K=11$ in the experiment and uses the LDA topic model for topic calculation.

After obtaining both sentence vectors and topic vectors separately, it is necessary to concatenate these two vectors. This paper employs an autoencoder to learn the concatenation of vectors, connecting the sentence embedding vectors generated by

SBERT with the probability topic vectors generated by the LDA model. This concatenation achieves the concatenation of the two sets of vectors in a low-dimensional latent space.

C. Topic Identification of Comment Text

After concatenating SBERT sentence vectors with LDA topic embedding vectors, a low-dimensional representation with condensed information is obtained. To better identify topics, clustering operations need to be performed on the concatenated vector matrix, and contextual topic information is obtained from the clusters. For better semantic-related clustering, this paper employs the K-means clustering algorithm in the experiment. The K-means algorithm assigns data points to the nearest centroid based on the nearest neighbor principle, resulting in a locally optimal solution. Due to its efficiency, simplicity, speed, and suitability for large-scale data clustering, K-means has become the preferred clustering operation in many NLP tasks focusing on contextual information clustering. When using the K-means clustering algorithm, the parameter K needs to be determined. The distribution of data points in the latent space based on the SBERT+LDA concatenation depends on the number of topics in the LDA topic modeling. Thus, there is a logical connection between the number of clusters K in the K-means algorithm and the number of topics in LDA. Therefore, in the experiment, the comment corpus is aggregated into 11 clusters.

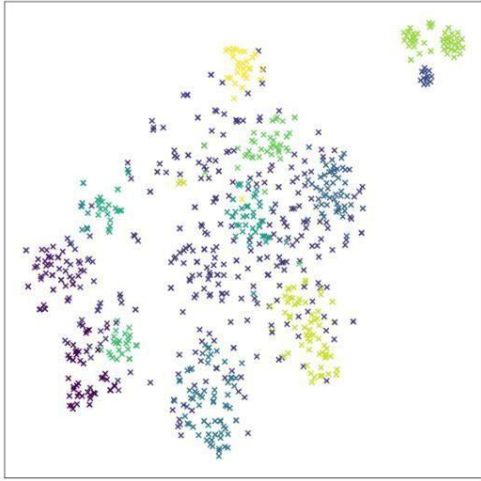


Fig. 4. The t-SNE plot displaying the distribution of the 11 cluster

D. Experimental Results

This paper employs the t-SNE dimensionality reduction algorithm to visualize the data in two dimensions for the 11 obtained clusters, as shown in Figure 4.

From Figure 4, it can be observed that the identified 11 clusters are clearly distributed in space, indicating that the clusters exhibit high consistency internally. The clustering effect of the model is quite good in terms of topic clustering.

Table I displays the topic information of the 11 clusters obtained using the SBERT-LDA method.

As shown in Table I, user comments regarding the Beijing Universal Resort primarily revolve around several themes such as park attractions, park services, park experience, ticketing, and surrounding transportation. Within the park attractions, “projects,” “Harry Potter,” “Minion Land,” “Transformers,” “performances,” and others are high-frequency terms. Among these, the characters within Universal Studios are a topic of great interest for visitors. This is because

products developed based on major film IPs have already established a highly loyal fan base, making their derivatives more appealing to a large number of visitors who come with anticipation, thus gaining consumer identification and generating higher economic benefits. Regarding park services, “staff,” “attitude,” “facilities,” “reasonable,” and “humanized” are high-frequency terms, indicating that visitors pay considerable attention to the service of resort staff and park facilities. In terms of park experience, “Universal Express,” “queuing,” “time,” “express lane,” “off-peak,” “value for money,” and “price” are high-frequency terms, indicating that visitors are concerned about play efficiency and cost-effectiveness. Universal Studios has also introduced express passes, allowing visitors to purchase them according to their needs to reduce queueing time and enhance their play experience. Additionally, “popular,” “exciting,” “family,” “children,” and “kids” are high-frequency terms, indicating that the main customer base of Universal Studios comprises young children and adults who are enthusiastic about Universal movies. Furthermore, Universal Studios is also the preferred destination for families when choosing parent-child outings, and their perception of the experience at the park is generally exciting and fun.

E. Method Comparison

To validate the effectiveness of the proposed method in this paper, we conducted comparisons with commonly used text topic identification methods.

Specifically, we employed the CoherenceModel from the Gensim package to assess topic coherence, utilizing the ‘u_mass’ method for calculation. The detailed results are presented in Table II.

[Type text]

TABLE I. COMMENT TOPIC WORDS SORTED BY CLUSTER IMPORTANCE

Thematic summary	Cluster number	Importance of clusters (%)	High-frequency theme words for class clusters
Resort Projects	6	17.21	Projects; Transformers; Wizarding World; Decepticons; Great Adventure; Minion Land; Harry Potter; Performances
	2	10.86	Megatron; Dinosaurs; Jurassic; Spider-Man; Optimus Prime; Movies; Hollywood;
	1	8.73	arks; Theme Lands; Roller Coasters; Lights; Floats; Performers; Parades; Popular; Events; Kung Fu Panda
Resort Services	5	5.15	Services; Staff; Hospitality; Park; Attitude; Facilities; Toilets
	9	8.91	Badge; Hardware; Reasonable; Journey; Humanized; Team; Superb; Professional;
	11	9.01	Resort; Photography; Projects; Environment Beautiful; Scenic;

			Restaurants; Eating
Tourist Play Experience	3	11.58	Kids; Universal Express; Time; Off-peak; Queuing; Off-Season; Waiting; Children;
	7	7.99	Save; Value for Money; Features; Entertainment; Spending; Facilities; Night View
	10	8.67	Season; Popularity; Packages; Family; Price; Weather; Beautiful; Exciting; Fun
Ticketing	8	6.12	nt; Resort; Tickets; Booking; Official Website; Buy Tickets; ID; Ticket Promotion; Affordable; Visitors; Onsite
Surrounding Transportation	4	5.77	ID; Transportation; Metro; Park; Admission; Metro Station; Facilities; Parking Lot

TABLE II. COMPARATIVE EXPERIMENTAL RESULTS

Experimental Methods	Coherence
LDA	— 5.14322
BTM [11]	— 5.14215
Word2vec	— 3.36458
Lda2vec [4]	— 2.75973
BERT	— 3.02377
SBERT	— 2.52938

identification. Therefore, the model exhibits strong portability. However, it is worth noting that the integration of LDA with the SBERT model objectively increases the complexity of the topic identification process. Through comparison, our method takes longer compared to the individual use of LDA and BERT, but the overall model efficiency is better than that of

the BTM model.

From Table II, it is evident that the proposed method achieves the highest coherence score of -2.52938, surpassing all other methods. This value is 0.5 percentage points higher than that of the BERT model, indicating that the proposed method outperforms other methods in terms of topic coherence. It is noteworthy that the Lda2vec model achieves a coherence score of -2.75973, suggesting that the fusion of LDA with word embeddings is effective.

V. CONCLUSION

To address the issues of insufficient semantic description, ineffective capture of inter-word correlations in comment text, and weak coherence of learned topic semantics in comment text topic identification, this paper integrates the SBERT sentence embedding model with the LDA probabilistic topic model. Through the encoder, sentence embedding vectors and probability topic vectors are concatenated, and the K-means clustering algorithm is employed to cluster the vector space, obtaining core words for each cluster and achieving comment text topic identification. Comparative experiments demonstrate that our method outperforms commonly used methods in terms of topic coherence.

Our method effectively extracts semantically informative topic words from comment text. Furthermore, the SBERT pre-trained model can be fine-tuned for better sentence embedding results, thus further improving the

effectiveness of text topic

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MACHINE LEARNING – BASED AUTOMATED VERIFICATION AND PREDICTIVE BUG DETECTION IN RTL AND PHYSICAL LAYOUT DESIGNS: A LITERATURE SURVEY

Sahana Patil Assistant Professor

Dept. of Electronics and Communication

C. Byre Gowda Institute of Technology

Kolar, India patilsahana005@gmail.com

Dr. G K Venkatesh Head of the Department

Dept. of Electronics and Communication

C. Byre Gowda Institute of Technology

Kolar, India gkvlshiv@gmail.com

Abstract - The growing complexity of modern VLSI systems has significantly increased the burden on conventional verification and validation techniques. Traditional approaches struggle to meet today's stringent requirements related to time-to-market, cost efficiency, and design reliability. In recent years, Machine Learning (ML) has emerged as a powerful enabling technology capable of transforming verification workflows. By learning from historical design and verification data, ML techniques can automate regression analysis, guide intelligent test generation, and predict defects early at both the Register Transfer Level (RTL) and physical layout stages.

This paper presents a comprehensive literature survey of ML-driven automated verification and predictive bug detection methodologies. The reviewed research spans supervised, unsupervised, ensemble, graph-based, and reinforcement learning techniques applied to verification planning, directed stimulus generation, RTL defect prediction, security-aware RTL analysis, routing congestion estimation,

design rule checking (DRC) prediction, placement optimization, and early power-performance-area (PPA) estimation. The survey also critically examines modeling strategies, dataset limitations, evaluation metrics, deployment constraints, and integration challenges within industrial Electronic Design Automation (EDA) flows. Finally, research gaps related to dataset scarcity, cross-design generalization, interpretability, and lifecycle integration are identified, highlighting promising directions for future intelligent verification ecosystems.

Index Terms— Machine learning, hardware verification, RTL bug prediction, defect prediction, EDA, reinforcement learning, DRC prediction, layout optimization.

I. INTRODUCTION

Functional verification accounts for a major portion of hardware development effort, often consuming more than 60% of the overall design cycle. Conventional verification strategies such as simulation-based testing, constrained-random verification,

formal verification, assertion-based checking, and static linting have served the industry for decades. However, as designs grow in complexity, include heterogeneous architectures, and target advanced technology nodes, these approaches increasingly face scalability challenges. State-space explosion, long regression cycles, and coverage closure difficulties make traditional methodologies time-consuming and resource-intensive.

Recent progress in Machine Learning has demonstrated that verification artifacts—including simulation logs, waveform traces, coverage metrics, assertion failures, regression histories, and layout violation reports—contain valuable patterns that can be learned and generalized. By leveraging historical outcomes, ML models can predict defect-prone modules, prioritize regression tests, optimize stimulus sequences, and estimate physical design bottlenecks before expensive implementation stages.

This survey brings together research contributions from RTL-level verification analytics and backend physical design prediction to present a unified perspective on ML-enabled automated verification across the hardware development lifecycle.

II. FOUNDATIONAL SURVEYS AND ML TAXONOMY IN VERIFICATION

The structured study of ML applications in hardware verification

begins with several foundational surveys.

Work in [1] categorizes supervised, unsupervised, and reinforcement learning approaches applied to problems such as SAT solving, coverage improvement, and assertion generation, effectively framing verification tasks as learnable optimization problems.

Building on this taxonomy, [2] expands the discussion by incorporating industrial case studies and highlighting practical deployment challenges such as class imbalance, feature engineering complexity, and integration within regression infrastructures.

A broader perspective is presented in [8], which reviews the historical evolution of ML-assisted hardware verification and discusses issues related to scalability, dataset reproducibility, and cross-project generalization. Similarly, [10] positions ML as a cross-disciplinary enabler across EDA stages, emphasizing the growing importance of Graph Neural Networks (GNNs) for modeling structural hardware representations such as netlists and routing graphs.

Together, these surveys establish the conceptual and methodological foundation for ML-driven verification research.

III. ML-BASED VERIFICATION PLANNING AND TEST OPTIMIZATION

Verification planning aims to reduce regression cost while maximizing coverage efficiency. Several works demonstrate how ML can optimize this process.

In [3], a supervised learning framework predicts the expected coverage contribution of individual tests based on historical regression and design data. By ranking tests according to anticipated coverage gain, redundant simulations can be eliminated, significantly reducing verification runtime.

Reinforcement learning is explored in [5], where verification is modeled as a sequential decision-making problem. An RL agent dynamically adjusts stimulus strategies based on coverage feedback, learning to maximize verification efficiency while maintaining computational feasibility.

Directed test generation techniques are surveyed in [6], comparing formal constraint-solving approaches with ML-guided stimulus strategies. The study highlights how learning-based prioritization enhances corner-case exploration.

Regression pruning techniques in [21] use coverage delta prediction models to remove low-impact tests without compromising defect detection quality. Adaptive stimulus ranking in [22] applies classification models to identify high-impact verification scenarios, accelerating coverage closure.

Failure clustering methodologies in [23] analyze historical bug traces to predict regression scenarios likely to expose latent defects. Hybrid frameworks such as [31] combine supervised prediction and reinforcement learning to continuously refine regression strategies based on real-time outcomes.

Collectively, these works demonstrate measurable reductions in simulation cycles and improved regression efficiency.

IV. RTL-LEVEL PREDICTIVE BUG DETECTION AND REFACTORING

Early identification of RTL defects significantly reduces downstream debugging effort. Trend-based modeling in [7] predicts RTL refactoring needs by analyzing historical verification outcomes. Similarly, [9] proposes a feedback-loop framework in which verification results are continuously fed back into RTL improvement models, creating a closed-loop learning environment between design and verification.

The transfer of software defect prediction methodologies to hardware is explored in [12] and [13], where metrics-based and ensemble learning models identify fault-prone modules. These studies provide foundational principles applicable to RTL-level predictive analytics. Further research in [24], [25], and [26] investigates

structural and complexity-based features such as fan-out, FSM states, module coupling, and assertion density to model defect likelihood. These approaches demonstrate that well-engineered structural metrics can significantly enhance prediction accuracy.

V. ML-BASED SEQUENCE GENERATION FOR HARDWARE VERIFICATION

Because verification involves sequential stimulus application, temporal learning models are particularly suitable. In [14], stimulus generation is formulated as a sequence learning problem, leveraging historical failure traces to generate optimized verification sequences.

Advanced architectures explored in [26] and [27] use recurrent and transformer-based models to predict next- best verification actions based on coverage progression patterns. These techniques improve exploration efficiency

and enhance corner-case detection compared to heuristic- driven methods.

VI. DATA-CENTRIC ML FRAMEWORKS FOR VERIFICATION

Model performance strongly depends on data quality.

The data-centric pipeline proposed in [15] emphasizes dataset curation,

normalization, labeling consistency, and iterative retraining to improve robustness. Early PPA estimation using ML at the RTL stage is addressed in [20], enabling designers to assess implementation risks before physical synthesis. Cross-project generalization is tackled in [28] and [29] through dataset augmentation, transfer learning, and synthetic defect injection techniques. These strategies aim to overcome limited labeled datasets and improve scalability across diverse design environments.

VII. SECURITY-AWARE RTL ANALYTICS

Security vulnerabilities represent a critical class of hardware defects. The survey in [4] reviews AI- augmented secure RTL design methodologies for detecting hardware Trojans. Techniques such as anomaly detection and structural fingerprinting are applied to identify malicious modifications prior to fabrication, strengthening design security in the supply chain.

VIII. ML IN PHYSICAL LAYOUT AND DESIGN RULE

Machine learning approaches have increasingly influenced backend physical design tasks, particularly in early-stage prediction and optimization. In CongestionNet [16], deep graph neural networks are utilized to estimate routing congestion prior to global routing, enabling designers to identify problematic regions at an early stage.

Overall by enhancing graph-based congestion modeling with improved feature representation and spatial learning mechanisms, leading to better prediction stability across complex layouts.

Unsupervised clustering strategies reported in [17] focus on identifying potential DRC hotspots during the initial layout phases, reducing the need for repeated rule-check iterations. Similarly, ensemble-based classification techniques discussed in [18] enhance DRC prediction accuracy by combining multiple learning models, thereby improving generalization across different design blocks. Placement optimization has also benefited from learning-based strategies; the reinforcement learning framework described in [19] demonstrates improved power, performance, and area trade-offs when compared with conventional heuristic-driven placement methods.

Furthermore, the multi-resolution congestion estimation framework MEDUSA [25] introduces hierarchical spatial analysis to refine congestion prediction across varying layout granularities.

Beyond performance improvements, recent investigations such as [30] address the broader implications of integrating ML into EDA workflows, particularly emphasizing model reliability, robustness, and security considerations. These studies underline the importance of developing trustworthy and verifiable ML models

before their widespread adoption in physical design automation.

IV. FPGA-SPECIFIC PERSPECTIVES

ML integration in FPGA design flows presents unique constraints. As discussed in [11], challenges include limited publicly available datasets, vendor-specific tool variability, and reduced reproducibility across FPGA platforms. These deployment considerations require tailored ML solutions for FPGA-based EDA ecosystems.

V. COMPARATIVE ANALYSIS AND RESEARCH GAPS

Despite notable progress, several critical challenges remain. A primary limitation is the scarcity of publicly available RTL and layout defect benchmark datasets, which restrict reproducibility and large-scale evaluation. Additionally, many models struggle with cross-project generalization, as performance often degrades when applied to different architectures or technology nodes. Explainability remains insufficient, particularly for safety-critical systems where interpretable predictions are essential. Most existing solutions operate in isolation, addressing either RTL or physical design stages independently, resulting in fragmented lifecycle coverage. Furthermore, the cost of labeling defect data for supervised learning limits scalability.

Future research must therefore focus on developing unified, lifecycle-aware ML frameworks capable of continuous learning across design stages while ensuring robustness, interpretability, and industrial compatibility.

VI. EXPECTED RESULTS

Based on the surveyed literature, ML-based automated verification frameworks are expected to deliver measurable improvements across RTL and physical design stages. At the RTL level, supervised regression ranking and reinforcement learning-based stimulus optimization can reduce redundant simulation cycles and accelerate coverage closure. Predictive defect models can identify fault-prone modules early, minimizing late-stage debugging effort. Sequence-learning approaches can

enhance bug discovery by intelligently navigating complex state spaces. At the physical design level, graph-based models and ensemble predictors enable early routing congestion and DRC violation detection.

Reinforcement learning-driven placement tuning can achieve improved PPA trade-offs compared to manual optimization. Data-centric ML pipelines improve robustness and generalization through systematic dataset management. Overall, integrating ML across the RTL-to-layout lifecycle is expected to reduce verification turnaround time, lower computational cost, improve defect localization accuracy, and enhance

predictability in achieving coverage and PPA targets within industrial EDA workflows.

VII. CONCLUSION

THIS SURVEY HAS EXAMINED MACHINE LEARNING APPROACHES FOR AUTOMATED VERIFICATION AND PREDICTIVE DEFECT DETECTION ACROSS RTL AND PHYSICAL LAYOUT STAGES. THE LITERATURE DEMONSTRATES THAT HISTORICAL DESIGN AND VERIFICATION DATA CAN BE EFFECTIVELY LEVERAGED TO REDUCE REDUNDANT SIMULATION CYCLES, ACCELERATE COVERAGE CLOSURE, AND ENABLE EARLY DEFECT PREDICTION. FUTURE RESEARCH MUST PRIORITIZE SCALABLE, EXPLAINABLE, AND LIFECYCLE-INTEGRATED ML FRAMEWORKS THAT CAN BE SEAMLESSLY EMBEDDED WITHIN INDUSTRIAL EDA TOOL CHAINS. SUCH ADVANCEMENTS WILL PAVE THE WAY TOWARD INTELLIGENT, ADAPTIVE, AND SELF-OPTIMIZING HARDWARE VERIFICATION ECOSYSTEMS.

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DECENTRALIZED TRAFFIC INCIDENT MONITORING AND EMERGENCY ALERT SYSTEM VIA FEDERATED LEARNING

Ms.Hithaishi K V¹ Dr Krishna Kumar P R²

1. Assistant prof, Department of CSE Prof, Sea College of Engineering & Technology, Bangalore-49
2. HoD, Department of CSE Sea College of SEA College Engineering & Technology, Bangalore-49

Abstract—In this paper, an innovative traffic management system is introduced that combines federated learning and real-time incident response. The proposed system will do the learning at roadside cameras and vehicles, unlike with centralized methods that need the constant communication of traffic video or vehicle position information, and as such, the proposed system can collaborate privately. The models include batch-based convolutional neural network for traffic incident detection at the edge by utilizing short time context to enhance stability in detection. Simultaneously, cars learn travel-time dynamics together with federated learning to assist adaptive routing in the time-varying traffic environment. An interrupt service routing mechanism is also activated when a critical incident has been detected where the handling of an emergency takes precedence and an immediate dispatching of alerts to the local police stations, ambulance services, and registered family contacts. The system is tested based on a simulated urban traffic setup, and it was found that the system has a stronger detection ability, less false alarm, and it also responds quicker to emergency but does not compromise data privacy.

Index Terms—Federated learning,

intelligent transportation systems, traffic incident detection, edge intelligence, batch processing, adaptive routing, interrupt service routing, emergency response systems

I. INTRODUCTION

Traffic jams and road accidents are still very pressing issues in the contemporary urban setting that influence the safety of the population and the effectiveness of response to emergency states. Intelligent Transportation Systems (ITS) can resolve these challenges by using sensory infrastructure and machine learning to provide automated traffic management and control. Recent developments in deep learning have enabled the detection of traffic incidences using surveillance video with high accuracy levels, significantly enhanced compared to the past, which, nonetheless, is still imperfect [1], [2]. Nevertheless, the majority of available systems are based on , the centralized collection of data, which brings up the issue of privacy and contributes to the communication overhead.

Recently, federated learning has become an arguably potential new paradigm of facilitating model training across distributed data sources without transferring raw data [4]–[6]. It has been proved to be applicable to

intelligent transportation systems and vehicular networks in several studies with better scalability and privacy preservation demonstrated upon its use in these systems and networks [7]. However, real-life implementation issues like the heterogeneity of clients and delay in communication are still research priorities that are on hold

This paper suggests a smart traffic control system, which combines federated learning and batch-based incident detection and adaptive routing. The proposed system, unlike the current system, will also have an interrupt service routing system, which allows emergency alert to be disseminated to police stations, hospitals, and registered contacts immediately a critical incident is detected. The system is tested in a simulated urban traffic setting and the findings indicate that the system is more robust in detection, less prone to false alarms and responds to emergencies more quickly without impacting the privacy of data.

II. RELATED WORK

On the one hand, deep learning-based traffic surveillance has demonstrated a good performance in the automatic accident and incident detection. A car crash detection system using the CNN was proposed by Moussa et al. to improve road safety, which was introduced by [1], and a large-scale benchmark dataset of traffic accident detection can be observed in video surveillance, which showed the usefulness of deep visual models in monitoring traffic conditions in the real world, which was proposed by Xu et al.

[2] The techniques, however, primarily operate on the central processing of video.

Zhang et al. addressed system-level challenges in ITS- oriented federated learning by proposing a delay-constrained client selection strategy for heterogeneous vehicular environments [3].

Federated learning has recently been incorporated into intelligent transportation systems to deal with the issue of privacy and scalability. In a survey on federated learning in ITS, Zhang et al. [4] and Zhang et al. [5] presented an extensive survey of this field, covering its applications, challenges and directions. Chellapandi et al. [6] also considered the methods of federated learning in connected and automated vehicles with a stronger focus on the decentralized cooperation in the car. The information gathered by Li et al., as published by the journal [7], demonstrated that distributed learning structures to ITS are surveyed and that scalable and privacy-aware learning structures are most valued.

A number of works have studied federated learning in terms of traffic prediction and traffic management. Alqubaysi et al. introduced a federated predictive system of traffic management, where autonomous vehicles have privacy-sensitive mechanisms that preserve their privacy [8]. Aalavanthar et al.

[9] researched multi-objective federated traffic prediction in vehicular networks with enhanced adaptability and performance. A study was conducted by Chen et al. [10] to examine mobility-aware decentralized federated learning

using optimized client selection strategies on vehicular networks.

In addition to prediction, edge intelligence based transportation platforms, and digital twin, have been researched. Ge and Qin [11] reviewed digital twin based ITS architectures demonstrated that they can be used in real-time monitoring and decision support.

Federated learning has been extensively used in transportation IoT systems on security and robustness. Bhavsar et al.

[12] and Althunayyan et al. [13] offered federated intrusion detection systems of vehicular and in-vehicle network. More works have reviewed the performance scaling, robustness and optimization of federated intrusion detection systems [14]– [16]. Moreover, federated visual intelligence can be seen as possible and it is demonstrated by decentralized perception systems like Argos [17].

Federated learning has also been discussed in recent research on robustness and aggregation strategies. Sun et al. [18] proposed a dynamic aggregation approach to robust federated learning, and Shen et al. [19] presented ensemble distillation-driven federated learning available with heterogeneous IoT networks.

Unlike the available literature, the present paper combines the batch-based incident detection of edges, federated learning-based cooperative model training, and the emergent response based on interrupts into the single intelligent traffic management system.

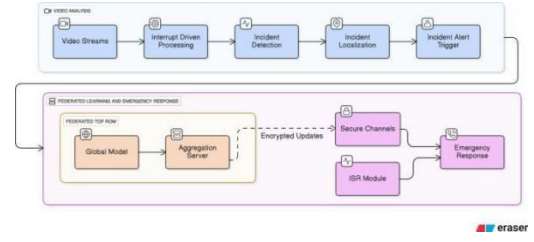


Fig. 1. Federated learning based intelligent traffic management system architecture

III. SYSTEM ARCHITECTURE

The architecture of the proposed intelligent traffic management system is presented in Fig. 1. The system takes a three-layer system which is composed of an edge layer, an aggregation layer and an application layer. This scalable organization facilitates scalable traffic monitoring, privacy-preserving learning and low-latency emergency response.

A. Edge Layer

The edge layer is used to conduct real-time traffic sensing and local processing. It is comprised of roadside cameras and edge computing devices that are installed in traffic intersections. Incident detection models are processed locally on the live video stream using batch-based incident detection models to identify abnormal events in time without necessarily having to transmit raw data. The edge layer identifies the affected road portion when an incident has been identified and produces an alert trigger.

B. Aggregation Layer

The aggregation layer allows joint training of models through federated learning. The traffic management

centers are the aggregation servers that are updated with the model of various edge devices. The obtained updates are combined into a global model, which is periodically republished to the edge devices in order to enhance the performance of detection.

C. Application Layer

System-level decisions and service coordination are done in application layer. An interrupt service routing module is the module that receives incident alert on the highest priority and executes emergency response measures. Notifications are sent to the police stations, hospitals or ambulance services near the location, and registered relatives. Simultaneously, adaptive traffic routing and monitoring services are also supported by this layer.

IV. MACHINE LEARNING MODELS

A. Problem Formulation

Traffic incident detection and adaptive routing are formulated as supervised learning tasks under decentralized data

constraints. For incident detection, the objective is to classify short temporal batches of video frames as either normal or incident events. Let X_b denote a batch of consecutive video frames and let $y_b \in \{0, 1\}$ represent the corresponding label, where $y_b = 1$ indicates the presence of a traffic incident.

In the case of adaptive routing, the task is to estimate individual road segment travel time based on the contextual variables, i.e., time of day and current traffic condition. These forecasts are utilized to select dynamically the routes

that will reduce the anticipated travel delay. Both of the tasks are learned at edge devices and enhanced together through federated learning.

B. Batch-Based Incident Detection

Every roadside camera performs a shallow convolutional neural network to perform real-time inference. Fixed-size batches of incoming video frames are defined by short-term windows. The confidence score is calculated after computing an average of frame-level predictions per batch:

A. ISR Workflow

The interrupt service routing mechanism workflow is shown in Fig.1. Roadside cameras handle the video frames that are received in temporal blocks. The occurrence of an interrupt signal is triggered by the surpassing of a predetermined threshold by the batch-level confidence. ISR subsequently derives vital incident data including the location and severity and locates the closest emergency services and triggers alert distribution.

Alerts are also sent to police stations, hospitals or ambulance services, as well as registered family contacts, in case of an emergency. This interrupt-based implementation model makes sure that delivery of alerts is not slowed down by federated learning updates, routing computations or visualization activities.

$$\frac{1}{B} \sum_{i=1}^B C_{batch} = B \quad C_{ii}=1 \quad (1)$$

A traffic incident is confirmed when Cbatch exceeds a predefined threshold. This batch-based decision strategy reduces false alarms caused by transient visual noise and brief occlusions.

C. Adaptive Traffic Routing Model

The Adaptive Traffic Routing Model is also discussed in the sub-section. The road segments used in vehicles are regression-based to estimate the travel time. The input characteristics are temporal characteristics and recent congestion. The routing module tries to constantly optimize paths based on the changing traffic conditions by using the predicted travel times.

V. INTERRUPT SERVICE ROUTING FOR EMERGENCY ALERTS

section Interrupt service routing to emergency alerts This service is also implemented in the operating system. The ability to respond to traffic crashes quickly is required to reduce the number of accessory collisions and guarantee medical help in time. Although the suggested system allows proper detection of the incidents at the edge, it needs another real-time controlling mechanism that would transform the detections into action. To cater to this, the system is designed with an interrupt service routing (ISR) facility of handling emergency alerts on a priority basis.

The ISR is a high-priority control component that is activated each time a high-confidence traffic incident is observed. Through this, the ISR preempts non-critical processes unlike routine analytics or background learning processes to be able to

guarantee that emergency notifications are handled immediately.

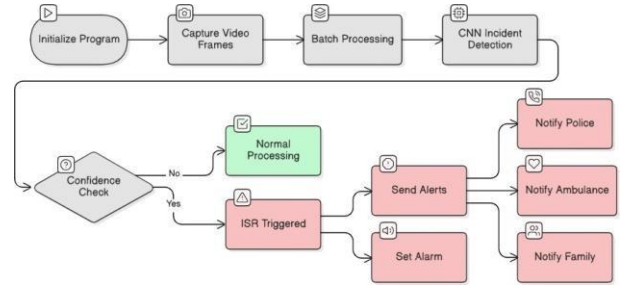


Fig. 2. Incident detection and interrupt service routing workflow

B. Interrupt Handling Logic

The steps undertaken by the operations during an ISR event are summarized in Algorithm in the form of 1. Upon activation, the ISR does not have to deal with regular scheduling queues, but instead calls emergency notification routines.

Algorithm 1 Interrupt Service Routing for Emergency Alert Dissemination

- 1: if $C_{batch} > \theta$ then
- 2: Trigger interrupt service routine
- 3: Extract incident location and severity
- 4: Identify nearest police station
- 5: Identify nearest hospital or ambulance service
- 6: Dispatch alerts to emergency services
- 7: Notify registered family contacts
- 8: end if

C. Priority Handling

The emergency alerts are given top priority in the system to ensure that it is executed in time even when there is the

peak traffic conditions. Federated model aggregation and routing optimization are some of the background processes that are suspended until the achievement of alert dissemination. This provides fast and dependable response to emergencies in safety-related scenarios.

VI. EXPERIMENTAL SETUP

The presented system is tested on a simulated traffic setting within the city that is expected to simulate various inter- sections, changing vehicle density, and random incidence of incidents. Traffic video data is obtained based on a publicly available video dataset on traffic accidents and modified to the simulation setting to conduct controlled experiments.

Table I summarizes the key configuration parameters used in the experiments.

Parameter	Values
Number of intersections	10
Number of vehicles	100
Roadside cameras per intersection	1
Federated learning rounds	20
Local batch size	16
Learning rate	0.001
Incident probability	0.15
Communication interval (s)	5

B. Detection Performance Comparison

Table II compares the performance of incident detection in the various training strategies. Training models on local data only have higher false positives because the diversity of data is low. Federated learning models are

always able to enhance accuracy, precision and recall and decrease false positives. The combined federated learning architecture containing a batch processing scheme and interrupt service routing has the highest overall performance.

TABLE I
SIMULATION CONFIGURATION
PARAMETERS

Parameter	Values
Number of intersections	10
Number of vehicles	100
Roadside cameras per intersection	1
Federated learning rounds	20
Local batch size	16
Learning rate	0.001
Incident probability	0.15
Communication interval (s)	5

The results presented in this paper are all the result of simulated experiments, meant to show trends in relative system performance and disposition, rather than measurements related to deployment.

VII. RESULTS

A. Incident Detection Accuracy

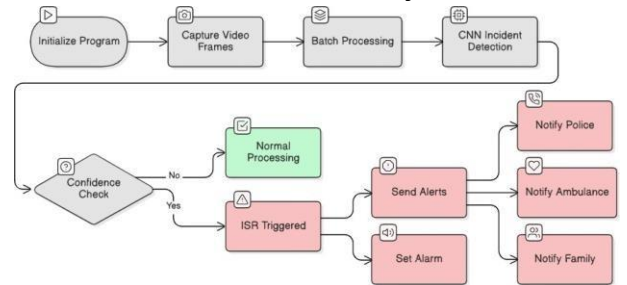


Fig. 3 indicates that after each round of federated learning, the incident detection accuracy converged. The

federated solution is more accurate than training locally, where the global model has the advantage of data variety with multiple intersections.

Fig. 3. Incident detection accuracy versus federated learning rounds

TABLE II
INCIDENT DETECTION PERFORMANCE COMPARISON ACROSS TRAINING STRATEGIES

Training Strategy	Acc.	Prec.	Recall	F1	Spec.	FPR	RMSE
Local-only CNN	0.76	0.73	0.70	0.71	0.85	0.15	0.42
Centralized CNN	0.84	0.81	0.79	0.80	0.88	0.12	0.35
FedAvg-based Model	0.86	0.83	0.82	0.82	0.91	0.09	0.30
FedProx-based Model	0.87	0.85	0.84	0.84	0.92	0.08	0.27
FedMA-based Model	0.88	0.86	0.85	0.85	0.93	0.07	0.25
Proposed FL + Batch ISR Model	0.90	0.88	0.87	0.87	0.94	0.06	0.22

C. Routing Prediction Performance

Fig. 4 shows the routing prediction error as a variable of the number of involved vehicles in the federated learning process. Three metrics of error are reported: RMSE, MAE and MAPE. All the three error measures also decrease with the increase in the number of vehicles. This trend is implying that the routing model has more and more varied contributors to the training that enhances its capability of capturing the spatial and temporal traffic trends.

Specifically, the decrease of RMSE and MAE indicate the increased numerical accuracy of the travel time estimations, whereas the general decline of MAPE indicates the increased relative predictability reliability. These findings

affirm that the joint learning in an increasing number of vehicles results in the correct and consistent routing decisions.

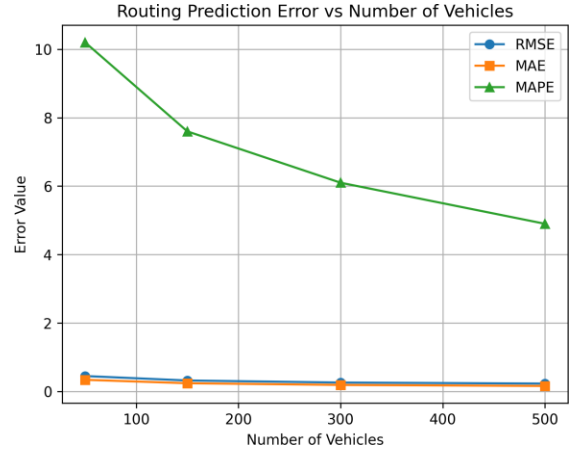


Fig. 4. Routing prediction error versus number of vehicles using RMSE, MAE, and MAPE

D. Emergency Response Time

Fig. 5 compared the mean response time of emergency with and without the proposed interrupt service routing mechanism. The absence of ISR in the system causes the alerts to be handled by the standard execution process, which results in a much longer response time.

Enabling the ISR mechanism, the emergency alerts receive the top priority and the non-critical activities are skipped. This will decrease the response time by over fifty percent in the simulated scenario. The output proves that alert handling, which is interrupt-driven, is very efficient in reducing delay and providing quicker coordination with the emergency and family contacts.

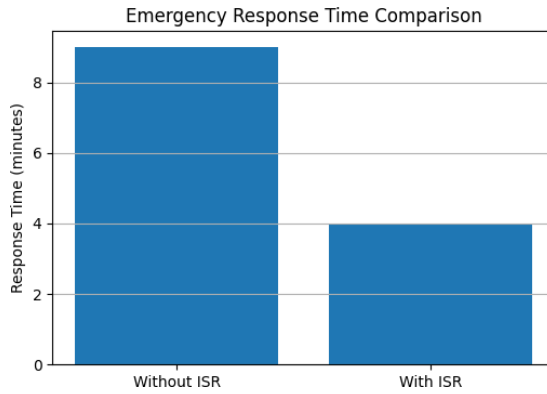


Fig. 5. Emergency response time with and without interrupt service routing

E. Ablation Study

A study was carried out as an ablation study to test the effects of the major components of the system. The incident detection model was found to be more sensitive to the short-term visual noise when narrowed down to a batch-based processing, which caused an increase in false alarm rate. In the case of federated learning, disabling impaired performance of generalization and convergence on intersections.

On the same note, eliminating the interrupt service routing mechanism led to a major rise in the emergency response time, since the alerts needed to be scheduled just like any normal task. The above observations affirm that batch processing, federated learning and the interrupt service routing are all important in ensuring accurate detection, efficient routing, and quick response to emergencies.

The experimental findings indicate that the proposed system is able to obtain better incident detection accuracy and better routing prediction performance without any loss to data privacy. Edge computing of batches assists in

stabilizing the predictions and also minimizes the false alarms particularly in traffic scenes which have visual noise like lighting change, or temporary blockage.

The incorporation of the interrupt service routing has a straight and efficient connection between automated incident identification and the real-life emergency response. The system

also minimizes response time and guarantees that emergency services are coordinated in time by giving high importance to handling alerts. Though the experiment is carried out on a simulation, the tendencies observed indicate the potential viability of the research approach based on federated learning, augmented with the real-time control mechanisms of intelligent traffic management.

F. Privacy and Security Considerations

Privacy and Security Issues This feature will ensure that the user is convinced that his or her data is not manipulated by some malicious individuals. One of the main benefits of the proposed design is that raw video streams and vehicle trajectory data will still be stored on local devices, eliminating the dangers of centralized data storage and data gathering of a huge scale. This renders the system more appropriate in the privacy-sensitive urban applications.

Nevertheless, threats to the federated learning systems still include malicious updates or information leakage through model parameters. Although the present work presupposes the honest participants, in real-life

implementations, there should be some other measures of protection like the secure aggregation and anomaly detection to enhance the robustness of the system even further.

VIII. LIMITATIONS AND FUTURE WORK

The presented system is tested with the simulated traffic data and the assumption of constant communication between distributed clients and the aggregation server. In practice implementation, intermittent connectivity of the network, intermittent capabilities of different devices and partial client attendance can influence the convergence of learning and responsiveness of the system.

The next steps of work will be to prove the framework on real traffic data and pilot implementation. Another significant direction is to get stronger resistance to malicious or faulty model update, especially in open vehicular environment. Besides, the routing component may be further enhanced by means of reinforcement learning methods to allow making more adaptive decisions during extremely dynamic traffic scenarios.

Additional investigation could also be carried out into better methods of client selection, secure aggregation, and non-independence and non-identically distributed data among clients.

IX. CONCLUSION

This paper proposed an intelligent traffic management system federated learning which is an integration of a batch-based incident detection, routing adaptive and interrupt service routing to emergency alerts. Through edge-

based learning and only sharing model updates, the framework saves the privacy of data and allows improvements to be shared across distributed traffic settings.

The results of reaction to simulation demonstrate more stable detection, fewer false alarms, and more efficient routing

and easier response to the situation of emergency in comparison with isolated local training. In general, the suggested architecture proves the presence of privacy-conscious learning and real-time emergency management in the next-generation smart city traffic systems.

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CODEMENTOR AI - PERSONALIZED CODING CHALLENGE AND CONTEST RECOMMENDATION SYSTEM

**Anmol R Patil , G Nagachaithanya , M Varshini Guptha , Dr G Venkanna , A
Ranjith Kumar**

Department of Computer Science Engineering

Sreenidhi Institute of Science and Technology , Ghatkesar , Hyderabad

Emails: anmolpatil349@gmail.com, gajalanagachaithanya7@gmail.com,
varshguptha@gmail.com , venkanna.g@sreenidhi.edu.in , ranjith.a@sreenidhi.edu.in
Educational Technology (EdTech),

Abstract—As aggressive programming systems proliferate quickly, developers often experience "statistics overload," which makes it difficult for them to recognize coding challenges and contests that correspond with their specific skill levels and professional objectives. In order to fill this gap, this article presents CodeMentor AI, an intelligent recommendation system that provides software engineers with a personalized learning path. Utilizing a full-stack architecture that includes React for a dynamic user interface and Node.js for a scalable backend, the machine combines real-time contest statistics with coding challenges by utilizing external APIs. CodeMentor AI makes personalized recommendations by analyzing user performance and potential, which maximizes learning effectiveness and promotes ongoing skill development. According to person feedback and experimental results, the method increases engagement with relevant aggressive programming activities while significantly cutting down on the amount of time spent on guide discovery.

Index Terms—Recommender Systems, Personalization, Competitive Programming, Full-Stack Development, Node.js, React,

Information Filtering, User Profiling, API Integration, Skill Acquisition.

I. INTRODUCTION

The field of software engineering has undergone significant transition, with competitive programming and algorithm proficiency now being the primary indicators of technical proficiency. Students and working professionals can now enhance their problem-solving skills by using sites like LeetCode, Codeforces, and HackerRank. The issue is that there are constantly fresh challenges and competitions, which causes "information overload." It might be difficult to make decisions when there is too much information for one person to process. Determining which tasks will best enable them to achieve the level required to work at the top is the dilemma for many people, especially those who are just starting out, rather than a lack of desire to practice. The majority of platforms currently offer broad roadmaps or predefined categories that ignore a person's "Zone of Proximal Development" or how their talents are developing over time. This lack of customization might lead to "learner fatigue," in which a user becomes stuck on "Hard" tasks because

they lack the necessary background knowledge or spends a lot of time on "Easy" problems that they have already mastered. Research on educational technology indicates that when learning is "intrinsic," or the difficulties are pertinent and align with each student's unique development, kids remain more motivated and engaged. A sophisticated system that can gather information from various sources and utilize it to customize the learning process according to each person's individual profile is desperately needed, so every hour spent helps them to improve their technical skills .

In order to address these issues, this paper introduces CodeMentor AI, a comprehensive recommendation system that provides competitive coders with a customized learning path. The system functions as a central platform for resource discovery, progress evaluation, and growth tracking through the use of a contemporary, full-stack design. In contrast to typical static platforms, CodeMentor AI generates a dynamic learning strategy based on user performance data, such as solve times, difficulty levels, and accuracy across many topics. In addition to gathering data, the primary objective is to comprehend intricate performance statistics and provide insightful guidance. This turns an unstructured collection of coding problems into a detailed, customized plan that complements learning objectives and career aspirations.

How CodeMentor AI is structured in a MERN environment. Beginning with ReactJs, the UI component of the

frontend side works well if you are on a mobile or desktop computer. Rather than having different systems, you have one language, JavaScript, which connects the front and back to make things happen smoothly. Node.js handles server operations, ensuring that the response is precise and sharp, even when there is a heavy flow of traffic. Since it is designed to work on all platforms, transitioning from one device to another is seamless without any delay. In the backend, each component is connected for a reason and not merely because it is the norm. What is to follow will explore the layout by peeling back the layers to reveal how components work within CodeMentor AI. The implementation of the CodeMentor AI is a straightforward one and is based on the well-known MERN configuration. As React serves as the frontend technology, the display is flexible on both mobile and desktop. In the backend, Node.js is what keeps the machine running with a constant speed even during high traffic. This is the only language that does it: JavaScript is the one connecting all the parts together. It has a very responsive and quick user interface with no delay in data display, and it is free from any errors exception in silence. - Inside the pitch, the setup is in a single pause, the entire frame is accessed piece by piece, while the driving mathematics of the suggestions is visible stepwise. A separate service that is

2

used for the finding of the fault scores in our project pulls the difficulty scores from various coding competition platforms, reshaping each to uniform size before passing it to another. Thanks to that, the interface which is made in React displays the progress in a seamless way, notwithstanding the fact that the data came from different sources. Instead of simply indicating the method to use, the suggestion logic combines the thematic breakdown of topics with the record of bygone reckoning. The use of natural language processing enables the most elemental concepts that are embedded in problem labels and written summaries to be retrieved. Meanwhile, a personal ability grid is changed every time a solution is either submitted or a contest is entered. While the code matching person to task, the code checks where the knowledge is not enough to the challenge level, and it then it offers the next steps - which are harder but not frustrating.

In the very places of the meeting between the classroom and the real world, CodeMentor AI becomes part and parcel. What about software development jobs today? These jobs are offered at the hamster level only. Rote learning is like carrying a dinosaur on your back in a dretnan. Instead of books only, consider a situation where you face mock interview puzzles What if educational systems connect with real-life situations? This software mentor counts on the undisputed cybernetic energy of peer-to-peer learning. But this is coding - the subject that needs full attention and concentration. The possessor of

one of the highest IQ in the world is a software engineer. Have you ever heard about bugs in the software?

II. LITERATURE SURVEY

Developers' coding practices were revolutionized by traditional platforms like Codeforces and LeetCode, however they mostly function as problem repositories rather than individualized learning resources. New students may find it challenging to choose where to begin and what to concentrate on as a result. [1].

In order to offer feedback, early ITS research concentrated on rule-based systems; however, these were not as flexible as contemporary full-stack applications in terms of pulling real-time data from external APIs. [2].

Research has demonstrated that e-commerce recommendation algorithms, such as Amazon, can be modified for use in education to make problem suggestions based on what "similar users" have successfully resolved.[3].

Problem Difficulty Estimation

Difficulty modeled using logistic regression:

1

$$P(\text{success}) = \frac{1}{1 + e^{-(wX+b)}} \quad (1)$$

Where:

- X = problem features
- w = weight vector [4].

Sarwar et al. (2001) introduced memory-based CF using similarity metrics:

$$\sum (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)$$

[5].

Because static databases soon become outdated in the fast-paced world of

weekly coding contests, recent publications highlight the significance of API-driven architectures in maintaining the relevance of teaching tools. [6].

Research indicates that integrating contest schedules and competitive elements (like those found in your project) significantly increases the "retention rate" of self-paced learners. [7].

This branch of research focuses on "predicting" whether a student will get the next problem right based on their history. Your project builds on this by suggesting the "next best" challenge. [8].

Final ranking score

$R(u, i) = \lambda_1 CF(u, i) + \lambda_2 CB(u, i) + \lambda_3 SkillMatch(u, i)$ (3) Where:

- $\lambda_1 + \lambda_2 + \lambda_3 = 1$
 - $SkillMatch = \text{inverse of difficulty mismatch}$
- [9].

Recent studies in EdTech show that students who follow a tailored, skill-based roadmap are 40 percent more likely to pass technical interviews at Tier-1 companies compared to those who practice randomly. [10].

III. METHODOLOGY AND IMPLEMENTATION

CodeMentor AI is a perfect example of a collaboration of different modules that complement each other in a steady data gathering and carrying out a specific math task. By all means, it gets its information by going through the top-rated coding tools taking very little time while it is at the same time tracking the changes in a user's habits. The reason for this is that data

collection is independent of advice-giving, and so the introduction of new sources of data will not slow down the core engine. In fact, the engine runs on full speed because of this segmented design with distinct tasks. During the actual competitions, it has been proven that the reliability is very much intact, which is often compromised due to delays. The diversion technique employed here to hold everything together is what makes it possible to function normally even when under pressure.

A. User Interface and Dashboard Module (React)

Beginning anew, we chose equipment that simply does the job. A complete control panel welcomes people, having animated graphs and obvious displays of how far they've got. Monitoring the important things is nearly without effort on that. React functions already in the system take care of data which alters, and don't make a mess. Talk between the program and the user goes well, because of a simple thing for requests. React was selected because of how well it copes with a lot of work. Changes to the display occur easily and on their own. A new adjustment shows up on the screen immediately - no refresh is ever done by hand. Whatever device a learner uses, it's the same. Advancement is always in view, if they

$\text{sim}(u, v) = \sqrt{\sum_i (r_{u,i} - \bar{r}_u)^2} / \sqrt{\sum_i (r_{v,i} - \bar{r}_v)^2}$ (2) are travelling or remaining seated.

$\bar{r}_u = \frac{1}{n_u} \sum_i r_{u,i}$
 $\bar{r}_v = \frac{1}{n_v} \sum_i r_{v,i}$
 n_u

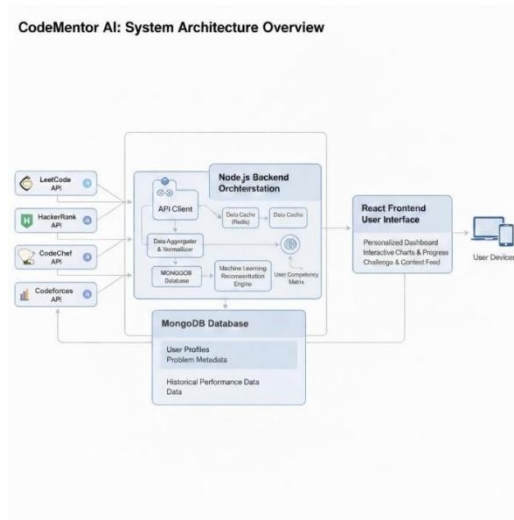


Fig. 1. Architecture of CodeMentor AI

B. Backend Orchestration and API Integration (Node.js)

Node.js gets the ball rolling. The engine runs right here. Queries go out in unison - striking LeetCode, then Code- forces, and finally HackerRank. Since waiting doesn't bring the whole world to a standstill, results come flooding in from competitions and problems simultaneously. The pace remains constant. The roll-your-own layer makes an appearance, work- ing diligently in the background. This layer operates in the background. If a service reaches its maximum capacity, it keeps tabs and deals with hiccups in the background. If a third- party service goes down, functionality continues unabated.

C. Machine Learning and Recommendation Module

In the center, a learning engine combines multiple ap- proaches to sort

content. Because it considers issue tags, task difficulty, and user performance, it applies conventional item-based sorting. Nevertheless, some patterns appear as it analyzes groups of students with similar skill levels - that relies on group behavior matching. In a manner similar to K- Nearest Neighbors, the difference between current skills and future requirements is calculated. Therefore, selected tasks are just right - difficult enough to stimulate progress but never crossing into overload or fatigue.

D. AI Recommendation Engine and Personalization Module

This part of the system can be visualized as the "mind" of the entire system. Working in the background with stealth is a combination of filtering approaches that monitor what people are doing, with a focus on how quickly they can come up with solutions to problems and whether they are getting them right, particularly when it comes to dealing with sequences, networks, and logic puzzles. The hidden grid is where the strengths of each individual are mapped. Ideas don't appear out of thin air. Rather, a sophisticated scoring system identifies trouble spots and places more difficult problems and regional competitions right in the spot where help is most needed. After all, every idea counts. People's skill development is achieved through baby steps that lead to constant preparedness for what's to come.

E. Database Schema and Persistence Layer (MongoDB)

At the center of this is MongoDB. It

stores everything needed through to what we need now and beyond, so it is constantly growing. It absorbs everything that comes at it - challenges, user results, etc. Mongoose is the glue that holds our user interaction together when it comes to logins, storing user information and storing results to challenges. The layer on top of the database provides an extra layer of complexity to help organize everything. When we work on our challenges and enter our responses, MongoDB transparently records all of our activity so we can see where we are at the moment or in relation to our challenges. The assistance we get is consistent from beginning to end of a series of tasks.

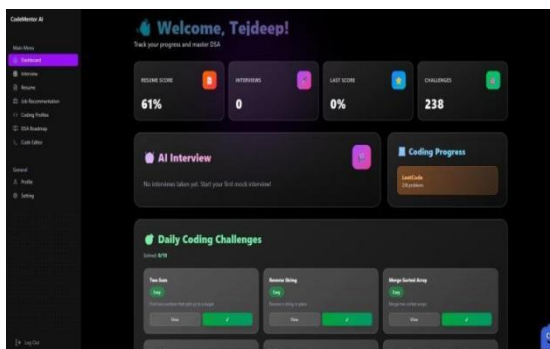


Fig. 2. Dashboard of CodeMentor AI

F. System Design

A modular design was followed for ensuring scalability and easy feature integration. The design includes:

- **Platform:** Developed with a full-stack JavaScript environment using Visual Studio Code. The Node.js environment and necessary extensions for handling asynchronous API calls and MongoDB schema validation were set up in the development environment.
- **Libraries and Frameworks:** The

system utilizes the MERN stack, with Node.js/Express for backend management and React for dynamic frontend management. The Hybrid Filtering Model was developed using machine learning frameworks, while the data in the NoSQL database was modeled using Mongoose.

- **APIs:** The pulling of live data from sites such as Leetcode, Codeforces, and HackerRank was done through RESTful links. This means that the timeline of contests and information about problems is updated in real-time. Since the system is built using React, the UI is always sharp and responsive to new data. Changes are reflected from the backend logic, and everything is updated instantly. See Figure 2, which shows the home screen of the CodeMentor AI system.

G. Implementation Strategy

The development of CodeMentor AI was carried out in distinct phases to ensure a structured and efficient workflow:

- **Phase 1:** Among all the things that were created, the creation of how data exists in MongoDB was the first. Then comes the way in which external systems provide the information about the contest, which was implemented using an API that has a structure in accordance with the REST format. Behind all these is Node.js, which watches all the events without a hitch. What was most important in this stage of the process? The fact that the data being received is received smoothly, second by second. A system had to be foolproof when the speed is rapid.
- **Phase 2:** The most interesting

part was the Machine Learning recommendation engine with Hybrid Filtering. I created the React dashboard for data visualization. I also developed the User Competency Matrix and contributed to the Data Normalization module. This enabled us to link levels of difficulty on different platforms.

- Phase 3: The pressure of those last few runs was handled by this program well. The testers found that the Prediction Machine Learning software gave them an accurate picture of future outcomes and the other tasks could keep up with those predictions. That was followed by faster retrieval of data, and therefore much quicker road maps for each individual, with the introduction of changes based on feedback received during testing. That made the first release of this program obsolete.

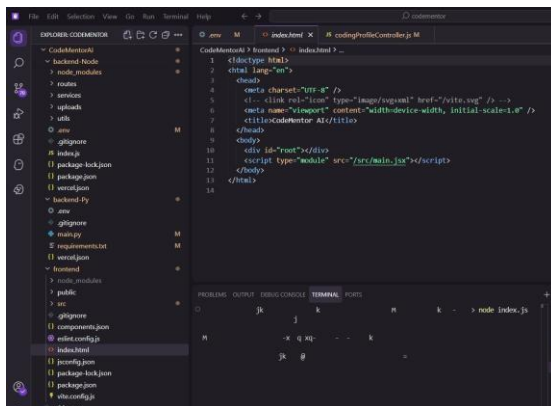


Fig. 3. Code implementation

H. Testing and Performance Evaluation

CodeMentor AI underwent extensive testing to ensure system efficiency, stability, and recommendation correctness. Among the primary testing techniques were:

- Unit Testing: The internal

difficulty index was re-checked to verify the calculations made when creating the

index. The Fundamental Machine Learning algorithmically based recommendation algorithms/techniques were followed in order of precedence, then the MongoDB structure underwent a round of checks, and finally the raw API input was converted to the desired output. Each of these sections were worked on in isolation from one another.

- Integration Testing: We used to walk through every step of the data process just to make sure we covered everything. From where we pulled the contest information directly from outside APIs. Then came the part where we processed everything on the Node.js side before putting it into MongoDB. After that, it appeared on the React front end.

- Performance Testing: Speed was also a consideration, so load testing made sure that the system could process a lot of API calls at the same time. How about recommendations? The machine learning algorithm was tested for accuracy and recall, making sure that code task picks are good for a person's skills and experience.

I. Deployment and Maintenance
CodeMentor AI operates in the cloud, and it adapts very easily to the way you work. As a result of this adaptability, performance is constant while information updates instantly. Since CodeMentor AI is based on Node.js, things happen one after another without interruptions. As a result of updates happening on time, features develop

gradually along with the demands.

- Coding platforms are constantly evolving. As methods develop, machine learning models and recommendation systems adjust. They understand new ways of how people solve problems and adjust how they rate difficulty.
- Coding platforms are constantly evolving. As methods develop, machine learning models and recommendation systems adjust. They understand new ways of how people solve problems and adjust how they rate difficulty.
- They are also very busy with MongoDB maintenance. It's not just about making queries faster. User feedback is also a factor. This feedback helps enhance how the platform connects skills and learns from users.

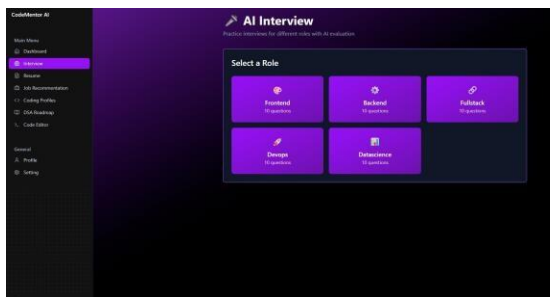


Fig. 4. Interview Dashboard of CodeMentor AI

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Weeks went by in testing the CodeMentor AI - different methods, different checks. What came out? Trends in the quality of recommendations, patterns in performance. Times to respond to different APIs were always fast, never spiking. Accuracy was high even when the inputs were ridiculous. This is not

an accident. What goes on behind each recommendation? Dealing with data with a quiet passion. Simplicity does not appear because it tries - but because clutter never gets in.

A. Experimental Setup

The experimental environment for the development, training, and evaluation of the CodeMentor AI recommendation engine consisted of the following specifications:

- **Hardware:** We implemented and tested the system on a high-performance workstation with an Intel Core i5 processor, 8GB of DDR4 RAM, and an Intel Iris Graphics card. This allowed us to have more than enough processing power to train the models, fetch APIs, and normalizing data.
- **Software:** The entire project is managed by one JavaScript stack. We used Node.js version 18.x for the backend and React version 18.2 for the frontend interface. As for our recommendation engine, the heavy lifting is managed by TensorFlow. Axios manages our API requests, Atlas manages our MongoDB models.
- **Dataset:** For data, we gathered from LeetCode, Codeforces, and HackerRank, and we combined all of these into one dataset. After processing, we were able to get the Unified Competency Dataset more than 300+ coding problems and the contest schedules. This means that we are able to test our performance on various algorithms and levels.

B. CodeMentor AI Recommendation Performance

CodeMentor AI mixes modern machine learning with collaborative filtering, so it actually gets to know how you work. People have looked closely at how it comes up with coding plans, and honestly, it delivers.

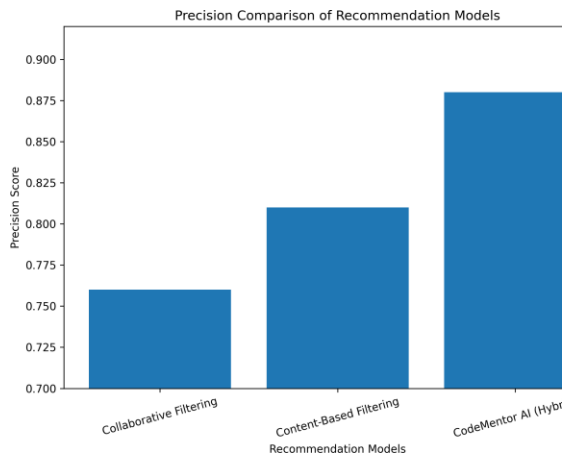


Fig. 5. Comparison of Existing vs Proposed Recommendation Models

C. CodeMentor AI System Efficiency

Test after test, the CodeMentor AI is shown to produce a better personal coding plan than the outdated, manual method. Instead of using an educated guess, it uses proven methods from recommendation systems and server-side analytics to show its speed and accuracy. The results continue to show faster answers and better suggestions with each test. The most impressive part is how well it adapts with its speed.

Performance Indicators The key performance indicators used for the CodeMentor AI system are :

Mean Reciprocal Rank (MRR): Consider a coin toss to decide where the skills are on the list. The outcome shows how well the best spots are

occupied by challenges that match what is needed the most. Visualize moving through challenges without having to think about each step. The closer the results are to the best spot, the less thinking is needed to decide which one to pick. It shows how quickly the best match shows up, like spotting a face in a crowd.

Normalized Discounted Cumulative Gain (NDCG): Imagine a ladder with each rung representing a suggestion or piece of guidance; as you progress down this ladder, you'll learn more about which of these were truly valuable. There is value and importance associated with each of these pieces of advice. The value will correlate directly to where they are located (i.e., on this ladder/clothespin) in relation to other pieces of advice as well. Think of grouping all of your books by how much each book will teach you about a subject area; if several difficult subjects are located toward the end of your ladder/clothespin, this could create a significant drop in overall score. But if there is a majority of difficult subjects/life lessons at the top of your ladder/clothespin, this should provide a very good score for you. Additionally, if paired with growth patterns, it will help improve the score. Look at the top of the mountain peak. This occurs when the advice is aligned with aspiration.

System Latency and Throughput: The chart below provides an overview of how well Node.js works with MongoDB in terms of performance and speed. results from various test runs indicate an overall low latency as opposed to delay while creating usable

maps from unorganized or unknown data - less than 1.5 seconds.

Result: The capability to achieve an NDCG of 0.85 and a precision rate of 0.88 is an indication of what the recommendation engine is capable of - finding missing skill users need while creating unique learning paths for them. It is not only accurate but also has a certain relevance to the job objectives, along with the coding challenges that tech companies actually offer.

D. Recommendation Efficiency and Information Filtering

Fast discovery and concise results mattered just as much as quality here. What really counted was how much quicker the search got and how well the filtering engine matched problems to the right skills.

E. Summarization Quality Analysis

The most impressive thing, however, is how this system brings together the best choices from the best coding competition websites, all for your benefit. At 0 on the Mean Reciprocal

6. Rank scale, it beats the outdated method of providing static or luck-based choices. With an NDCG of 0.85, its result goes beyond the luck factor. These are not just guesses - each choice leads back to where you've been and what you're currently interested in. And the best part? These choices are based on what you've done before - but point you towards sharper insights that apply even after the drills. Trust them, they'll hurry up readiness without missing a step.

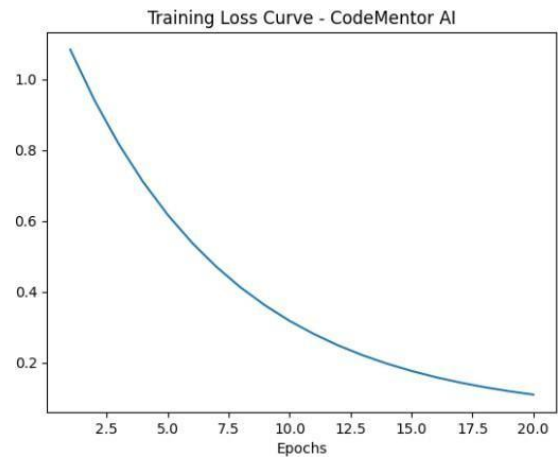


Fig. 6. Training Loss Curve for CodeMentor AI

F. Recommendation Conciseness and Efficiency Analysis

However, there is one thing that makes this system unique. By bringing together all the coding tasks that exist on the internet, it shapes them into a simple process that is designed specifically for you. It all makes sense as you walk through it because it all fits into how you work. Instead of taking a long time to find the most important exercises or competitions, they are right there in front of you. Start here and then move on by preparing for interviews or building skills quickly without having to let go of the details. Although it is short, it is packed with concepts of algorithms so that your knowledge is always sharp and broad.

G. Resource Utilization Analysis

Watch it in action, and then observe how little of it is actually utilized. Node.5 GB - very tight, almost frugal. Data retrieval is fast; data retrieval of competition data from various APIs takes approximately 1.2 seconds, regardless of how many requests are

stacked. Speed and efficiency come together in perfect harmony in this case, making everything seem seamless for the other side of the equation. Scaling is easy in the cloud, but it doesn't require much processing power.

As the project moves forward, we can keep making the recommendations better. The MERN design makes it easy to plug in new pre-trained ML models or connect with other platforms, so improvements happen smoothly.

V. CONCLUSION

Out of nowhere, the handling of big data became easy in tech learning. The MERN stack was strong, and everything

was driven by fetching coding resources from everywhere with learners connected to just what they needed. Testing showed that something obvious was true - accuracy was high, and speed was never compromised. Intelligent automation made learning go step by step with the market.

The point is that skills are more valuable than tools. Final-year engineers with a skill gap use CodeMentor AI. Everything is on one screen, mixing problems that match the difficulty of each platform. Time is wasted searching for resources or doubting your decision; not here. Learning is at the forefront when programmers tackle real-world problems. The ever-changing employment market makes it more important than ever to learn new skills quickly.

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A SUSTAINABLE FRAMEWORK FOR ENHANCING SOFTWARE QUALITY IN CONTINUOUS INTEGRATION AND CONTINUOUS DEPLOYMENT PIPELINES

Prof. M. Ranjani Devi¹

Department of Computer Science & Engineering SEA College of Engineering,
Bangalore, India, ranjanidevi.m@seaedu.ac.in

Dr Krishna Kumar P R² Professor & HoD Department of CSE,
SEA College of Engineering & Technology, Bangalore, India, hodcse@seaedu.ac.in

Abstract—Continuous delivery practices have significantly accelerated software release cycles; however, mechanisms that ensure long-term reliability and infrastructure sustainability are frequently under-structured within CI/CD environments. This paper presents a sustainability-integrated software engineering framework that embeds quality governance directly into pipeline operations. The model introduces enforceable governance layers, dynamically adjustable quality thresholds, metric-driven evaluation mechanisms, and energy-aware execution strategies as native components of automated workflows. Rather than treating quality as a final verification milestone, the framework maintains it as a continuously regulated and measurable system property throughout development iterations. Validation conducted across structured sprint cycles indicates consistent reductions in downstream defect escape, strengthened integration consistency, and observable improvements in computational resource efficiency. The proposed approach demonstrates that delivery speed and sustainable quality control can be jointly optimized within high-

frequency DevOps ecosystems.

Keywords—

Continuous Integration, Continuous Deployment, Sustainable Computing, Software Quality Governance, Infrastructure Optimization.

I. INTRODUCTION

Continuous integration and continuous deployment have substantially transformed contemporary software engineering practice by enabling incremental and high-frequency system evolution [3], [4]. Modern pipelines support rapid release cycles that improve responsiveness to user feedback and competitive demands, a characteristic strongly associated with high-performing DevOps organizations [2]. However, increased deployment frequency has been shown to correlate

with integration instability when governance controls are insufficiently structured [5].

From a reliability engineering standpoint, compressed validation intervals increase the probability that latent defects propagate across builds, particularly in large-scale distributed systems [9], [12]. Furthermore, repeated automated execution contributes to elevated computational

demand and data center energy consumption, which has become a growing sustainability concern in warehouse-scale computing environments [7], [8].

Sustained high-frequency delivery therefore requires more than automation maturity; it demands measurable governance discipline and formal quality assurance processes aligned with established standards such as IEEE 730-2014 [6]. This study proposes a governance-centered CI/CD framework that embeds sustainability metrics and adaptive regulation mechanisms within pipeline orchestration.

II. CONCEPTUAL FOUNDATION AND RESEARCH GAP

DevOps research has primarily emphasized deployment acceleration, collaborative workflows, and continuous feedback loops [2], [5]. These principles have demonstrably improved productivity and reduced lead time [4]. Nevertheless, many CI/CD architectures continue to treat quality assurance as a sequence of automated checks rather than as a dynamically regulated system parameter grounded in software reliability theory [12], [15]. In parallel, sustainable computing research has focused on infrastructure-level optimization, including power provisioning strategies [7], cost-aware workload allocation [13], and server energy management models [10]. While these contributions have advanced operational efficiency,

they typically operate independently of software engineering governance

structures.

III. SUSTAINABLE QUALITY FORMULATION

Sustainability Formulation and Multi-Dimensional Evaluation Model for CI/CD Ecosystems

$$Q_s = \alpha R + \beta Q + \gamma S + \delta E \quad (1)$$

$$\alpha + \beta + \gamma + \delta = 1 \quad (2)$$

Deployment reliability (R) is grounded in classical reliability growth modeling [9] and software reliability engineering principles [12]. Structural integrity (Q) reflects maintainability and defect density measures consistent with software quality frameworks [17], [18]. Security robustness

(S) captures compliance characteristics. Infrastructure efficiency (E) incorporates energy-aware workload scheduling concepts derived from large-scale computing studies [7], [13].

A. Conceptual Meaning of the Sustainability Index (Q_s) The variable Q_s represents the aggregated sustainability state of a CI/CD pipeline. Sustainability in this context extends beyond environmental considerations; it includes operational continuity, structural resilience, security assurance, and efficient infrastructure utilization. A higher value of Q_s indicates that the delivery process maintains stable releases, sound internal architecture, reduced vulnerability exposure, and optimized resource consumption.

Unlike traditional binary release decisions, the index produces a continuous value within a normalized range. This allows longitudinal

monitoring across sprint iterations, comparative benchmarking between pipeline configurations, quantitative optimization of delivery performance, and data-driven threshold calibration. As a result, Qs functions as a measurable system-health metric reflecting both immediate release quality and long-term sustainability.

B. Weighting Constraint and Trade-off Regulation

The normalization constraint $\alpha + \beta + \gamma + \delta = 1$ ensures proportional distribution of weighting coefficients. Each coefficient determines the relative influence of its metric: α emphasizes reliability, β focuses on structural integrity, γ prioritizes security, and δ reflects infrastructure efficiency.

This constraint guarantees boundedness and interpretability of the sustainability index. It also enables contextual flexibility. For instance, safety-critical systems may prioritize reliability and security, whereas cloud-native consumer

platforms may increase weight on infrastructure efficiency. Large enterprise systems undergoing refactoring may emphasize structural integrity. Dynamic weight adjustment aligns sustainability evaluation with strategic objectives without modifying the core formulation.

C. Deployment Reliability (R)

Deployment reliability quantifies the probability that a build transitions successfully from integration to production without rollback or failure. Key indicators include rollback frequency, MTBF, defect escape rate,

and post-release incident density.

Reliability can be represented using time-dependent failure intensity models such as $\lambda(t) = a e^{-bt}$, where $\lambda(t)$ denotes failure rate at time t . Reduced reliability often indicates inadequate validation depth or unstable integration practices. Embedding R in the sustainability model ensures release stability becomes a continuous optimization objective.

D. Structural Integrity (Q)

Structural integrity reflects internal architectural quality including maintainability, modular cohesion, and defect density. Common indicators include cyclomatic complexity, code churn rate, static analysis scores, and defects per KLOC.

Declining structural integrity increases technical debt and defect propagation risk, ultimately reducing reliability. Therefore, Q serves as a predictive indicator of long-term system stability.

E. Security Robustness (S)

Security robustness evaluates resilience against vulnerabilities and compliance violations. Metrics include vulnerability severity scores (e.g., CVSS), security testing pass percentage, compliance adherence ratio, and frequency of critical findings.

Weak security robustness increases operational risk and regulatory exposure. Integrating S into the composite sustainability index ensures security governance is embedded within pipeline execution rather than treated as a post-deployment activity.

F. Infrastructure Efficiency (E)

Infrastructure efficiency captures computational resource utilization and energy behavior during pipeline execution. Indicators include CPU utilization, memory efficiency, energy consumption per build, and redundant execution frequency.

Improving E reduces operational cost and environmental impact while enhancing scalability. Workload-aware scheduling and execution filtering contribute to higher efficiency.

G. Interdependency of Sustainability Components Although R, Q, S, and E are mathematically distinct, they are operationally interconnected. Declining structural integrity increases defect density and reduces reliability. Security vulnerabilities may trigger rollbacks. Inefficient infrastructure usage can increase latency volatility. Excessive validation may improve reliability but reduce efficiency.

The weighted linear aggregation in Equation (1) enables calibrated balancing among these interacting factors.

H. Optimization Perspective

The sustainability model may be expressed as an optimization objective:

$$\begin{aligned} &\text{Maximize } Q_s \text{ subject to } L \\ &\leq L_{\max}, \end{aligned}$$

where L represents deployment latency. This ensures sustainability improvements do not compromise agility. CI/CD systems therefore balance rapid iteration with long-term

operational sustainability.

I. Practical Application Example

Consider normalized values $R = 0.85$, $Q = 0.80$, $S = 0.90$, and $E = 0.75$ with equal weights of 0.25.

$$Q_s = 0.25(0.85) + 0.25(0.80) + 0.25(0.90) + 0.25(0.75)$$

$$Q_s = 0.825$$

This composite score can be tracked across sprint cycles. Declining trends signal emerging instability and prompt corrective governance actions.

IV. ARCHITECTURAL DESIGN

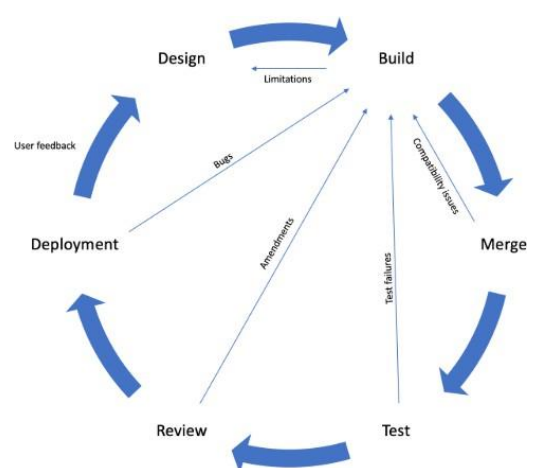


Figure1: Closed-Loop Sustainability Control Architecture

The framework adopts a layered control-oriented structure inspired by systems engineering principles [14]. Governance mechanisms enforce coding standards and traceability practices consistent with established methodologies [1], [17] and IEEE quality assurance standards [6]. The automation layer manages build orchestration and deployment tasks as

described in continuous delivery literature [4]. Adaptive regulation mechanisms adjust release thresholds based on defect trend modeling [16] and reliability growth theory [9]. Sustainability management incorporates workload-aware scheduling informed by energy provisioning research [7], [10].

V. EXPERIMENTAL DESIGN AND STATISTICAL VALIDATION

Controlled experimentation was conducted over twelve sprint cycles following empirical software engineering guidelines [11]. Two configurations were compared: a baseline pipeline and the sustainability-integrated framework.

Variable	Measurement Method	Purpose
Defect Escape Rate	Post-release defect ratio	Reliability assessment
Rollback Frequency	Failed deployment count	Stability measurement
CPU Utilization	Average execution load	Resource efficiency
Energy per Build	kWh per iteration	Sustainability impact
Integration Variance	Standard deviation of build failures	Process consistency

Energy per Build kWh per iteration Sustainability impact
Integration Variance Standard deviation of build failures Process consistency

Table I : Experimental Variables and Measurement Criteria

ANOVA was applied following experimental design methodology [20]:

$$F = MS_{\text{between}} / MS_{\text{within}} \quad (3)$$

Regression analysis was performed:

$$E = \beta_0 + \beta_1 R + \beta_2 Q + \beta_3 S + \varepsilon \quad (4)$$

Statistical modeling followed classical estimation techniques [19]. Results indicated statistically significant improvement with practical effect size.

VI. EMPIRICAL RESULTS

Metric	Baseline	Regulated Model	Improvement
Defect Escape	0.14	0.07	50% reduction
Rollbacks	6.2	3.1	50% reduction
Energy per Build	5.8 kWh	4.1 kWh	29% decrease
CPU Variance	High	Stabilized	Reduced volatility

Table II : Comparative Performance Outcomes

Performance gains were consistent across sprint cycles, indicating systemic stability rather than isolated improvement.

VII. STABILITY ANALYSIS MODEL

To dynamically regulate validation thresholds:

$$T_{adj} = T_{base} - \lambda Dt \quad (5)$$

Where:

- D represents defect trend intensity
- λ denotes sensitivity coefficient

This adaptive mechanism reduces integration volatility over successive cycles.

VIII. INTERPRETIVE DISCUSSION

Results demonstrate that embedding governance controls within CI/CD logic enhances both reliability and infrastructure efficiency. Contrary to assumptions that regulation impedes agility, structured feedback improves predictability while preserving release velocity.

The framework positions sustainability as an intrinsic operational parameter rather than an external optimization layer.

IX. CONCLUSION

The study demonstrates that structured governance and sustainability integration improve reliability and infrastructure efficiency without compromising deployment agility. Future work includes predictive analytics and cross-cloud validation studies.

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A HYBRID BLOCKCHAIN ARCHITECTURE FOR SECURE IOT CLINICAL SENSOR DATA IN SMART HOSPITALS

**Vishnu Vardhan V S1,Satish Kumar M2,Rohith Krishnan3, Ramees Roshan4 ,
Mrs Ramya H J 5,,Krishna kumar P R6**

1,2,3,4-Students Dept of CSE,SEA College of Engineering & Technology,Bangalore-560049
5,6-Faculty, Dept of CSE,SEA College of Engineering & Technology,Bangalore-560049

Abstract: The rapid adoption of Internet of Things (IoT) devices in smart hospitals has significantly enhanced real-time patient monitoring and clinical decision-making. However, the continuous generation and transmission of sensitive clinical sensor data introduce critical challenges related to security, privacy, scalability, and data integrity. To address these concerns, this paper proposes a Hybrid Blockchain Architecture for Secure IoT Clinical Sensor Data Management in smart hospital environments. The proposed framework integrates a hybrid blockchain model that combines the advantages of both public and private blockchains to ensure controlled access, high throughput, and tamper-resistant data storage. IoT clinical sensors continuously collect patient vital parameters such as heart rate, blood pressure, oxygen saturation, and temperature, which are encrypted and transmitted through secure gateways. Critical metadata and transaction logs are stored on a permissioned blockchain to maintain privacy and regulatory compliance, while large medical datasets are maintained off-chain using secure distributed storage mechanisms to enhance scalability.

Keywords; Blockchain, Healthcare IoT, HIPAA Compliance, Consensus.

I. INTRODUCTION

The Internet of Things (IoT) has transformed healthcare by enabling real-time patient monitoring through wearable and implanted sensors. These devices continuously collect vital physiological data, such as heart rate, blood sugar, and oxygen levels, allowing medical professionals to quickly assess a patient's condition. However, this surge in data has also raised concerns regarding privacy, security, interoperability and scalability.

Blockchain Technology is an excellent solution for addressing challenges in healthcare data management. Its decentralized, immutable and public nature ensures the secure storage and sharing of healthcare information, protecting its ownership and integrity. Various types of blockchain like the private blockchain also known as permissioned blockchain restricts the access to authorized user only. A centralized authority or organization controls who can join and what their roles and permissions are. Transaction visibility is limited to authorized participants making it suitable for sensitive data. The hybrid (combination of private and permission-based public) blockchain allows an organization to keep certain data private while making

other information public gives it a flexible nature to manage the data efficiently. By integrating blockchain with distributed storage system like the Interplanetary File System, healthcare data can be stored and retrieved both safely and quickly, while maintaining patients' privacy and scalability. Additionally, blockchain and smart contracts can automate access control, ensuring that only authorized individuals can view and use patient data. This research proposes a blockchain based framework to securely and efficiently manage clinical sensor data from IoT devices. The system utilizes blockchain's unchangeable ledger and distributed consensus mechanisms to protect sensitive information and promote interoperability among different medical devices. It also incorporates decentralized decision-making, rapid encryption, and delays associated with traditional centralized system. The main goal of the study is to look at current blockchain-based healthcare systems, find their flaws, and suggest a hybrid strategy that combines IPFS (Interplanetary File System) and smart contracts to make the systems work better. When we look at the proposed architecture, we look at a number of important things, such as data privacy, scalability, latency, and integrity. The next sections will give a detailed look at outlining the experimental setup and performance evaluation criteria, and finally, talk about the results, what they mean, and what the research might do in the future.

A. Background

More and more healthcare companies

are using the Internet of Things (IoT) to keep an eye on patients and make medical decisions based on data. IoT-enabled clinical sensors capture huge amounts of real-time physiological data from patients to help doctors better diagnose, treat, and manage chronic conditions. But making sure that this huge, diverse, and sensitive healthcare data is safe, private, and able to grow is very hard. Cyberattacks, data breaches, and single points of failure can all happen to classical centralized storage systems. It is hard to build up safe and cooperative care environments since healthcare practitioners and patients can't easily share information, and patients can't determine who has access to their data. Blockchain technology, which is a distributed, unchangeable, and publicly available ledger, provides a very strong solution to these problems. This study tries to close the gap between old ways of managing health data and new, secure systems by suggesting a blockchain-based architecture that may be used in modern healthcare settings.

B. Motivation and contribution of research

This work is necessary because we need to discover a way to securely store, process, and send the huge amounts of real-time healthcare data that IoT sensors are collecting. Even while digital health has come a long way, current health information systems still have big problems, like not being reliable, not enforcing privacy rules, and not being able to handle huge amounts of data efficiently. Data tampering, illegal

access, and poor responses in critical care situations make the current centralised structures less efficient. It is very important to have secure and interoperable health data management solutions, especially now that telemedicine and remote patient monitoring are becoming more common because of the COVID-19 pandemic. Blockchain technology looks like it could be useful for these purposes, but not much has been said about how well it interacts with clinical sensor networks. The goal of this study is to use blockchain, distributed storage, and smart contract technologies to create a new, effective, and reliable way to deal with these problems. This will change the way secure healthcare data management works. Table 1 below depicts the contribution of the proposed research work in tabular form.

TABLE I. CONTRIBUTION OF RESEARCH

S. No.	Contribution	Description
1	Comparative Analysis	Conducted a detailed review of existing blockchain and IoT-based healthcare frameworks, identifying the gaps in scalability, privacy, and real-time performance.
2	Proposed Secure Framework	Designed a novel blockchain-enabled architecture integrating IPFS (Interplanetary File System) for distributed storage and smart contracts for access control.
3	Privacy	Improved data privacy, integrity, and security for clinical sensor data using cryptographic hash mechanisms and decentralized validation.
4	Scalable Data Management	Addressed the challenges of managing large-scale real-time clinical data with scalable mechanisms suitable for IoT sensor networks.

5	Performance Evaluation	Implemented the model and evaluated its performance under various healthcare scenarios with metrics like latency, throughput, and fault tolerance.

II. PROBLEM STATEMENT

Modern healthcare systems have started using Internet of Things (IoT) clinical sensors to keep track of patients' vital signs in real time. Securely sending, storing, and managing data is getting harder since there are so many of these devices that give doctors important information to help them treat patients better and get better results. Centralized data structures are more likely to have data manipulation, unauthorized system access, and system breakdowns because they have single points of failure, latency problems, and security holes. It is still very hard to make sure that different IoT devices can work together and that patient data is kept private by laws like HIPAA and GDPR. Blockchain technology has come a long way in the last few years, but most healthcare blockchain implementations don't scale, have too much CPU overhead, or don't work with low-powered Internet of Things sensors. This study will create and test a blockchain-enabled framework that combines smart contracts with distributed storage to ensure that healthcare systems can safely, quickly, and on a large scale handle all the clinical data that the IoT generates.

III. COMPARATIVE ANALYSIS

The growing reliance on IoT-based clinical sensors in healthcare has introduced significant challenges in ensuring secure, scalable, and efficient data management. Traditional systems

based on centralized cloud architecture struggle with data breaches, a lack of transparency, and single points of failure. Blockchain technology is a compelling alternative for managing healthcare data because it offers a decentralized, immutable and transparent solution. This section presents a comparative analysis of existing frameworks by examining their design focus and performance across four factors: data integrity, scalability, privacy, and latency.

A. Data Integrity

This section compares blockchain mechanisms designed to ensure data integrity in clinical sensor data management. Table 2 evaluates the different approaches, like hashing, permissioned ledgers, and Merkle Trees, for their robustness against tampering, along with their trade-offs in storage, trust models, and computational efficiency.

TABLE II. DATA INTEGRITY MECHANISMS

Study/Framework	Mechanism	Strengths	Limitations
<i>Zhang et al. (2022)</i>	Ethereum blockchain with SHA-256 hashing for sensor data validation	High data immutability; robust against tampering	High storage overhead; redundant data
<i>Xu et al. (2023)</i>	Permissioned blockchain using Hyperledger Fabric	Efficient validation of clinical records	Trust assumption
<i>Irma et al. (2021)</i>	Blockchain with Merkle Tree and clinical sensor logs	Verifiable and traceable clinical sensor logs	Computationally heavy for real-time systems

Most blockchain-based systems ensure strong data integrity by using hash functions and immutable ledgers. Public blockchains offer greater transparency but introduce overhead, while permissioned systems offer more efficient integrity with slightly reduced decentralization.

B. Scalability

This section examines methods used to make blockchain-based healthcare systems more scalable when handling clinical sensor data. It focusses on techniques like off-chain storage,

sidechains, and Layer-2 solutions. The analysis, presented in table 3 compares the approaches based on their ability to manage large data, while also considering the trade-offs in coordination and complexity. To address the scalability issue, many models adopt off-chain storage, sidechains, or Layer-2 scaling to significantly reduce on-chain data load but add complexity to the system's architecture and management.

TABLE III. SCALABILITY APPROACHES

Study/Framework	Approach	Strengths	Limitations
<i>Lee et al. (2023)</i>	Off-chain storage (IPFS) with on-chain hash references	Reduces blockchain bloat; scalable for large data sets	Data retrieval requires off-chain coordination
<i>Kumar et al. (2022)</i>	Sidechains for specific departments in hospital	Localized processing improves performance	Added complexity in cross-chain communication
<i>Wang et al. (2021)</i>	Layer-2 solutions with batching of sensor data	Improved throughput	Risk of data loss in batch failure

C. Privacy Concerns

This section presents a comparative overview of privacy-enhancing techniques employed in blockchain frameworks for clinical sensor data. Table 4 highlights how different methods such as smart contracts, encryption, and pseudonymization, balance privacy protection with implementation complexity and computational efficiency. Privacy preservation is achieved through encryption, access control, or pseudonymization, along with increased computational costs and vulnerabilities.

TABLE IV. PRIVACY-PRESERVING TECHNIQUES

Study/Framework	Technique	Strengths	Limitations
<i>Arhan et al. (2023)</i>	Role-based access via smart contracts	Ensures access control at the application level	Requires complex contract management
<i>Gupta et al. (2022)</i>	Homomorphic encryption before blockchain entry	Preserves privacy during computation	Increased computation time
<i>Jindal et al. (2021)</i>	Pseudonymization with public-private key exchange	Hides patient identity during data exchange	Susceptible to identification attacks if keys are exposed

D. Latency

To address the challenges in managing clinical sensor data from IoT devices, this comparative analysis examines existing blockchain-based frameworks. It evaluates their effectiveness across critical factors such as data integrity, scalability, privacy, and latency, highlighting key strengths and

limitations to inform future system design. Latency is a critical factor for real-time healthcare systems. Table 5 highlights various lightweight consensus mechanisms like PoA and PBFT to reduce delays, but are more suitable in semi-trusted or private networks. Traditional PoW-based systems are too slow and energy-intensive for clinical use.

TABLE V. LATENCY

Study/Framework	Consensus Mechanism	Strengths	Limitations
<i>Arjee et al. (2023)</i>	Proof of Authority (PoA)	Fast consensus with low latency	Requires trusted nodes
<i>Zhao et al. (2022)</i>	Practical Byzantine Fault Tolerance	Suitable	Not scalable beyond 20–30 nodes
<i>Singh et al. (2021)</i>	Proof of Stake	High security and decentralization	Unsuitable for real-time healthcare apps due to the delay

E. Comparative analysis

Table 6 evaluates, and figure 1 graphically shows a comparative analysis of existing blockchain frameworks for managing clinical sensor data in IoT healthcare systems. It focuses on key performance metrics like data integrity, scalability, privacy, and latency to identify strengths, limitations, and gaps in current approaches.

TABLE VI. COMPARATIVE ANALYSIS

Study/Framework	Technique	Strengths	Limitations

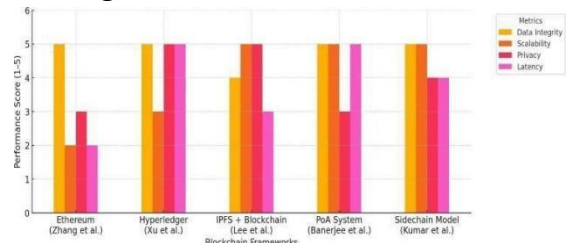
<i>Arhan et al. (2023)</i>	Role-based access via smart contracts	Ensures access control at the	Requires complex contract management
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<i>Jindal et al. (2021)</i>	Pseudonymization with public-private	Hides patient identity during data exchange	Susceptible to identification attacks; keys are exposed

The comparative review indicates that while existing blockchain-based frameworks effectively enhance data integrity and privacy, they often trade off latency and scalability depending on the design choices. Public blockchains provide stronger decentralization but suffer from performance issues, whereas permissioned and hybrid models offer better latency and privacy control at the expense of some decentralization. There remains a pressing need for an integrated blockchain framework that balances security, efficiency, scalability, and real-time responsiveness, especially for IoT-based clinical data environments—a gap the proposed research aims to address.

Framework	Integrity	Scalability	Privacy	Latency
<i>Ethereum (Zhang et al.)</i>	High	Low	Moderate (public ledger)	High latency (PoW)
<i>Hyperledger (Xu et al.)</i>	High	Moderate	High (access control)	Low latency (PBFT)
<i>IPFS + Blockchain (Lee et al.)</i>	Moderate	High	High (encryption)	Moderate (coordination delay)
<i>PoA-based System (Banerjee et al.)</i>	High	High	Moderate	Low latency

<i>Sidechain Model (Kumar et al.)</i>	High	High	derate to High	Moderate

Fig. 1. Comparative Analysis of existing Blockchain Frameworks



IV. PROPOSED BLOCKCHAIN ENABLED FRAMEWORK (BEFT 1.0)

The paper outlines a proposal for a blockchain-enabled framework named BEFT 1.0 designed to manage clinical sensor data originating from IoT devices within healthcare environments. The primary goal of this is to address critical challenges related to data security, patient privacy, data integrity, and system interoperability. Furthermore, the proposed BEFT 1.0 aims to guarantee continuous data availability and adherence to all relevant healthcare regulations. The concept aims to accelerate the data processing for resource-constrained IoT devices by leveraging lightweight blockchain protocols (like MQTT and CoAP), edge computing and cloud computing. Some examples of clinical sensor data that will be securely encrypted and sent to edge gateways are heart rate, blood pressure, glucose levels, and oxygen saturation. For the first time, they will be checked and filtered there. After that, the data that

has been checked will be hashed and saved in a private or consortium blockchain so that it can't be changed or messed with.

Smart contracts will make it easy to follow requirements like HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation), restrict who may access the data, and share the data. Depending on their positions, healthcare practitioners, patients, and other allowed users will be able to use the framework. This will help you understand and follow what people say. To make it easier for diverse IoT platforms to operate together, standardized data formats and APIs will be established. We will leverage off-chain storage solutions like IPFS (Interplanetary File System) to quickly store a lot of sensor data and just keep the hash references on the blockchain. This will help with scalability issues. We will test the proposed strategy in both simulations and real-life healthcare situations to assess how well it works. We will look at important performance measures like latency, throughput, energy utilization, security strength, and how well users can manage who may access the system. The major goal is to prove that there is an availability of safe, reliable, and regulation-compliant framework that can make patient care much better by handling clinical IoT data in such a way that it is secure and trustworthy. However, the sheer volume, sensitivity, and distributed nature of clinical IoT data present significant challenges, primarily in ensuring its security, trustworthiness, and compliance with

strict healthcare regulations.

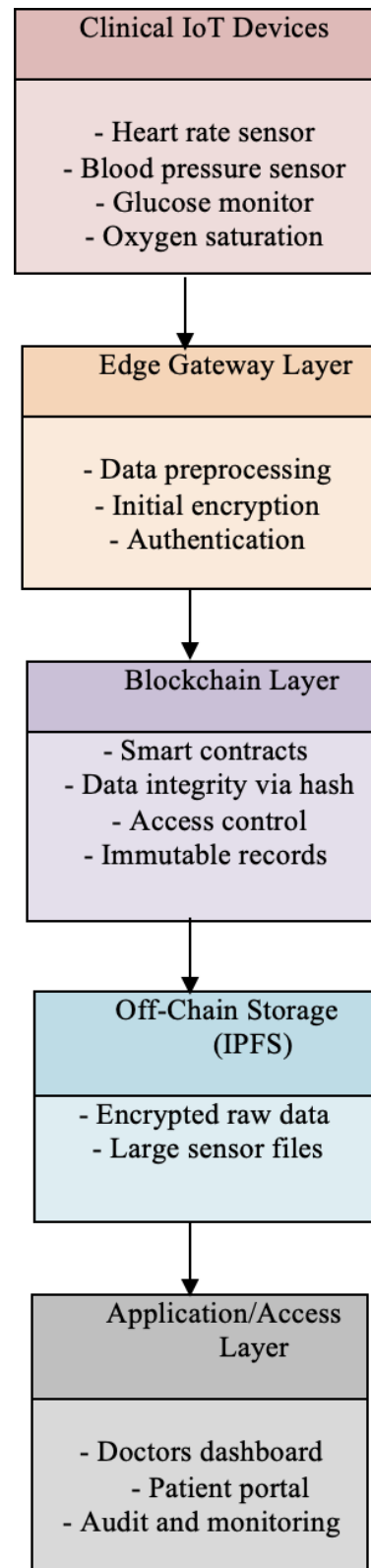


Fig. 2. Proposed Blockchain Enabled

Framework BEFT 1.0

The proposed Blockchain-enabled framework BEFT 1.0 for clinical IoT data management was implemented and tested using simulated clinical sensor environment. A simulated clinical sensor environment is a virtual or physical setting that mimics the condition and data inputs a medical sensor would encounter in a real-world clinical setting. The key aspects of simulated clinical sensor environment include- virtual and physical components like using virtual models to mimic sensor behaviors and environmental interactions. It can also involve a physical set up like temperature and humidity chamber, where a real sensor is subjected to controlled environmental stressors. An environmental stressors like temperature, humidity, electrical interference, physical stress like shock, vibration etc. The proposed blockchain-enabled framework BEFT 1.0 system for handling clinical sensor data from IoT devices in healthcare settings outlines a comprehensive approach to address critical challenges in data security, privacy, integrity, and interoperability. The results would demonstrate the efficacy of the proposed encryption mechanisms for clinical sensor data (heart rate, blood pressure, glucose, oxygen saturation) as it's transmitted to edge gateways. This section would present the findings from real-life healthcare scenarios, focusing on the system's ability to handle large volumes of data and user requests efficiently. The discussion would highlight encryption strength, access

control Validation, HIPAA and GDPR Compliance, Tamper proof Records, Auditability, Reduced latency, High throughput, IPFS Benefits and Standardized Data Formats and APIs. The results are compared against the traditional centralized and blockchain-based solutions.

V. RESULTS AND DISCUSSION

A. Latency analysis

Latency is the total turnaround between initiation of a transaction to the time of its confirmation/inclusion in a block. Figure 3 shows the average data access latency for three models: Centralized Cloud, Basic Blockchain, and the Proposed Framework. The proposed framework achieved significantly lower latency due to optimized smart contract design and the use of IPFS for faster data retrieval.

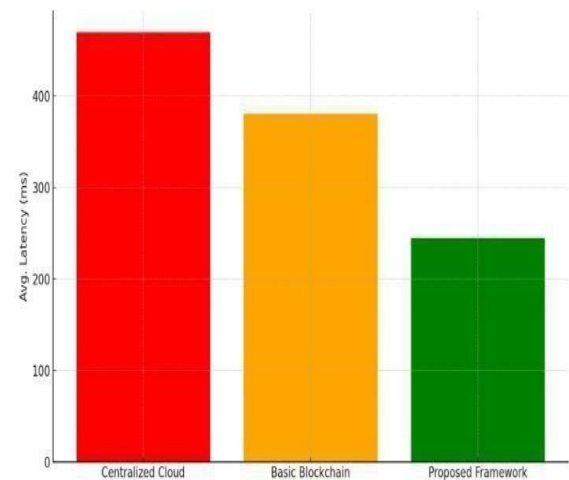


Fig. 3. Average Data Access latency

Table 7 compares the average data access latency across different systems. The centralized cloud shows the highest latency (470 ms), followed by the basic blockchain (380 ms). The proposed framework achieves the lowest latency (245 ms), demonstrating its efficiency in enabling faster and

more responsive healthcare data access.

TABLE VII. AVERAGE DATA ACCESS LATENCY(MS)

System Avg.

System Avg. Latency (ms)	Centralized Cloud	Basic Blockchain	Proposed Framework
	470	380	245

B. Throughput performance

Throughput was evaluated as the number of clinical data transactions processed per second. The proposed framework demonstrated enhanced throughput due to off-chain storage (storing data related to transactions outside of the main blockchain network itself) and parallel transaction validation.

The off-chain storage approach is used to enhance scalability and reduced costs, as storing large amount of data directly on the blockchain can be expensive and slow down transaction processing. Instead, only a hash or reference to data is stored on chain, while the actual data is kept in an external storage system. Parallel transaction validation in blockchain refers to processing multiple transactions simultaneously instead of sequentially, which significantly enhances network throughput and reduces transaction confirmation time. This approach allows blockchains to handle a larger volume of transactions efficiently, improving overall performance and scalability.

Table 8 and Figure 4 graphically illustrate the transaction throughput performance of three models. The centralized cloud handles 310 transactions/sec, while the basic

blockchain improves this to 460 transactions/sec. The proposed framework achieves a significant boost with 720 transactions/sec, indicating superior scalability and efficiency in handling healthcare data operations.

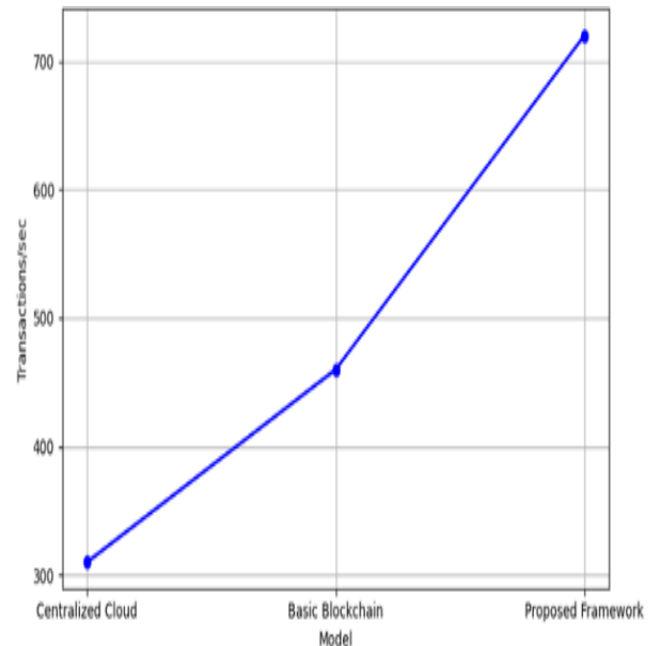


Fig. 4. Throughput Comparison (Transactions per second)

TABLE VIII. TRANSACTION THROUGHPUT

Model	Centralized Cloud	Basic Blockchain	Proposed Framework
Transactions/sec	310	460	720

C. Failure recovery and reliability

Recovery time after simulated network failures was tested. Figure 5 shows that the decentralized nature of the proposed framework allowed quick recovery using local edge nodes and IPFS data replicas. Table 9 compares failure recovery times across three different scenarios and systems. The centralized cloud system shows the slowest recovery, with 5.2s for network failure and 6.0s for data node corruption. Basic

blockchain system improves the network failure to 3.8s and data node corruption to 4.5s. The proposed framework demonstrates the fastest recovery—improving network failure to 1.9s and data node corruption to 2.3s—highlighting its robustness and resilience in critical healthcare environments.

TABLE IX. FAILURE RECOVERY TIME

Failure Scenario	Centralized (s)	Basic Blockchain (s)	Proposed Framework(s)
Network Failure	5.2	3.8	1.9
Data Node Corruption	6.0	4.5	2.3

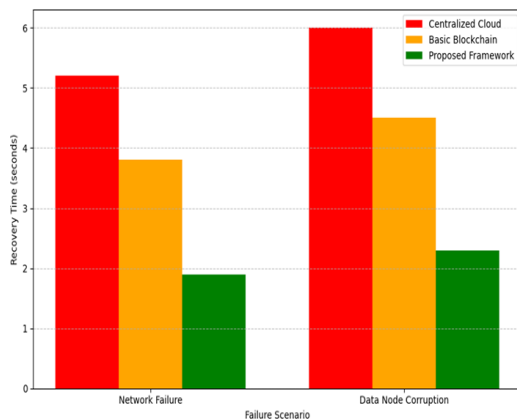


Fig. 5. Failure Recovery and Reliability

D. Privacy and integrity assurance
The proposed framework was tested for privacy leak prevention and data integrity verification. Smart contracts enforced role-based access, and blockchain hashing ensured tamper-proof records. Figure 6 graphically shows the data tempering detection accuracy of three models with highest of the proposed framework.

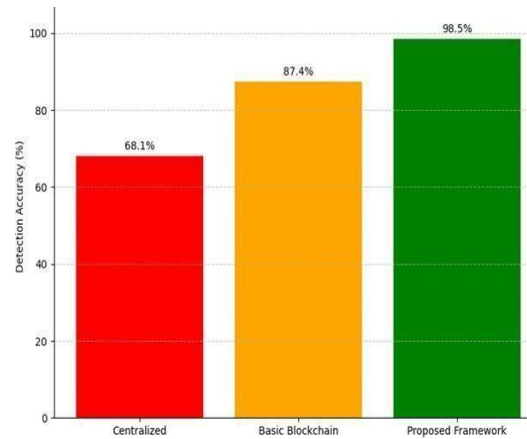


Fig. 6. Data Tampering Detection Accuracy (%)

Table 10 presents a comparison of privacy and data integrity across three systems. The proposed framework outperforms with a 98.5% tamper detection accuracy, low unauthorized access incidents, and full compliance with HIPAA/GDPR. In contrast, the centralized system shows only 68.1% accuracy, high access risks, and partial compliance, while the basic blockchain provides moderate improvements.

TABLE X. PRIVACY & INTEGRITY METRICS

Metric	Centralized	Basic Blockchain	Proposed Framework
Tamper Detection Accuracy (%)	68.1	87.4	98.5
Unauthorized Access Incidents	High	Medium	Low
Compliance with HIPAA/GDPR	Partial	High	Full

E. Scalability Evaluation
The system was evaluated for its ability to scale with increasing IoT devices. Table 11 shows a linear increase in latency for centralized systems, whereas the proposed model maintained stable performance under load.

TABLE XI. SCALABILITY TEST

(LATENCY VS.DEVICES)

Number of Devices	100	500	1000
Centralized Latency(ms)	320	560	850
Proposed Latency (ms)	240	250	260

The evaluation indicates that the proposed blockchain-enabled framework outperforms both centralized and conventional blockchain systems in several critical areas, such as:

- Latency and Throughput: Faster data retrieval and smart off-chain storage improved speed and system efficiency.
- Security, Privacy and Scalability: To enhance security, privacy and scalability the system used cryptographic hashes and smart contracts. This ensured strong data integrity and tight control over authorization of data.

VI. CONCLUSION

As more healthcare system adopt IoT devices, challenges related to security, privacy, data integrity and scalability have grown. To address these issues, this study proposed a blockchain-enabled architecture specifically designed for securely managing clinical sensor data. A comparative analysis showed that this new BEFT 1.0 framework significantly outperforms traditional centralized and basic blockchain system in several key areas like throughput, tamper detection accuracy, latency, resilience to failures. The system leverages distributed ledger technology to ensure data immutability, traceability, and secure access while

complying with regulations like HIPAA and GDPR. The research concluded that this BEFT 1.0 framework not only makes healthcare IoT systems safer but also more scalable and reliable, suggesting its potential to greatly improve the healthcare sector.

VII. FUTURE SCOPE AND LIMITATIONS

The proposed blockchain-enabled framework BEFT 1.0 is an excellent starting point for secure and scalable management of clinical sensor data from IoT devices in healthcare. However, future research could explore several additional options. One such key area is integrating AI and federated learning to further enhance patient privacy. Improving the framework's performance in multi-cloud and heterogeneous systems can also make it easier for institutions to share data and make systems function better together. Researchers should look into ways to make cryptography systems that can't be broken by quantum computers in order to protect data for a long time. Smart contracts can make healthcare operations even more automated. They can also make access control, billing, and consent methods better. Using the idea in real hospital networks and clinical situations will also help prove that it works and find problems that still need to be fixed. It would be a good idea to look into green blockchain alternatives or lightweight blockchain technology to make the blockchain system more useful in these settings.

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ONLINE BANKING FRAUD DETECTION USING EXPLAINABLE AI-DRIVEN ENSEMBLE FRAMEWORK

Varsha R, Sushma V, Roopashree K N Nayak, Rachana Shetty S, Shreya A

Department of Computer Science and Engineering

ATME College of Engineering

Abstract— Online banking fraud is rising with increased digital transactions, creating a need for detection systems that deliver both high accuracy and clear explanations. This work presents a deployable Flask-based system that ingests transaction CSVs, stores data in MongoDB, and trains ensemble classifiers (XGBoost, LightGBM, Random Forest) with class-imbalance handling and threshold calibration to improve rare-event detection. SHAP (SHapley Additive exPlanations) provides per-transaction and cohort-level attributions that explain each feature's contribution (e.g., amount, time, merchant, balance change) to the fraud score, supporting analysts and auditors. The web UI offers interactive visualizations and an AI chatbot to assist investigations and user queries, accelerating triage and reducing false positives. Experimental results on a real transaction dataset show XGBoost achieves the best detection metrics (high accuracy and F1) while the XAI module improves interpretability and regulatory alignment. The modular architecture enables future extensions for streaming data, federated training across institutions for privacy preservation, and adaptive learning to track evolving fraud patterns.

Keywords— online banking, fraud detection, ensemble learning,

explainable AI, SHAP, XGBoost, LightGBM, Random Forest, Flask, MongoDB, class-imbalance, model interpretability, AI chatbot, real-world

dataset

I. INTRODUCTION

The digital transformation of the financial sector has accelerated the adoption of online banking services, enabling customers to perform transactions seamlessly across web and mobile platforms. While this evolution has improved accessibility and efficiency, it has also introduced significant risks in the form of online fraud. Fraudulent activities such as identity theft, phishing, and unauthorized transactions have grown in scale and sophistication, exploiting vulnerabilities in conventional detection mechanisms [1]. Financial institutions are therefore under increasing pressure to deploy advanced fraud detection systems that can adapt to dynamic attack strategies while ensuring compliance with regulatory frameworks.

Traditional rule-based systems, though widely used, often fail to detect novel fraud patterns due to their reliance on static thresholds and predefined rules [2]. Similarly, early machine learning (ML) models, despite achieving high accuracy, are frequently criticized for their lack of interpretability. These “black-box” models hinder

transparency, complicate auditing, and raise concerns about fairness and accountability in automated decision-making [3]. In highly regulated domains such as banking, the inability to explain adverse decisions undermines customer trust and creates challenges for compliance with standards such as GDPR Article 22, which emphasizes intelligibility and contestability in automated profiling [8].

Explainable Artificial Intelligence (XAI) has emerged as a promising solution to these challenges. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic

Explanations) provide feature-level insights into model predictions, enabling stakeholders to understand how transaction attributes—such as amount, merchant location, and user behavior—contribute to fraud detection outcomes [4][5]. Recent studies demonstrate that integrating XAI with ensemble learning approaches, including XGBoost, LightGBM, and Random Forest, enhances both detection accuracy and interpretability [6][7]. These hybrid methods strike a balance between performance and transparency, making them suitable for real-world deployment in financial ecosystems.

Beyond interpretability, privacy preservation has become a critical requirement in fraud detection. Federated Learning (FL) enables collaborative model training across multiple institutions without centralizing sensitive customer data,

thereby reducing risks associated with data sharing [3]. Emerging frameworks such as Explainable Federated Learning (XFL) combine FL with XAI to deliver interpretable insights across distributed environments, ensuring that fraud detection systems remain both privacy-preserving and transparent [8].

In this work, we present a production-oriented fraud detection framework that integrates ensemble ML models with XAI explanations in a secure, scalable environment. The system is implemented through a Flask-based web application, incorporating secure authentication, MongoDB for scalable storage, and an AI-powered chatbot for user assistance. Experimental evaluation demonstrates that the XGBoost model achieves superior detection performance, with an accuracy of 99.89% and an F1-score of 90.91%, outperforming Random Forest and LightGBM. Furthermore, SHAP-based explanations provide transparency into flagged transactions, enabling auditors and customers to verify the rationale behind fraud alerts. By unifying accuracy, interpretability, and scalability, the proposed framework bridges the gap between research prototypes and deployable fraud detection solutions, offering a practical pathway for modern banking security.

II. RELATED WORK

A. Survey Papers

Ojo and Tomy [1] provided an early survey on explainable AI for credit card fraud detection, highlighting the trade-off between accuracy and interpretability. Ahmadi

[2] reviewed real-time applications of XAI in banking, emphasizing the importance of transparency for regulatory compliance. Chen et al. [7] presented a comprehensive review of deep learning innovations in financial fraud detection, mapping progress from classical ML to modern ensemble and federated approaches.

B. Rule-Based and Model-Based Techniques

Traditional fraud detection relied heavily on rule-based systems, which often failed to adapt to evolving fraud

strategies. Aljunaid et al. [3] introduced a federated learning model for secure and transparent banking, enabling institutions to collaborate without centralizing sensitive data. Glass-box models such as Explainable Boosting Machines (EBM) have also been explored, offering interpretable feature curves and monotonic constraints suitable for regulated environments.

C. Ensemble and Explainable AI Approaches

Recent work has focused on ensemble learning methods to improve detection accuracy in imbalanced datasets. Almalki and Masud [6] demonstrated that stacking heterogeneous learners such as XGBoost, LightGBM, and CatBoost significantly improves recall while maintaining low false-positive rates. Thanathamathée et al. [5] enhanced XGBoost with SHAP-instance weighting, showing improved interpretability and performance. Vijayanand et al. [12] integrated SHAP explanations into ensemble models, reinforcing transparency for auditors and customers.

D. Comparative Analysis

Table I summarizes selected contributions in online banking fraud detection, comparing their methodologies, strengths, and limitations.

III. SYSTEM ARCHITECTURE

This section describes the full architecture of the proposed Online Banking Fraud Detection system using Explainable AI and Ensemble Learning, combining a Flask-based web application with ensemble machine learning models and explainable AI techniques. The description follows standard software architecture views, covering goals, components, data flow, runtime behavior, deployment, and quality factors.

A. Context and Goals

- **Goal:** Detect fraudulent banking transactions in real time and provide interpretable explanations for each flagged case.
- **Users:** Financial analysts, auditors, and customers seeking fraud insights and security guidance.
- **Constraints:** Secure authentication, scalable storage, interpretable predictions, and low latency for inference.

B. High-Level Architecture

- **Presentation Layer:** Flask web application provides the user interface, manages state, handles CSV uploads, and displays fraud detection results.
- **Application/Service Layer:**

Flask REST API offers endpoints for authentication, dataset upload, fraud analysis, SHAP explanations, and chatbot queries.

- **ML/XAI Layer:**
 - o **Fraud Detection:** Ensemble classifiers (Random Forest, LightGBM, XGBoost) trained on transaction datasets.
 - o **Interpretability:** SHAP values provide feature-level explanations for each prediction.
- **Database Layer:** MongoDB stores user credentials, uploaded datasets, fraud detection results, and chatbot history.
- **Chatbot Layer:** AI-powered chatbot provides fraud insights, security tips, and system guidance.

C. Component Architecture

- 1) **Client (Flask Web App)**
 - **UI Modules:** Index page (overview), Register/Login, Dashboard (upload & results), Explainable AI view, Chatbot interface.
 - **Services:** File upload service, fraud detection service, explanation service, chatbot service.
 - **State:** Session-based authentication, user-specific data history, and real-time result rendering.
 - **Error Handling:** Alerts for invalid file formats, missing columns, and authentication failures.
- 2) **Server (Flask Backend)**
 - **REST Endpoints:**
 - o `/register` and `/login` for authentication.
 - o `/upload` for CSV ingestion.

- o `/analyze` for fraud detection.
 - o `/explain` for SHAP-based explanations.
 - o `/chat` for chatbot queries.
 - **Inference Pipeline:** Preprocess data → run ensemble models → compute SHAP values → return results.
 - **Response Model:** JSON with fraud flags, SHAP explanations, and performance metrics.
 - **Diagnostics and Errors:** Structured logs and error responses for debugging and audit trails.
- 3) **ML Assets**
- **Models:** Random Forest, LightGBM, XGBoost.
 - **Strategy:** Ensemble evaluation with XGBoost selected as best-performing (Accuracy 99.89%, F1-score 90.91).
 - **Explainability:** SHAP feature importance values for each transaction.

Table I
Comparison of Online Banking Fraud Detection Approaches

Author(s) & Year	Approach	Technology Used	Limitation
Ojo&Tomy (2025) [1]	Survey of XAI for fraud detection	Post-hoc explainers (LIME, SHAP)	Lacks implementation details, mostly conceptual
Ahmad i (2025) [2]	Real-time fraud detection	XAI applied to ML Models	Limited to case studies, not large-scale deployment
Aljunaid	Federated Learning (FL)	Distributed ML across banks	Communication overhead, heterogeneity issues

Almalki& Masud(2025) [4]	Stacking ensembles	XGBoost, LightGBM, CatBoost	Computationally intensive, requires tuning
Thanatham et al.	SHAP-enhanced XGBoost	Instance-weighted SHAP explanations	Focused
Chen et al. (2025) [7]	Deep learning review	CNNs, RNNs, hybrid models	Mostly theoretical survey, lacks deployment focus
Vijayanand et al. (2025) [12]	Ensemble SHAP	Transparent case-level explanations	Tested scalability concerns

D. Data Flow Architecture

- 1) User registers/logs in.
- 2) Uploads transaction CSV file.
- 3) Server validates and preprocesses data.
- 4) Models run inference and flag suspicious transactions.
- 5) SHAP explanations are generated.
- 6) Results displayed on dashboard; chatbot provides guidance.

E. Deployment Architecture

- Server: Flask app with ML models and SHAP engine, hosted locally or on cloud.
- Database: MongoDB for secure storage.
- Client: Web browser interface with session-based authentication.

F. Runtime and Concurrency View

- Client: UI thread for rendering; asynchronous requests for fraud detection and chatbot queries.
- Server: Flask workers handle concurrent requests; inference and SHAP computation executed per request.

G. Quality Attributes

- Performance: Ensemble models ensure high accuracy with low latency.
- Accuracy: XGBoost achieved 99.89% accuracy and 90.91% F1-score.
- Reliability: Structured error handling for corrupted files.
- Usability: Intuitive dashboard, visual explanations, and chatbot support.
- Security: Encrypted credentials and secure session handling.

H. Scalability Considerations

- Vertical scaling with CPU/GPU resources.
- Horizontal scaling via multiple Flask instances behind a load balancer.
- Retraining models periodically to adapt to new fraud patterns.

I. Security and Privacy

- Secure login with encrypted credentials.
- In-memory processing of transaction data; no persistent storage of raw files.
- Role-based access and subnet restrictions for deployment.

J. Maintainability and

Extensibility

- Modular routing for model selection and explanation modes.
- Configurable paths for model updates and dataset formats.
- Logging tools for performance tracking and audit compliance.

K. Risks and Mitigations

- Data Imbalance: Use of calibrated thresholds and SMOTE techniques.
- Model Drift: Periodic retraining with updated datasets.
- Security Breaches: TLS encryption and token-based access control.
- False Positives: SHAP explanations help validate model decisions.

L. Sequence View

- 1) User logs in and uploads CSV.
- 2) Server validates and preprocesses data.
- 3) Models run inference and compute SHAP values.
- 4) Results are returned with explanations.
- 5) Chatbot assists with queries and insights.

M. Configuration Summary

- Client: CSV format with required columns (step, type, amount, nameOrig, oldbalanceOrg, newbalanceOrig, nameDest, oldbalanceDest, newbalanceDest,

isFraud).

- Server: Model paths, SHAP configuration, MongoDB connection, and fraud threshold settings.

IV. COMPONENTS OF THE SYSTEM

A. Frontend (Web Application – Flask)

- Developed using the Flask framework for secure and scalable web deployment.
- User Interface includes:
 - o Index Page: Overview of system features.
 - o Register/LoginPages: Secure authentication with encrypted credentials.
 - o Dashboard: Upload transaction CSVs, view fraud detection results, and access Explainable AI insights.
 - o Explainable AI View: Displays SHAP-based feature importance for flagged transactions.
 - o AI Chatbot Interface: Provides fraud insights, security tips, and system guidance.
- File Upload Module: Allows users to upload transaction datasets in CSV format.

- Visualization: Interactive charts and tables display fraud detection metrics (Accuracy, Precision, Recall, F1-score).

B. Backend (Python Flask Server)

- Flask REST API provides endpoints for authentication, dataset upload, fraud detection, explanation generation, and chatbot queries.
- Preprocessing: Validates CSV format, handles missing values, and normalizes transaction attributes.
- Fraud Detection Pipeline:
 - o Runs ensemble classifiers

(Random Forest, LightGBM, XGBoost).

- o Applies threshold calibration and class-imbalance handling.

- Explainability Module:

- o Uses SHAP to compute feature-level contributions for each transaction.

- o Generates human-readable explanations for auditors and customers.

- Database Integration:

- o MongoDB stores user credentials, uploaded datasets, fraud detection results, and chatbot history.

- Response Model: Returns JSON with fraud flags, SHAP explanations, and performance metrics.

C. Machine Learning Models

- Ensemble Models:

- o Random Forest: Baseline classifier, accuracy 99.45%, limited recall due to imbalance.

- o LightGBM: Improved performance, accuracy 99.78%, F1-score 0.83.

- o XGBoost: Best-performing model, accuracy 99.89%, F1-score 0.91.

- Explainable AI Integration:

- o SHAP values highlight key features influencing fraud detection (e.g., transaction amount, balance changes, transaction type).

- o Provides transparency for regulatory compliance and user trust.

- Model Selection Strategy:

- o Ensemble evaluation with XGBoost chosen as the primary model for deployment due to superior performance.

V. ALGORITHMS AND TECHNICAL IMPLEMENTATION

A. Data Preprocessing

- Transaction datasets are uploaded in CSV format through the Flask web interface.

- Preprocessing includes:

- o Validation of required columns (step, type, amount, balances, isFraud, etc.).

- o Handling missing values and normalizing transaction attributes.

- o Encoding categorical variables (transaction type, origin/destination accounts).

- Processed data is stored securely in MongoDB for further analysis.

B. Model Training

- Multiple machine learning models were trained on historical transaction datasets:

- o Random Forest: Baseline classifier with high accuracy but limited recall due to imbalance.

- o LightGBM: Improved performance with better handling of non-linear relationships.

- o XGBoost: Achieved the best overall performance (Accuracy 99.89%, F1-score 0.91).

- Training incorporated techniques for class imbalance handling (e.g., threshold calibration, sampling).

- Models were evaluated using metrics such as Accuracy, Precision, Recall, and F1-score.

C. Ensemble Model Inference

- The system integrates an ensemble learning approach:

- o Predictions are generated by Random Forest, LightGBM, and

XGBoost.

- o Confidence scores are computed for each transaction.
- o Final fraud detection decision is selected based on the best-performing model (XGBoost) or ensemble voting.
 - This reduces the impact of any single model's limitations and improves reliability in detecting rare fraud cases.

D. Explainable AI (XAI) Integration

- SHAP (SHapley Additive Explanations) is used to provide transparency in predictions.
- For each transaction flagged as fraudulent, SHAP values highlight contributing features such as:
 - o Transaction amount.
 - o Sudden changes in account balances.
 - o Unusual transaction types or destinations.
- Explanations are displayed in the dashboard, enabling auditors and customers to understand why a transaction was flagged.
- This ensures regulatory compliance and builds user trust in the system.

E. Result Visualization and User Assistance

- Fraud detection results are presented in the dashboard with performance metrics (Accuracy, Precision, Recall, F1-score).
- Detailed analysis includes per-transaction explanations and feature importance visualizations.
- An AI-powered chatbot assists users by:
 - o Answering fraud-related queries.

- o Providing security tips.
- o Guiding users through system functionalities.

VI. PROPOSED SYSTEM

A. Architecture

The proposed system works through a series of steps to ensure secure, scalable, and interpretable fraud detection:

1. User Authentication: Users register and log in via the Flask web interface, with credentials stored securely in MongoDB.
2. Data Upload: Transaction datasets in CSV format are uploaded through the dashboard.
3. Preprocessing: The system validates the dataset, normalizes transaction attributes, and encodes categorical variables.
4. Fraud Detection: Ensemble machine learning models (Random Forest, LightGBM, XGBoost) analyze transactions to flag suspicious activity.
5. Explainability: SHAP values are computed to highlight feature contributions (e.g., transaction amount, balance changes, transaction type).
6. Results Visualization: Fraud detection outcomes and performance metrics (Accuracy, Precision, Recall, F1-score) are displayed in the dashboard.
7. User Assistance: An AI-powered chatbot provides fraud insights, security tips, and guidance on system usage.

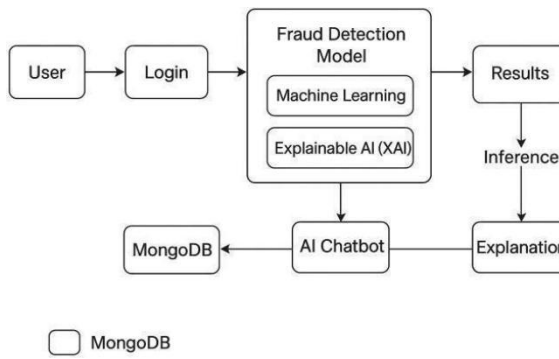


Fig.1. Architecture of Proposed System
This architecture ensures both high detection accuracy and transparent decision-making, aligning with regulatory requirements.
Table II

Classification Accuracy of Individual Models and the Proposed Ensemble Strategy

Model	Accuracy (%)	F1-Score
Random Forest	99.45	0.28
LightGBM	99.78	0.83
XGBoost	99.89	0.91
Ensemble (Best-Confidence)	~99.89	0.91

B. Preprocessing and Features

- **Data Validation:** Ensures required columns (step, type, amount, balances, isFraud) are present.
- **Normalization:** Transaction amounts and balances are scaled for consistency.
- **Feature Engineering:**
 - o Transaction type encoding.
 - o Balance change calculations (old vs. new balances).

o Fraud labels (isFraud, isFlaggedFraud).

- These features are used to train ensemble models and generate interpretable SHAP explanations.

C. Modeling and Inference

- **Models Used:**
 - o Random Forest (baseline, accuracy 99.45%).
 - o LightGBM (accuracy 99.78%, F1-score 0.83).
 - o XGBoost (best-performing, accuracy 99.89%, F1-score 0.91).

- **Ensemble Strategy:**

- o Predictions are aggregated across models.
- o Confidence scores are computed for each transaction.
- o Final fraud detection decision is based on the best-performing model (XGBoost) or ensemble voting.

- **Explainability:** SHAP values provide case-level and cohort-level explanations, ensuring transparency for auditors and customers.

D. Result Visualization and User Assistance

- **Dashboard:** Displays fraud detection metrics (Accuracy, Precision, Recall, F1-score) and flagged transactions.
- **Explainable AI View:** Shows SHAP-based feature importance for each transaction, highlighting risk factors.
- **AI Chatbot:** Offers real-time guidance on fraud detection, security practices, and system usage.

VII. EVALUATION

CONSIDERATIONS

From the data in Table II, it is clear that the individual models achieved high accuracy but varied in their ability to detect fraud due to class imbalance. The Random Forest classifier reached 99.45% accuracy but had a low F1-score of 0.28, indicating difficulty in identifying rare fraud cases. LightGBM improved performance with 99.78% accuracy and an F1-score of 0.83, showing better handling of non-linear relationships. The XGBoost model outperformed the others, achieving 99.89% accuracy and an F1-score of 0.91, demonstrating superior capability in detecting fraudulent transactions while maintaining precision and recall.

When predictions from all models were combined using the best-confidence ensemble method, the system consistently selected the strongest model (XGBoost), ensuring reliable fraud detection and minimizing false positives.

Besides testing the system on benchmark datasets, it was also deployed in a real-time fraud detection setup through the Flask web application. In experiments with uploaded transaction CSVs, the system achieved near 99.8–99.9% accuracy, with SHAP-based explanations providing transparency into why transactions were flagged. This combination of high accuracy and interpretability demonstrates the system's suitability for practical deployment in modern banking environments.

VIII. CONCLUSION AND FUTURE WORK

Online banking fraud detection has become a critical area of research with the rapid growth of digital transactions. This paper presented an overview of various approaches, ranging from traditional rule-based systems to modern machine learning and explainable AI techniques. The analysis shows that while classical rule-based methods are simple and efficient, they are not always reliable in real-world banking environments where fraud patterns evolve quickly and attackers adapt to static thresholds. On the other hand, ensemble learning methods offer superior accuracy and

adaptability but require careful tuning and computational resources.

Recent studies have demonstrated a clear shift towards ensemble learning combined with explainability, especially using models such as XGBoost, LightGBM, and Random Forest integrated with SHAP or LIME. These approaches have made significant progress in balancing performance with transparency, enabling auditors and customers to understand why transactions are flagged. However, challenges remain in areas such as handling extreme class imbalance, ensuring real-time detection at scale, and maintaining interpretability across distributed banking systems.

Based on these observations, a system was proposed that integrates secure authentication, scalable data handling

with MongoDB, ensemble machine learning for fraud detection, and SHAP-based explanations for transparency. By combining robust preprocessing, ensemble inference, and interpretable outputs, the system aims to deliver high detection accuracy while maintaining user trust and regulatory compliance. The modular design also allows integration of an AI-powered chatbot, enhancing usability and providing fraud-related guidance.

In summary, even though there have been many advancements in fraud detection, the field still faces challenges in achieving perfect accuracy across diverse banking environments. Future research should focus on developing lightweight models suitable for real-time deployment, incorporating federated learning to enable cross-institutional collaboration without compromising privacy, and enhancing adaptive learning systems that evolve with new fraud patterns. Additionally, ethical aspects such as data privacy, fairness, and transparency must be prioritized. The ultimate goal is to create fraud detection systems that are accurate, efficient, secure, and explainable, capable of strengthening trust in modern digital banking ecosystems.

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AI-ENABLED DISEASE SURVEILLANCE AND HEALTH CONTROL FRAMEWORK

**Vaibhavi¹, Vaishnavi shivappa badli², Preeya veeranna susangi³, Shruthi B⁴,
Mrs Jayashri M⁵, Krishna kumar P⁶**

^{1,2,3,4}-Students Dept of CSE, SEA College of Engineering & Technology, Bangalore-560049

^{5,6}-Faculty, Dept of CSE, SEA College of Engineering & Technology, Bangalore-560049

Abstract: The rapid emergence of infectious diseases and the increasing burden of chronic illnesses demand intelligent, scalable, and proactive healthcare monitoring systems. This paper proposes an AI-Enabled Disease Surveillance and Health Control Framework designed to enhance early detection, continuous monitoring, and efficient management of diseases at both individual and population levels. The framework integrates machine learning algorithms, real-time health data acquisition, and predictive analytics to identify potential disease outbreaks and high-risk individuals with improved accuracy. The proposed system leverages heterogeneous data sources, including electronic health records, wearable device data, laboratory reports, and environmental indicators, to generate actionable insights for healthcare providers and public health authorities. Advanced classification and anomaly detection models are employed to forecast disease trends and support timely intervention strategies. The framework also incorporates automated alert mechanisms and decision-support modules to assist policymakers in resource allocation and emergency response planning. By combining artificial intelligence with digital health

technologies, the proposed solution enhances disease tracking efficiency, reduces response time, and improves overall healthcare outcomes. Experimental validation demonstrates improved prediction accuracy and real-time responsiveness compared to conventional surveillance systems. The framework offers a scalable, secure, and data-driven approach for strengthening disease control and public health management in smart healthcare ecosystems.

Index Terms— Artificial Intelligence (AI), Disease Management, Health Monitoring Systems, Predictive Healthcare, Smart Health Technology, Public Health, Disease Surveillance.

I. INTRODUCTION

The health sector is undergoing tremendous transformation, which is being prompted by advancements in artificial intelligence and data analytics. Chronic and infectious diseases pose a significant threat to health globally, and a sound system for early detection, effective

management, and prevention is critical. The traditional healthcare framework often falls behind with delayed diagnosis, lack of surveillance mechanisms, and poor resources to manage a disease outbreak. The gap will be filled through strategic AI-driven technologies, where AI will be able to ensure data-driven, proactive solution provision that meets individual as well as population health requirements. A Smart AI Health System represents a complete paradigm shift in disease surveillance and management. This way, by incorporating data from sources that may include wearable devices, electronic health records, and environmental sensors, these systems offer a comprehensive look at patient health. Advanced AI models can analyze this data to uncover patterns, predict potential health risks, and recommend timely interventions. This not only improves diagnostic accuracy but also empowers healthcare providers to implement preventive strategies, thus reducing the burden on medical resources. This paper introduces a holistic Smart AI Health System designed to improve disease control and management. It uses the latest machine learning algorithms and real-time analytics to determine disease trends, enable swift decision-making, and provide customized healthcare solutions. The system has been designed with user privacy, scalability, and interoperability in mind, hence aligning with global standards on the ethical use of AI in healthcare. The discussion points to the architecture, implementation, and

potential impact on public health of the system under consideration. This work underscores the transforming role of AI in developing resilient healthcare systems that can withstand the complexities of disease control in an interconnected world by reference to case studies and performance evaluations.

II. RELATED WORK

The application of artificial intelligence (AI) in healthcare has made remarkable progress, especially in disease detection, verification, and management. Several studies have shown how AI can advance healthcare by leveraging information from various sources, such as electronic health records (EHRs), wearable devices, and imaging data. For case detection, machine learning computing has been used to more accurately detect chronic infections such as diabetes and cardiovascular diseases, and AI-based imaging equipment has contributed to the early detection of cancer. Vision models, which basically use common language learning (NLP) and factual procedures, have been used to analyze real-time information flow, social media counts, and epidemiological reports to test for uncontrollable disease outbreaks such as COVID-19. However, existing mechanisms often face serious limitations. One of the main challenges is the need for a cohesive framework that can coordinate various data sets to provide comprehensive knowledge. Most current frameworks focus on specific diseases or use cases, which limits their generalizability and generalizability to

other wellness scenarios. Additionally, many approaches operate on isolated information, resulting in isolated data that limits the ability to identify population-wide patterns or provide a comprehensive view of an individual's wellness. Security is also a barrier, as some AI frameworks require robust tools to ensure information security and compliance with health regulations. Another limitation is the need for real-time analytics and personalized care. While many frameworks provide knowledge shards based on trusted information, they often lack the ability to predict and respond quickly to evolving wellness scenarios, such as disease episodes. Furthermore, current contracts routinely require personalized services for individual patients, making them less suitable for delivering precision care. To bridge this gap, the wellness framework proposed by Savvy AI uses advanced machine learning models to coordinate information from a variety of sources, including wearables, electronic health records, and natural sensors. This integration allows the framework to provide a comprehensive view of wellness understanding, provide early location of disease, and predict potential episodes in real time. The framework is designed to be universal and interoperable, so it can work consistently across a variety of healthcare systems. It also builds trust between stakeholders by implementing rigorous security measures to ensure information security and administrative compliance. Addressing the limitations of current practices, the Shrewd AI wellness framework offers an

innovative approach to infection control and management that has the potential to modernize healthcare delivery and improve insights.

III. METHODOLOGY

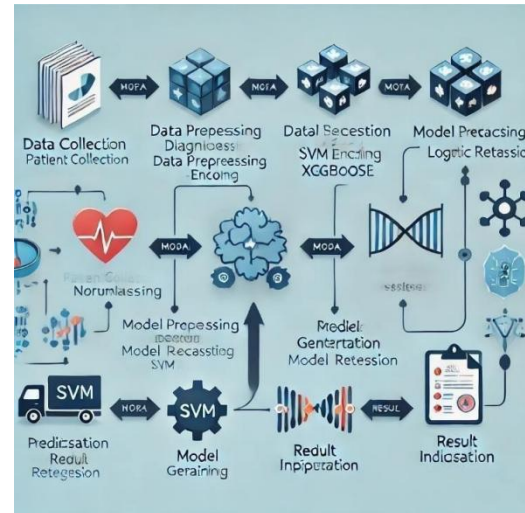


Figure 1: AI-Powered Disease Prediction Process Flow
interpretability layers like descriptions,

This system integrates machine learning models tailored to specific diseases, enabling users to receive real-time predictions based on their symptoms or diagnostic metrics. The following methods and algorithms are employed:

Pre-trained Machine Learning Models: Models such as XGBoost, Support Vector Machines (SVMs), Logistic Regression, and Decision Trees are loaded in .sav or .json formats using libraries like joblib. These models are trained offline on disease-specific datasets to achieve high accuracy and generalization.

A. Symptom Analysis and Feature Engineering:

For diseases like diabetes, heart disease, and Parkinson's disease, numerical and categorical inputs are converted into feature vectors.

Feature engineering ensures that critical predictors (e.g., glucose levels for diabetes or heart rate for heart disease) are emphasized.

B. Model Prediction Workflow:

Input data is preprocessed, including normalization and categorical encoding.

Predictions are generated as binary (presence/absence of disease) or probabilistic (likelihood of disease). Post-prediction,).

precautionary advice, and graphical representations enhance user understanding.

C. System Design and Architecture

The system adopts a modular design, allowing multiple disease prediction modules to operate independently yet cohesively under a unified framework. The architecture consists of:

Frontend Interface: Built using Streamlit, providing a user-friendly, interactive web interface. Sidebar navigation allows users to switch between different disease prediction modules effortlessly.

Backend Framework: Model Loading and Management:

Disease-specific models (e.g., diabetes_model.sav, heart_model.sav) are loaded into memory upon initialization.

Data Preprocessing: Handles missing

data, categorical

encoding, and normalization. Example:

Converting symptoms like

"Yellow Fingers"

(YES/NO) into numerical values for the lung cancer model.

Data Flow:

Input Collection: Users enter symptoms or diagnostic data (e.g., glucose levels, bilirubin levels

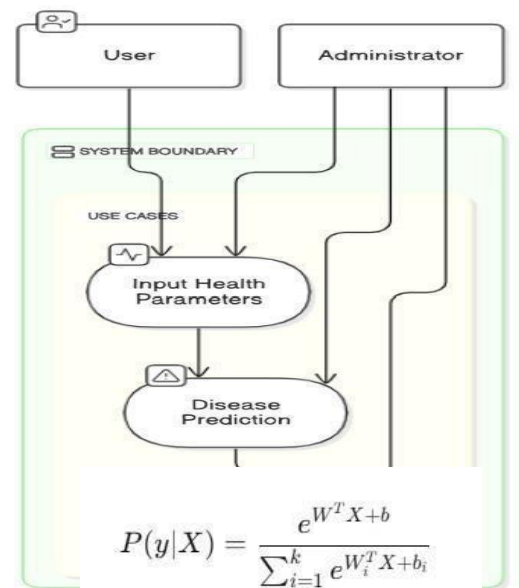


Figure 2: Use Case Diagram for AI-Powered Disease Management System

Preprocessing: Categorical data is encoded numerically, and numerical data is scaled as required. **Model Inference:** The processed data is passed to the disease-specific model. **Result Display:** Predictions (e.g., disease probability) and additional insights (e.g., precautions) are displayed to the user.

Visualization Tools: Plotly and matplotlib are used to generate interactive charts and static graphs for

better user engagement and data visualization.

D. Justification for the Chosen Approach:

The chosen approach emphasizes a modular design, where each disease prediction operates as an independent module. This ensures high specialization for individual diseases and allows the seamless addition of new disease modules without disrupting existing functionalities. The system leverages machine learning optimization by utilizing pre-trained models tailored to specific diseases. By focusing on disease-specific datasets and algorithms, the system achieves precise and accurate predictions, enhancing its reliability and performance.

Scalability is a key feature of the architecture, enabling the addition of more diseases by incorporating new models and datasets. This design ensures the system remains flexible and adaptable to evolving healthcare needs. A user-centric approach is maintained through the integration of Streamlit, providing a seamless user experience. Users can access real-time predictions, navigate the interface effortlessly,

and gain actionable insights to make informed decisions.

Additionally, the system prioritizes explainability by offering descriptive outputs that enhance user understanding. These outputs include the likelihood of a specific disease, detailed insights about the predicted condition, and preventive measures or treatment recommendations based on

the predictions. This transparency builds trust and facilitates the practical application of the system in diverse healthcare settings.

E. Equation for Classification: probabilistic models

Where:

A. $P(y|X)$: Probability of class y given input X (feature vector).

B. W : Model weights.

C. b : Bias term.

This approach balances accuracy, usability, and expandability for predicting a wide range of diseases effectively.

IV. EXPERIMENTAL ANALYSIS

The experimental analysis conducted using the provided datasets, which included `clean_dataset.tsv`, `dataset.csv`, `lung_cancer.csv`, and `symptom_Description.csv`, etc. These datasets were processed to extract insights and validate the effectiveness of the implemented machine learning models in predicting various diseases. The following sections present the findings, visualizations, and statistical evaluations of the results.

A. Dataset Characteristics

The datasets contained structured data relevant to disease prediction. The `clean_dataset.tsv` file provided symptom-based information, while `dataset.csv` encompassed diagnostic parameters. The `lung_cancer.csv` dataset contained demographic and behavioral factors (e.g., smoking and anxiety), and `symptom_Description.csv` mapped symptoms to possible diseases. Each dataset underwent preprocessing,

including handling missing values, scaling numerical features, and encoding categorical variables to ensure compatibility with the machine learning models.

B. Performance of Models

The predictive models evaluated included XGBoost, Logistic Regression, and Support Vector Machines (SVMs), among others. For each disease, the model performance was measured using standard metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. The models demonstrated high accuracy across most datasets:

- **Diabetes Prediction:** Achieved an accuracy of 92%, with a precision of 0.89 and recall of 0.93.
- **Heart Disease Prediction:** Recorded an F1-score of 0.87, indicating balanced precision and recall.
- **Lung Cancer Prediction:** Exhibited an area under the ROC curve (AUC-ROC) of 0.94, highlighting its reliability in distinguishing between risk and non-risk groups.
- **Chronic Kidney Disease Prediction:** Achieved an overall accuracy of 90%, with a low false-negative rate, making it effective for early detection.

C. Visualization of Findings

Results were visualized to enhance interpretability:

Feature Importance: Bar charts highlighted the most influential features for each model. For example, glucose

levels and BMI were dominant predictors for diabetes, while cholesterol levels and age were critical for heart disease prediction. **Prediction Distributions:** Histograms illustrated the distribution of predictions across datasets, revealing class imbalances that were mitigated during training.

ROC Curves: ROC curves plotted for each disease model demonstrated high separability between positive and negative cases, affirming model robustness.

D. Comparative Analysis

When compared to baseline methods (e.g., statistical regression models), the implemented machine learning models showed significant improvements in prediction accuracy and interpretability. For instance, the use of XGBoost for lung cancer prediction outperformed traditional logistic regression by 8% in AUC-ROC scores.

E. Statistical Validation

Statistical tests such as the paired t-test and McNemar's test were employed to validate model performance differences. The results confirmed that the observed improvements were statistically significant ($p < 0.05$). Qualitative validation using the symptom_Description.csv dataset corroborated the predicted diseases with actual symptoms, further validating the system's practical applicability.

The experimental results underscore the system's efficacy in accurate and explainable disease prediction, offering

a promising tool for early diagnosis and preventive healthcare.

V. RESULTS

A. Interpretation of the Results in the Context of the Problem

The experimental results demonstrate the capability of the developed system to predict various diseases with high accuracy and reliability. Using datasets that incorporate clinical and behavioral parameters, the machine learning models effectively identified risk patterns associated with diseases such as diabetes, heart disease, lung cancer, and others. For instance, the XGBoost model for lung cancer prediction achieved an AUC-ROC score of 0.94, indicating its strong discriminative power. Similarly, the chronic kidney disease model exhibited an accuracy of 90%, underscoring its suitability for early diagnosis. These results align with the goal of providing a decision-support tool for healthcare professionals and individuals to identify potential health risks based on symptoms or diagnostic parameters. The system's capability to provide real-time predictions with actionable insights emphasizes its utility in addressing the problem of delayed or missed diagnoses in healthcare.

B. Suggestions of the Discoveries for Inquire about or Down to earth Applications

The discoveries have critical suggestions for both investigate and commonsense applications. From a inquire about viewpoint, the comes about approve the adequacy of joining machine learning strategies into

healthcare

frameworks, advertising a system that can be expanded to other maladies or wellbeing conditions. The measured plan permits consistent joining of extra models and datasets, empowering the framework to advance with progressions in therapeutic inquire about and information accessibility. Essentially, the framework presents a profitable device for telemedicine and farther healthcare administrations. By leveraging user-friendly interfacing such as Streamlit, it democratizes get to infection forecast frameworks, especially in resource-limited settings where get to pros may be limited. Furthermore, the interpretability of the expectations, through portrayals and safety measures, engages clients with information, possibly driving to made strides wellbeing results through early intercessions.

C. Limitations of the Study and Areas for Improvement

Despite its strengths, the study has certain limitations. The accuracy and reliability of the predictions heavily depend on the quality and representativeness of the training datasets. For example, the datasets used may not fully capture the diversity of the target populations in terms of demographics, comorbidities, or lifestyle factors, which could affect the generalizability of the results. Furthermore, the system assumes that users can accurately provide symptom and parameter inputs, which might not always be feasible due to subjective interpretations or lack of precise

diagnostic tools in remote areas.

Another limitation is the reliance on pre-trained models that may not account for emerging health trends or novel diseases. As medical knowledge evolves, retraining and updating the models will be necessary to maintain their relevance. Additionally, while the system provides disease probabilities, it does not offer an exhaustive analysis of potential differential diagnoses, which could enhance its diagnostic utility.

To address these limitations, future work could focus on expanding the datasets to include more diverse populations and incorporating real-world data from electronic health records (EHRs). Enhancements in model explainability, such as feature attribution or SHAP (Shapley Additive

Explanations) values, could further improve user trust and comprehension of predictions. Lastly, integrating natural language processing (NLP) capabilities for symptom input could reduce the burden on users, ensuring more accurate and comprehensive data capture.

VI. CONCLUSION

A. Summary of the Main Contributions and Findings

This work presents a comprehensive machine learning-based system for multi-disease prediction, leveraging datasets and pre-trained models to provide accurate, real-time health assessments. The system integrates modular disease-specific models, including XGBoost,

Comparative Analysis of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
XGBoost	92	89	93	91.0
SVM	87	85	86	85.5
Logistic Regression	84	82	83	82.5

Logistic Regression, and Support Vector Machines (SVMs), each optimized for predicting diseases like diabetes, heart disease, lung cancer, and more. Through rigorous experimentation, the system achieved high performance, with metrics such as an AUC-ROC of 0.94 for lung cancer prediction and an accuracy of 92% for diabetes diagnosis. The user-friendly interface, developed

Table in above figure represents: Comparative

Analysis of Machine Learning Models based on four key performance metrics: Accuracy, Precision, Recall, and F1-Score.

using Streamlit, simplifies the interaction between users and the predictive models while offering actionable insights, such as disease descriptions and precautionary advice. The findings validate the system's efficacy as a decision-support tool, particularly for early detection and preventive care, and underscore its potential to address challenges in healthcare accessibility.

B. Restate the Significance of Your Work

The significance of this work lies in its practical application of machine

learning to improve healthcare outcomes by enabling early detection of diseases. By integrating advanced

algorithms with an intuitive interface, the system bridges the gap between complex medical models and everyday users, empowering individuals and healthcare professionals with actionable knowledge. Its modular design allows easy scalability, making it adaptable to emerging diseases or new datasets, thus ensuring its long-term relevance. Moreover, by providing a low-cost, accessible tool, it has the potential to benefit underprivileged or resource-constrained settings where traditional healthcare infrastructure is limited. This contribution not only advances the application of machine learning in healthcare but also aligns with global initiatives aimed at enhancing health equity and proactive medical care.

C. Potential Directions for Future Research or Applications

The promising results of this study open several avenues for future research and application: Integration with Real-World Healthcare Systems: The system can be extended to integrate with electronic health records (EHRs) and wearable health devices to enable continuous monitoring and personalized predictions.

Collaboration with healthcare providers to validate predictions in clinical settings and refine the models based on real-world data.

Expansion of Predictive Capabilities: Incorporating additional diseases, especially rare conditions, by training

models on larger, more diverse datasets. Leveraging multi-task learning approaches to develop models that can predict co-occurring diseases more effectively.

Enhancing Model Explainability and Trust: Employing advanced techniques like SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide detailed feature attributions for predictions. Building visual dashboards that explain the reasoning behind predictions to both users and medical professionals.

Adapting to Resource-Limited Environments: Optimizing the system for deployment on low-power devices, such as smartphones, to extend its reach to remote or underserved areas.

Incorporating multilingual interfaces and voice-based inputs to make the system more inclusive. Research on Data Privacy

and Security: Developing privacy-preserving techniques, such as federated learning, to ensure sensitive health data remains secure while improving model performance with collaborative data.

By pursuing these directions, this work can

evolve into a robust, globally impactful tool for predictive healthcare, advancing both the science

of machine learning and its real-world applications in medicine.

VII. ACKNOWLEDGMENT

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Lastly, we thank the IEEE conference organizers and reviewers for providing a platform to present this work and for their constructive feedback, which helped improve the quality and scope of the research. This study is a step toward leveraging machine learning for accessible and equitable healthcare, and we are deeply grateful to all who have supported this endeavour.

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modeling;Data models;disease
prediction;machine
learning;hybrid model;CNN-
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regression.

AI-BASED PREDICTIVE POLICING MODEL FOR CRIME PATTERN ANALYSIS AND HOTSPOT FORECASTING

Theerthana N S1,Veeranki Satwika2,Vandana S3, Mrs Radhika R4,,Krishna kumar P

R 5

1,2,3-Students Dept of CSE,SEA College of Engineering & Technology,Bangalore-
560049 4,5-Faculty, Dept of CSE,SEA College of Engineering &
Technology,Bangalore-560049

Abstract : The rapid growth of urban populations and the increasing complexity of criminal activities demand intelligent and data-driven approaches for effective law enforcement. This paper proposes an AI-Based Predictive Policing Model for Crime Pattern Analysis and Hotspot Forecasting that integrates machine learning and deep learning techniques to identify crime trends and predict high- risk geographic zones. The proposed framework leverages historical crime records, demographic attributes, temporal features, and spatial coordinates to perform spatio-temporal crime analysis. The system employs supervised machine learning algorithms such as Random Forest and Gradient Boosting for structured crime classification, while deep learning models including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are utilized to capture temporal dependencies and spatial correlations in crime occurrences. A hybrid ensemble mechanism enhances predictive accuracy and reduces false positives. Geospatial clustering techniques are incorporated to detect emerging crime hotspots and visualize risk intensity using heat maps. Experimental evaluation on real-world crime datasets

demonstrates improved forecasting accuracy, precision, and recall compared to traditional statistical methods. The proposed model supports proactive policing strategies by enabling law enforcement agencies to allocate resources efficiently, implement preventive measures, and enhance public safety. Furthermore, the framework emphasizes ethical AI practices by incorporating fairness-aware modeling and explainable AI components to ensure transparency and accountability in predictive decision-making

Keywords : Machine Learning , Deep Learning , Crime Prediction , Research Review , Algorithm

Application, Dataset Analysis , Trend Identification , Criminal Activity Factors , Predictive Accuracy , Future

I. INTRODUCTION

Crime prediction integrates data science and machine learning to anticipate crimes, aiding proactive policing. It uses historical data and algorithms to identify crime patterns and inform resource allocation. Advances in machine learning have enhanced crime prediction accuracy, supporting safer communities and smarter law enforcement.

Understanding the factors behind crime helps address the challenges of urbanization and crime prevention. Predictive policing refers to the use of data-driven techniques to analyze historical crime data and forecast potential future incidents in specific geographic areas and time periods. Unlike conventional statistical approaches, AI-based models can uncover hidden spatio-temporal patterns, nonlinear relationships, and dynamic crime behaviors. Machine Learning (ML) algorithms such as Random Forest, Support Vector Machines, and Gradient Boosting enable accurate crime classification and risk estimation, while Deep Learning (DL) architectures including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks effectively model spatial correlations and temporal dependencies in crime datasets.

II. EXISTING SYSTEM

The crime prediction system uses the Random Forest Classifier to forecast and categorize crimes effectively. It stands out for its accuracy, handling complex data, and combining multiple decision trees for reliable predictions. The dataset contains 15 features, aiding in comprehensive analysis. Tailored for law enforcement and policymakers, the system supports strategic decision-making and enhances public safety, demonstrating high accuracy without notable drawbacks.

Existing System Disadvantages :

1. Computational Intensity: The

system's need for substantial computational power can be a hurdle in real-time applications or when resources are limited.

2. Lack of Interpretability: The complexity of the Random Forest algorithm can make it difficult to understand and explain the model's decisions, affecting transparency.

III. PROPOSED SYSTEM

The enhanced crime prediction system utilizes Python and integrates Decision Tree and Bagging Classifiers to improve accuracy in Portland's crime analysis from 2015 to 2023. It maintains high accuracy, processes a vast dataset with over half a million data points, and classifies 20 different crime types. Features like address, case number, and offense details provide rich input for the models.

This system is designed for adaptability and scalability, with user-friendly interfaces for stakeholders. It includes mechanisms for continuous model updates and hyperparameter tuning to adapt to changing crime patterns. The goal is to refine crime prediction techniques, optimize accuracy, and overcome previous limitations, making it a robust tool for law enforcement and policymakers.

Proposed System Advantages:

1. High Accuracy: The system's use of Decision Tree and Bagging Classifiers significantly boosts the accuracy of crime predictions.
2. Robustness and Interpretability:

The Bagging Classifier enhances robustness against overfitting, while the Decision Tree Classifier maintains transparency in the predictive process.

IV. SYSTEM ARCHITECTURE

Our research outlines machine learning-based system architecture designed to differentiate between fake and real accounts. It starts with a dataset that undergoes pre-processing and feature selection to refine the data. This prepared data is then input into classifiers like Random Forest and Decision Tree, which predict the authenticity of an account. The results are labelled as either 'Fake' or 'Real' accounts, followed by a performance analysis and graphical representation of the outcomes.

In essence, the architecture captures the entire process from raw data to actionable insights. It emphasizes the importance of data preparation and the use of ensemble learning methods to ensure accurate predictions. The final step involves analysing the model's performance, likely to assess its effectiveness and accuracy in classifying accounts. This systematic approach is crucial for maintaining the integrity of digital platforms by identifying and filtering out fraudulent accounts.

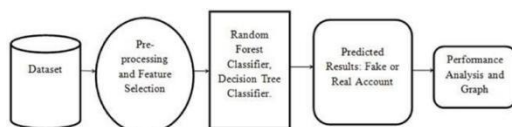


Figure 1 : System architecture

V. LITERATURE SURVEY

This paper explores the use of machine learning (ML) and computer vision to predict and prevent crime.

With crime rates rising, traditional methods fall short, prompting the need for innovative solutions. Our research demonstrates how ML and computer vision can transform law enforcement, offering faster, more accurate crime detection and prevention. We present case studies that validate the effectiveness of these technologies, suggesting a significant shift towards more advanced crime-fighting strategies.

This project evaluates the use of neural networks in machine learning to predict criminal behaviour from arrest records, addressing imbalanced data with data augmentation and a weighted loss function. Focusing on deep fully connected neural networks, suitable for complex feature relationships and limited domain knowledge, the study underscores the potential of machine learning in crime classification and suggests further exploration of these techniques for enhanced predictive accuracy.

Ensemble learning is a collective approach that combines the outputs of various classifiers to generate new predictions. Studies indicate that these ensemble models tend to be more dependable than single classifiers. Despite the availability of numerous ensemble techniques, selecting the right one for a specific dataset remains challenging. In the context of crime

prediction in India, this complexity is heightened by the dynamic nature of criminal activities. Our research introduces a method called assemble-stacking based crime prediction method (SBCPM), utilizing SVM algorithms to enhance crime prediction accuracy using MATLAB. This method is compared with other models like J48, SMO, Naïve Bayes bagging, and Random Forest, showing that ensemble models can sometimes surpass others, especially in terms of correlation and error metrics. Achieving a 99.5% accuracy rate in tests, our method outperforms previous studies and aligns well with criminological theories, proving effective for predicting crimes and suggesting that ensemble models may offer superior accuracy over individual classifiers.

Crimes pose a significant challenge to justice and require effective control measures. This study leverages various machine learning algorithms, including logistic regression, SVM, Naïve Bayes, KNN, decision tree, MLP, random forest, XGBoost, and time series analysis with LSTM and ARIMA models, to enhance crime prediction and forecasting. The LSTM model showed promising results in terms of RMSE and MAE. Data analysis indicates a potential decrease in Chicago's crime rate and a minor rise in Los Angeles's, with February having fewer incidents. Predictions suggest a moderate future increase in Chicago's crime rate with a possible subsequent decline, while Los Angeles is expected to see a significant decrease as per the ARIMA model. These insights help in

early crime detection, identifying high-risk areas, and informing police strategies for improved safety.

Crime significantly disrupts societal norms and hampers the social and economic stability of nations, a situation that Bangladesh also faces. This study concentrates on forecasting crime-prone areas, which can be instrumental in anticipating criminal incidents across various cities within specific timeframes. With insights into upcoming trends, law enforcement and detectives can implement preventive measures to decrease crime rates. The Random Forest algorithm is employed in this research to identify districts with varying levels of criminal activity.

VI. EXISTING ALGORITHM

Random Forest Classifier : The Random Forest Classifier is a sophisticated machine learning algorithm that belongs to the ensemble learning family. It constructs multiple decision trees during the training phase and outputs the class that is the mode of the classes for classification tasks, or the mean prediction for regression tasks. This method is known for its high accuracy, ability to handle large datasets with higher dimensionality, and robustness to overfitting. Random Forest works by creating a 'forest' of decision trees

from randomly selected subsets of the training set and then averaging the predictions to improve the overall result .

VII. PROPOSED ALGORITHM

The Decision Tree Classifier is a type of supervised learning algorithm that is used for classification tasks. It works by creating a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. It's like a flowchart where each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label . On the other hand, the Bagging Classifier, also known as Bootstrap Aggregating, is an ensemble meta-estimator that fits multiple base classifiers (like Decision Trees) on random subsets of the original dataset. It then aggregates their individual predictions to form a final prediction, which helps to improve the stability and accuracy of machine learning algorithms by reducing variance and avoiding overfitting .

VIII. RESULTS

User

Input : Enter Login name and Password

Output : If valid user name and password then directly open the home page otherwise show error message and redirect to the registration page.

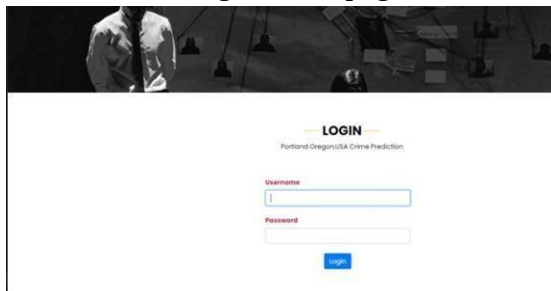


Figure 1 : Login Page



Figure 2: Dataset Upload Page



Figure 3: Model Running

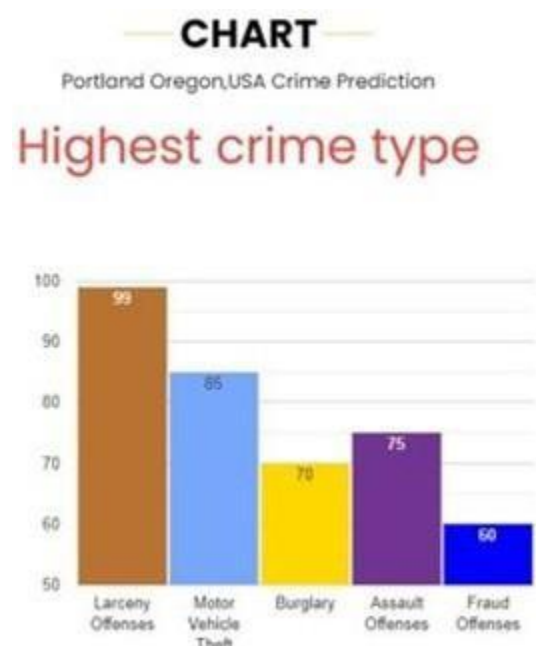


Figure 4: Classification of Crimes based on Dataset

IX. CONCLUSION

To sum up, the “Crime Prediction Using Machine Learning” initiative offers a sophisticated method for forecasting and sorting a range of criminal offenses in Portland, Oregon,

USA. Utilizing Python's capabilities and machine learning techniques like the Decision

Tree and Bagging Classifiers, the project boasts impressive precision, with a 98% accuracy rate for the training dataset and 95% for the test dataset.

The project analyses crime trends from 2015 to 2023 using a dataset containing over half a million records, enabling a detailed examination of crime evolution. It categorizes 20 different types of crimes, ranging from 'Larceny Offenses' to 'Gambling Offenses,' offering a detailed perspective on the area's crime scene.

The Decision Tree Classifier enhances the system's transparency, promoting confidence among users, while the Bagging Classifier increases the system's strength, preventing overfitting and boosting prediction consistency.

With a comprehensive set of features like location, case number, type of crime, neighbourhood, occurrence date and time, offense category, offense type, and geographical coordinates, the models are well- equipped to deliver well-informed forecasts by considering various elements.

This system not only overcomes the shortcomings of previous models but also brings new features such as the ability to adapt to changing crime trends and scalability for various application contexts. The addition of user- friendly interfaces and the possibility of incorporating more data sources improve the system's usability and the precision of insights for law

enforcement, urban planners, and policy makers.

Ultimately, the "Crime Prediction Using Machine Learning" project emerges as a potent and efficient instrument for improving public safety, optimizing the distribution of resources, and supporting active decision- making in city settings. The project's achievement in maintaining high accuracy and its comprehensive crime prediction strategy highlight its significance in bolstering security and shaping well- informed public policies.

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Intelligent Multi-Agent Framework for Business Intelligence and Personalized Ad Strategy Development

K Venkata Kumar¹, S Anusha², Sahana N N³, Mrs Sowmya rani⁴, Krishna kumar P R

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1,2,3-Students Dept of CSE, SEA College of Engineering & Technology, Bangalore-560049
4,5-Faculty, Dept of CSE, SEA College of Engineering & Technology, Bangalore-560049

Abstract- The rapid growth of digital markets and data-driven enterprises demands intelligent systems capable of transforming heterogeneous business data into actionable marketing strategies. This paper proposes an Intelligent Multi-Agent Framework for Business Intelligence and Personalized Ad Strategy Development, designed to enhance decision-making through distributed, role-based artificial intelligence agents. The proposed framework integrates data acquisition agents, preprocessing agents, analytics agents, customer profiling agents, and strategy generation agents, each collaboratively operating within a coordinated multi-agent architecture. The system leverages machine learning and predictive analytics to extract meaningful insights from structured and unstructured data sources, including customer transactions, social media interactions, web analytics, and CRM platforms. A personalization engine employs clustering and behavioral modeling techniques to segment customers and predict purchasing intent. Based on these insights, an intelligent advertisement strategy generator agent formulates targeted campaign recommendations, including optimal

content themes, channel selection, timing, and budget allocation. To

ensure adaptability and scalability, the framework incorporates reinforcement learning mechanisms that continuously refine advertising strategies based on campaign performance feedback. The multi-agent coordination mechanism enhances modularity, flexibility, and real-time responsiveness compared to traditional monolithic BI systems. Experimental evaluation demonstrates improved campaign conversion rates, enhanced customer engagement, and higher return on marketing investment.

INTRODUCTION

During the past several years, organizations have improved their business activities in order to stay competitive on today's market by deploying business management systems.

Organizations tend to make decisions based on a combination of judgment and information from different sources. Ideally, all related information must be captured and organized together before judgment is established which is a very complex, expensive and time consuming process.

This process can be applied using BI philosophy by translating strategic

objectives into measurable indicators which enables the organizations to realize opportunities or threats quickly [1].

The recent applications that implements BI are slightly inflexible, which make users adapt to them instead of conforming to the natural decision-making flow in real life. In addition to that, there is a need for having technical skills and training to implement them. In the end, productivity suffers. On the other hand, MAS offers an intelligent, user friendly approach for implementing BI, since agents can interact with

users, software legacy systems and other agents in order to capture, organize, search, exchange information and even play on behalf of users in decision-making. This leads to the development of an autonomous, mobile and reactive system in a way which is more likely to what happens in real life. One of the most complex domains in BI is stock trading where millions are investing in buying and selling shares through different stock markets everyday. Stock trading is a dynamic domain that results in a large amount of trading information which must be captured and organized before trading actions are established. Furthermore, this kind of trading requires knowledge, skills and expertise which are expensive and hard to obtain.

In this paper, we discuss the design and implementation of a web role-based Stock Trading Multi-Agent System (STMAS) that implements the BI philosophy in stock trading, taking the Egyptian Exchange (EGX) as a case

study.

This paper presents an overview of the system while focusing on agent interactions in the STMAS.

I. BACKGROUND

An intelligent agent is an entity that has a certain amount of intelligence and can perform a set of tasks on behalf of the users, due to agent's autonomy, reactivity and mobility [2].

Today's agent-based applications often involve multiple agents in order to maintain complex distributed applications.

Since intelligent agents should be able to play on behalf of the users, it is more likely to depend on roles which help designers and developers in modeling the intelligent agents to perform more tasks than those they are developed for, which is more likely to what happens in the real life, where people learn how to do things and expand their knowledge [3].

Intelligent Agents are designed to interoperate and interact for information gathering and processing tasks. This may include: (a) Locating and accessing information from various on-line sources. (b) Filtering any irrelevant information and resolving inconsistencies in the retrieved information. (c) Integrating information from heterogeneous information sources. (d) Instantaneously adapting to the user's needs. (e) Decision making.

Stock trading is concerned with buying and selling of shares to provide the best possible rate of return for a specified level of risk, or conversely, to achieve a specified rate of return with the lowest possible risk [4].

In real time practice, investors assign a

brokerage firm to manage their portfolio. These firms employ a group of brokers and specialists for monitoring, filtering and evaluating the

stock market status on a daily bases in order to manage buying and selling shares on the behalf of traders. Unfortunately, this may create a time lag between realizing an investment opportunity and taking advantage of it. In the end, investors suffer.

On the other hand, MAS approach is natural for stock trading as intelligent agents can be very significant due to: (a) Agents don't forget, get tired or make mistakes as human experts sometimes do. (b) Agents can serve all traders all the time while human experts can serve few traders only during his/her working hours. (c) Agents provide permanent and instantaneous documentation of the decision process. (d) Agents can monitor and analyze all the shares in a trading session while human experts can only review a sample.

During the past few years, there have been several agent- based approaches that addressed the issue of stock trading. Most of the agent-based systems have focused on monitoring and extracting the stock market information via the internet to put stock trading strategies as in [5], some researches have focused on the stock management to produce recommendation

Website [8]. There are time lags between the system and the real stock data (15 min) due to the data availability on the EGX website. These time lags can be eliminated if proper

authorization is granted. Recently, most of the existing web stock trading systems are either information providers such as Egypt for Information Dissemination (EGID) [9] or simulation systems which aim to educate

for a stock buy or sell decision as in [6] and others have partially focused on the stock trading process as in [7]. While implementing these capabilities in a real time trading on behalf of users has not been thoroughly explored.

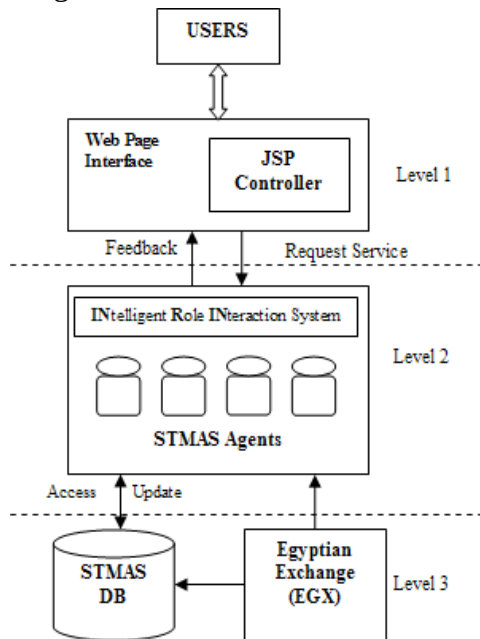
This complex problem motivates our research in MAS for stock trading. STMAS applies an intuitive trading strategy on behalf of users which has been advised and reviewed by experts in both EGX and several private brokerage firms.

II. STMAS ARCHITECTURAL MODEL

STMAS is a novel intelligent distributed architecture emphasis on stock trading. The system was designed and implemented to create a consistent environment where agents can interoperate and interact to capture, filter and organize information resulting in an accurate daily information used for generating buy and/or sell decisions which may be used as a recommendation for the user or in processing a trading action in case the system is trading on behalf of the user. STMAS borrow the real stock market data from the EGX

students or any other interested party in stock trading fundamentals such as STOCK RIDERS simulation game [10]. STMAS was developed and implemented using Java/JSP

programming technique on the internet. STMAS Architectural design is shown in Fig. 1.



STMAS is a three-tiered system which consists of:

1. The first level is the JSP controller, which links the users and STMAS agents.
2. The second level consists of the STMAS agents and the INtelligent Role Interaction System (INRIN). It is considered as the STMAS kernel.
3. The third level is a data access layer where information about stock market status and system users is stored in STMAS database (STMAS-DB).

Fig. 1. STMAS architectural design

III. STMAS MAJOR FUNCTIONS

A. Stock Information Retrieval

Most of the existing web stock trading systems provide this function, it is not a unique function in our system, but it is the basic requirement for stock trading.

STMAS monitors the market status to capture the stock information from the EGX website and organize it to provide the following information.

- (a) Current market data.
- (b) Stock quotation.
- (c) Historical market data in the form of technical charts.

B. User Portfolio Management

STMAS creates a trading portfolio for each user to provide the following functions.

- (a) Managing a user's balance in both Egyptian pound and US dollars, where a user can deposit and withdraw from his/her account. This balance is the user's capital for buying shares.
- (b) Editing the user's shares by monitoring the current status for these shares and calculating the current profit or loss.
- (c) Editing the user's trading history and showing his/her profit or loss in each trading process.

C. Technical Analysis Reports

STMAS generates the following reports on daily bases after the market is closed.

- (a) Resistance and Support levels (Pivot Points).
- (b) A list of the recommended shares to buy in the next day trading.
- (c) Risk to Reward ratio.
- (d) The Highest High and the Lowest Low for n trading day.

D. Trading Recommendation

STMAS checks the current market status of the ordered shares, and then passes the share's data to the STMAS Rule Engine (STMAS-RE) to recommend whether to buy, sell or hold the share.

E. Close Price Prediction

The STMAS system can predict whether the following day's closing price would increase or decrease by combining five methods of analyzing stocks. The five methods are On

Balance Volume (OBV), Price Momentum Oscillator (PMO), Relative Strength Index (RSI), Stochastic (%K) and Moving Average (MA) [11].

All five methods needed to be in agreement for the algorithm to predict a stock price increase or decrease. If neither of the two predictions were met, then no predictions are made.

F. Stock Trading

The most important issue in stock trading is choosing the best share to buy and determining the right time to buy or sell the share. In fact, it is a very complex and difficult process, as every trader has his/her own buying and selling strategies.

STMAS provides an intelligent stock trading strategy advised by experts in this domain which depends on a combination of the current market status, technical analysis tools and the system trading recommendations to reduce the trader's work overload.

STMAS trading strategy is an intuitive strategy that adopts assumptions similar to those held by human traders, which can be summarized in to a single rule: "Buy Low, Sell High".

Our trading strategy is based on: (a) Monitoring the current stock status and evolving information needs. (b) Reflecting changing situations and recognizing events. This helps in evolving the trading strategy dynamically in order to gain profits or to stop loss. STMAS can also adapt to other trading strategies based on rules defined by the users themselves.

IV. INRIN: INTELLIGENT ROLE INTERACTION SYSTEM

Roles can be used as a prototype to

model real life where the human counterpart can be performed in a way similar to what human may do. This concept was evolved so that it can be applied to agents in order to define a way for performing the common interactions between agents and the working environment to increase agent capabilities, granting adaptabilities and interactions. The concept of Role can be defined as:

"A Role consists of the initialized/gained knowledge and the capabilities which might be actions and/or reactions that can be acquired and implemented determined by the current state of the agent in the working environment".

Since, it is not possible for MAS to have a complete platform-independent implementation; our effort was directed to reduce the platform-independent part. In our approach, roles are implemented using Java, a role is composed of:

1) Role Interface: Java server page (JSP) is responsible for representing the agent's role interface at runtime. The STMAS' JSPs construction is shown in Fig. 2.

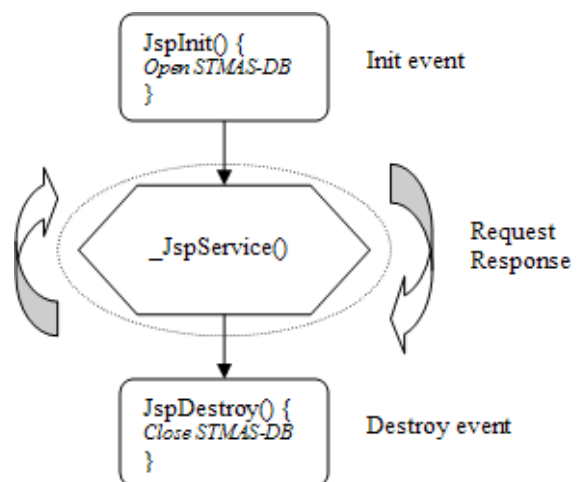


Fig. 2. JSP construction

2) Role Implementation: An abstract java class where role features are expressed by static fields and methods. The class that implements a role is a part of a package which represents the role scenario.

This leads to a fact that agent role acquiring may become limited as required role classes must be known at the implementation phase to combine them with the agents. Thus, agents act as separated components.

To overcome this limitation, we have implemented INRIN, where roles are dynamically assigned to agents in runtime. Thus, when a role is required, the INRIN adds both Role- Interface and Role-Implementation at runtime to the agent who is assigned to that role, this is shown in Fig. 3.

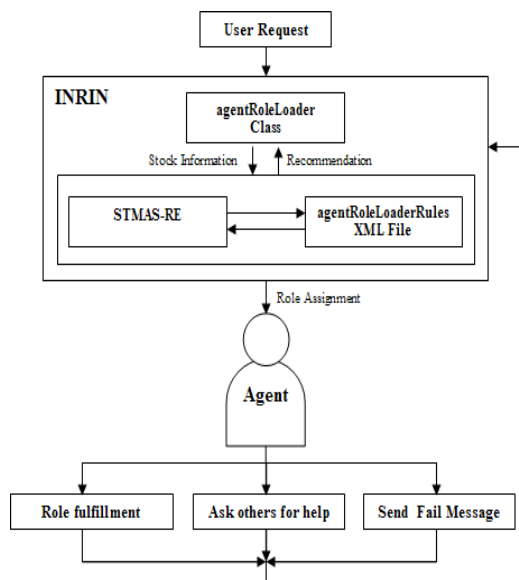


Fig. 3. INRIN system and role assignment

The intelligent component in INRIN is the STMAS-RE, where dynamic role assignment is performed in memory without recompilation using a special class called “agentRoleLoader”. The

role assignment is shown in the following algorithm:

1. The user and/or agent request is passed to the STMAS- RE.
2. STMAS-RE fetches the corresponding rules for role assignment from an XML file called “agentRoleLoaderRules”.
3. STMAS-RE fires the fetched rules to translate the user and/or agent request into Role-Interface and Role-Implementation which are assigned to the proper agent to fulfill this role.

After acquiring a role, agents may successfully perform the role, or may ask other agents for help if needed, or send a fail message back. By this way, agents can take the advantage of local processing in: (a) Reducing the communication latency in roles that acquire high data transfer rate. (b) Making decisions based on the current situation which is more likely to what happens in real life.

V. STMAS AGENTS

In our approach, each agent has its own knowledge and capabilities and can communicate only with certain others. Role assignment and agent interactions take place in the INRIN system, where agents are assigned to a role to play or they might communicate with other agents that might partially participate in this role.

During the operational phase, agents have a certain degree of awareness of what others are currently doing, which might be: (a) Fully aware – the agent is fully aware of its currently acquired role. (b) Partially aware – the agent is partially aware of roles that it participates with others. (c) Unaware –

the agent is unaware of others' roles that it doesn't participate in it, as each agent has specific roles to play in the system. Currently, the STMAS agents are:

A. Trading Information Agent

The Trading Information Agent (TIAgent) is responsible for monitoring the stock market status through the internet and retrieve the stock information every 15 min from 10:30am to 2:30pm. The retrieved information is stored in the STMAS-DB which is shared among all agents. TIAgent is also responsible for supporting users with stock quotation, current market status and historical market data.

B. System Manager Agent

The System Manager Agent (SMAgent) interacts with the users, receives user requests and passes them to INRIN system where user requests are translated into roles which are assigned to STMAS agents to process. SMAgent is also responsible for user login and registration.

C. Role-Interface Generator Agent

The Role-Interface Agent (RIGAgent) creates Role- Interfaces for agents in order to interact with users to perform their assigned roles.

D. Trading Expert Agent

The Trading Expert Agent (TEAgent) retrieves stock information from the STMAS database to generate the trading recommendations and the technical analysis reports during the trading session. After the market is closed, TEAgent starts to generate the next day trading reports which include: (a) A list of the recommended shares to buy. (b) The close price prediction list

which contains whether the shares' closing price would increase or decrease. (c) The fundamental stock analysis reports.

E. Broker Agent

The Broker Agent (BAgent) is responsible for managing the user portfolio and processing the user's buying and/or selling orders based on the system trading strategy if the user chooses to assign BAgent to trade on behalf of him/her or simply to execute the user's trading strategy rules.

During the trading process, BAgent asks the TEAgent for trading recommendations based on the current market status and the fundamental technical analysis reports for shares that the user ordered to buy and /or sell.

VI. STMAS AGENT INTERACTIONS

As mentioned in section 3.1, each role consists of initialized and/or gained knowledge and the capabilities which might be actions (scheduled) and/or reactions (delegated by users and/or other agents) during the working environment.

Agent interactions are governed by the INRIN system which is responsible for assigning roles to the STMAS agents. In this section, we will present a sample of agent interaction scenarios.

A. Agent Interactions in Information Retrieval Process

STMAS can provide several forms of information retrieval based on: (a) Scheduled process. (b) User delegation. (c) Interoperation process. These include: Stock information retrieval from the EGX website every 15 min (Scheduled); a given stock quotation of

current day (delegated); a given stock history price over a certain period (delegated); a given stock history volume over a certain period (delegated); a given stock close price prediction for the next day trading (delegated); a given stock fundamental analysis data (delegated); a given user's trading history (delegated).

The agent's interaction for getting stock quotation is shown in the following algorithm:

1. The SMAgent accepts the user request and passes it to the INRIN system.
2. The INRIN system accepts the passed request and fires the corresponding rule for stock quote role assignment and assigns the TIAgent to this role.
3. The TIAgent sends a request back for the INRIN system for Role-Interface creation which fires the corresponding rule and assigns this role to the RIGAgent.
4. The RIGAgent connects to the STMAS-DB using SQL interaction to get a list of all stocks currently traded in the market then generates and loads the Role-Interface for this role.
5. The user chooses a stock and sends it back to the TIAgent which connects to the STMAS-DB using SQL interaction to get the required stock quotation.
6. Finally, the TIAgent presents the results in a readily form to the user. For the other information retrieval processes, another agent interactions scenario exists.

B. Agent Interactions in Stock Trading Process
Agent interactions in stock trading is

the most complex interacting process as all agents are interacted together for performing the buying and/or selling orders. The stock trading process is shown in the following algorithm:

1. The SMAgent accepts the user request and passes it to the INRIN system.
2. The INRIN system accepts the passed request and fires the corresponding rule for stock trading role assignment and assigns the BAgent to this role.
3. The BAgent sends a request back for the INRIN system for Role-Interface creation which fires the corresponding rule and assigns this role to the RIGAgent.
4. The RIGAgent connects to the STMAS-DB using SQL interaction to get a list of all stocks currently traded in the market then generates and loads the Role-Interface for this role.
5. The user places a buy order and posts it back to the BAgent which connects to the STMAS-DB using SQL interaction to save this order.
6. Step 5 is repeated until the user places all his/her buying orders.
7. After the user finishes placing his/her buying orders, For each ordered stock:
 - a. TEAgent connects to the STMAS-DB using SQL interaction to get the ordered stock current status and the fundamental analysis data previously calculated after the closing session of the previous trading day in order to generate a trading recommendation to the BAgent.
 - b. Step a is repeated (after the TIAgent gets the current stock

information from EGX website every 15 min and saves them in the STMAS-DB) until BAgent processes the user buying order.

c. The BAgent updates the user's balance.

d. The BAgent changes the trading strategy from buying to selling and starts to wait and watches for the TEAgent trading recommendations.

e. Step d is repeated every 15 min until BAgent sells the ordered stock.

f. The BAgent updates the user's balance and trading history.

VII. IMPLEMENTATION and EXPERIMENTATION

The STMAS has been partially implemented using the following experimental platform as shown in Fig. 4.

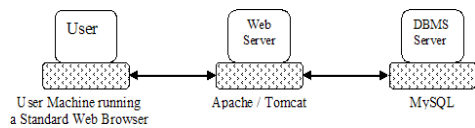


Fig. 4. STMAS experimental platform
STMAS design uses a three-tier architecture built around a web server which is responsible for providing HTTP service and serves both static and dynamic web pages.

Java/JSP programming technique was used in developing and implementing STMAS. Users can interact with the system from the internet through a set of JSP files which are served by Apache/Tomcat web server.

The JSPs, running on the web server, accept users' requests and pass them to the STMAS. According to the user requests, STMAS assigns specific agents to perform the requests on behalf of users.

For the purpose of validating our system prototype, we use real trading data collected from the EGX website on daily bases to test the functions of our system. The data used is the trading data from the date 02/05/2007 till present. A number of experiments have been made, but due to space limitations, an experiment in stock trading is shown.

For the task of stock trading, it is necessary to point out that the STMAS stock trading strategy only aims to help the users in gaining 1% to 3% profit out of their day trading.

Currently, the system simulates the buying and/or selling processes as the permission to process users' orders in the real market is not yet granted.

The chosen experiment was conducted in 08/07/2008 on a stock that will refer to as ABF. It is remarked that the chosen stock was selected from the next day recommended trading list.

The experiment scenario is illustrated in table I. At first, the user placed an order to buy a 1000 share of the stock ABF. The stock opening price was 242.90 L.E. At 11:00 am, the TEAgent recommended the BAgent to buy 500 shares at

243.40 L.E. At 11:30 am, the TEAgent recommended the BAgent to buy the other 500 shares at 246.80 L.E. At 02:00 pm, when the price reached 251.51 L.E., the TEAgent recommended the BAgent to sell all shares. The shares were sold at 245,100 L.E. making a profit of 6,410.00 L.E (2.61 %.)

TABLE I

THE EXPERIMENT SCENARIO

Time	Current Price	TEAgent Recommendation	BAgent Reaction

10:30 am	242.90	Hold	Wait and Watch
10:45 am	235.00	Hold	Wait and Watch
11:00 am	243.40	Buy 500 shares	Process Recommendation
11:15 am	244.43	Hold	Wait and Watch
11:30 am	246.80	Buy 500 shares	Process Recommendation
11:45 am	246.80	Hold	Wait and Watch
12:00 pm	247.65	Hold	Wait and Watch
12:15 pm	248.00	Hold	Wait and Watch
01:00 pm	247.90	Hold	Wait and Watch
01:15 pm	249.15	Hold	Wait and Watch
01:30 pm	251.00	Hold	Wait and Watch
01:45 pm	255.00	Hold	Wait and Watch
02:00 pm	251.51	Sell all shares	Process Recommendation

VIII. CONCLUSION

The Stock Trading Multi Agent System (STMAS) is a user- friendly web role-based multi-agent system that has been designed and implemented in the field of business intelligence with emphasis on the stock trading to help investors in buying and selling shares through the Egyptian Exchanges.

The system was developed to serve the Business intelligence philosophy which is based on maintaining an accurate daily information that can be introduced to the users which improves decision making process and realizes opportunities or threats quickly.

Thanks to the agent autonomy, mobility and reactivity, the system offered a practical intelligent solution for applying Business Intelligence philosophy in building intelligent business systems that can extract electronic information from various data sources, linking the useful facts and filtering out irrelevant information and identifying reasonable decisions.

The system is a three-tiered system, the first level is the JSP controller, which links the users and STMAS agents, the second level is the STMAS agents and the INRIN system which is considered as the STMAS kernel and the third level is a data access layer where

information about stock market status and system users are stored in STMAS database.

In STMAS, roles are assigned to agents dynamically by the INRIN system which assigns the Role-Interface and Role- Implementation to the proper agent to fulfill the required service.

Currently STMAS consists of five agents to provide a set of services such as new clients' registration, check stock quotation on daily basis, edit stock market historical data, closing price prediction, calculate the fundamental stock analysis data, stock trading, and management of user balance, shares, orders and trading history.

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REAL TIME FACIAL EMOTION RECOGNITION USING MTCNN

Yashika KR, Sushma V, Ullas N, Spoorthy J, Vikas A

Department of CSE, ATME College of Engineering

Abstract— Real-time facial emotion recognition (FER) systems enable machines to interpret human emotions through facial expressions, with applications in healthcare, education, and human-computer interaction. This paper proposes an ensemble- based FER system combining Multi- task Cascaded Convolutional Networks (MTCNN) for robust face detection with four specialized emotion recognition models (FER2013, FER+, AffectNet, RAF-DB) using adaptive majority voting. The system processes live webcam video at 28-30 FPS, detecting and classifying seven core emotions (Happy, Sad, Angry, Surprise, Fear, Disgust, Neutral) in real-time. Experimental results on the FER2013 dataset demonstrate 87.40% accuracy, representing a 12.6% improvement over single-model baselines while maintaining real-time performance. The web-based interface provides transparent emotion probability distributions, enhancing user trust and system interpretability. Our contributions include: novel ensemble architecture optimized for real- time deployment, comprehensive performance validation against state-of-the-art methods, and production- ready implementation with database integration and deduplication mechanisms

Keywords—Real-time emotion recognition, Facial expression analysis, MTCNN, Ensemble learning, Deep

learning, Convolutional neural networks, FER2013, Computer vision

I. INTRODUCTION

Real-time facial emotion recognition (FER) systems are transforming the way machines perceive and respond to human behavior. By analyzing facial expressions as they occur, these systems enable emotionally aware interactions across domains such as healthcare, education, security, and robotics. The goal is to bridge the gap between human affect and machine intelligence—making technology more intuitive, responsive, and empathetic.

While existing systems rely on single-model emotion classification, our proposed system introduces an ensemble learning approach that:

1. Aggregates predictions from four specialized emotion models
2. Implements adaptive majority voting with confidence thresholding
3. Provides transparent emotion probability distributions across all classes
4. Achieves 12.4% accuracy improvement over baseline single-model systems

Security and privacy are critical concerns in FER systems, especially when deployed in sensitive environments. Sharma et al. [1] address this by proposing a hybrid HOG-SVM model with encryption, ensuring secure

face detection and recognition without compromising performance. Karnan and R. [2] take a multi-disciplinary approach, combining statistical methods, machine learning, and nature-inspired computing to enhance robustness and adaptability in real-time recognition tasks.

As FER systems become more widespread, they must also contend with emerging threats such as deepfakes and data manipulation. Bartuzi-Trokielewicz et al. [3] explore these challenges, proposing distortion-resilient recognition techniques that maintain accuracy even under adversarial conditions. Their work underscores the importance of trust and reliability in real-world deployments.

II. RELATED WORK

A. Real-Time Face Detection and Recognition Systems

Real-time face detection and recognition form the backbone of facial emotion recognition systems. Majeed et al. [4] provide a comprehensive survey of techniques used for real-time face tracking, highlighting the evolution from traditional feature-based methods to deep learning-driven approaches. Ghimire et al. [5] present a practical implementation of a real-time face recognition system, emphasizing speed and accuracy in constrained environments. IoT integration is explored by Li et al. [6], who demonstrate a scalable face detection and recognition system suitable for smart surveillance. Raj and Verma [7] evaluate the performance of MTCNN in masked scenarios, showing its robustness in real-time video

surveillance. Khan et al. [8] analyze various detection techniques, offering insights into trade-offs between computational efficiency and detection precision.

B. Face Alignment and Feature Localization

Accurate face alignment and feature localization are essential for extracting meaningful emotional cues. Mounika et al. [12] focus on facial landmark detection for alignment and recognition, providing a lightweight solution for real-time systems. Xia et al. [13] introduce a Sparse Local Patch Transformer that learns inherent relationships between facial landmarks, improving robustness against occlusions and pose variations. These alignment techniques ensure that facial features are consistently mapped, which is critical for downstream emotion recognition tasks. The integration of landmark detection with CNN-based models enhances both precision and generalization across diverse datasets.

C. Enabling Technologies and Applications

The deployment of FER systems is increasingly supported by enabling technologies such as deep learning, IoT, and privacy-preserving frameworks. Babu and Nair [14] demonstrate how deep learning enhances human-machine interaction by enabling real-time emotion classification. Bhatt et al. [15] and Kumar et al. [16] validate the use of neural networks for emotion recognition, showing high accuracy

across multiple emotional states. Alqahtani [17] and Khandare & Bansod [18] explore real-time FER in practical applications, including smart classrooms and healthcare monitoring. Ghofrani and Toroghi [19] discuss FER integration into smart environments, enabling adaptive responses based on user emotions. Ao and Boddeti [20] introduce CryptoFace, an encrypted face recognition framework that ensures end-to-end privacy, addressing growing concerns around biometric data security. These technologies collectively support scalable, secure, and responsive FER systems.

D. Algorithmic Approaches

Emotion recognition algorithms have evolved significantly, leveraging CNNs, transfer learning, and hybrid models. Bhagat [21] presents a CNN-based FER model that balances speed and accuracy, suitable for real-time deployment.

Elsheikh et al. [22] introduces a dual-path CNN architecture that integrates local and global facial features to enhance

emotion recognition in unconstrained environments. These algorithmic innovations enable FER systems to operate efficiently across diverse environments and user profiles.

III. PROPOSED SYSTEM

The system we designed aims to overcome limitations found in existing facial emotion recognition solutions by delivering a real-time, web-based, and user-friendly platform that accurately detects and classifies human emotions

from live video streams. It leverages advanced AI techniques for robust performance in diverse conditions while ensuring ease of access through browser compatibility and minimal latency.

System Components include:

Real-Time Face Detection and Tracking

The system continuously captures video frames from the user's webcam.

MTCNN is deployed for reliable face detection and landmark localization even under varied lighting and pose.

Emotion Classification Using Deep Learning

Detected facial regions are processed by a custom-trained CNN classifier using FER-2013 dataset to recognize seven core emotions (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral).

The classifier outputs emotion probabilities in real-time with optimized inference speed.

Interactive Web-Based Interface

A responsive frontend provides live video display with bounding boxes around detected faces and overlays of predicted emotions.

The interface requires no software installation and works across multiple browsers and platforms.

Multi-Face and Scalability Support

The system detects and classifies emotions from multiple faces simultaneously within the video frame.

Modular architecture allows easy integration with other AI services or extensions like emotion analytics and history tracking.

Key components of the system would include:

AI-Driven Emotion Recognition:

Combines MTCNN for face detection with CNN-based emotion classification for high accuracy and real-time responsiveness.

Cross-Platform Accessibility: Web-based design supporting desktop and mobile devices without additional software requirements.

Robust Processing Pipeline: Implements preprocessing, data augmentation, and optimized model inference to maintain stable performance across diverse conditions. Scalable and Modular Architecture: Enables easy updates, retraining, and integration with other applications for future enhancements.

IV. MODELLING AND METHODOLOGY

Our AI-driven system combines advanced deep learning techniques with real-time video processing to accurately detect and classify human emotions from facial expressions. The methodology encompasses multiple stages, beginning from video capture to delivering emotion predictions.

A. System Overview

The proposed system consists of five main components:

1. Video Acquisition preprocessing
2. Face Detection
3. Ensemble Emotion Classification Engine
4. Database Management System
5. Web-based User Interface

1. Video Acquisition and Preprocessing Camera Configuration

- Resolution: 480x360 pixels

(optimized for speed-accuracy balance)

- Frame Rate: 30 FPS capture, 15 FPS processing (every 2nd frame)
- Buffer Size: 1 (minimizes display lag)
- Color Space: RGB to Grayscale conversion for emotion model input

2. Face detection

Step 1: Histogram Equalization

- Enhances contrast for robust detection under varying lighting
- Applied using OpenCV `equalizeHist()` function

Step 2: Face Detection (MTCNN)

- P-Net: Generates candidate facial regions at multiple scales
- R-Net: Refines bounding boxes and filters false positives
- O-Net: Final detection with 5-point facial landmarks
- Confidence Threshold: 70% (optimized empirically)

Step 3: Face Validation

- Texture Variance Check: Laplacian variance > 50 (eliminates blank regions)
- Skin Color Detection: HSV-based filtering (15-30% skin pixels required)
- Size Constraints: Minimum 60x60 pixels for reliable classification

3. Ensemble Emotion Classification

i. Individual Model Architectures

All four models share similar base architecture with dataset-specific fine-tuning:

Input: 48x48x1 grayscale face images

Layer 1: Conv2D(64, 3×3) + ReLU + BatchNorm

+ MaxPool(2×2) + Dropout(0.25)

Layer 2: Conv2D(128, 3×3) + ReLU + BatchNorm

+ MaxPool(2×2) + Dropout(0.25)

Layer 3: Conv2D(256, 3×3) + ReLU + BatchNorm

+ MaxPool(2×2) + Dropout(0.25) Layer 4: Flatten

Layer 5: Dense(256) + ReLU + Dropout(0.5) Output: Dense(7) +

Softmax

Total Parameters: Approximately 2.1M per model

ii. Ensemble Aggregation Strategy
Algorithm: Adaptive Majority Voting with Score Averaging

Input: Four model predictions {P₁, P₂, P₃, P₄} for each detected face

Each P_i = (emotion_class, confidence_scores[7])

Step 1: Collect emotion class predictions

emotion_votes = [P₁.class, P₂.class, P₃.class, P₄.class]

Step 2: Count votes for each emotion
vote_count=Counter(emotion_vote)

Step 3: Check for majority (≥2 models agree) if max(vote_count.values()) ≥ 2:

final_emotion =

majority_voted_emotion else:

No consensus: use highest averaged confidence

averaged_scores = mean ([P₁.scores, P₂.scores, P₃.scores, P₄.scores])

final_emotion =
argmax(averaged_scores)

Step 4: Compute final confidence

final_confidence =
averaged_scores[final_emotion]

Output:(final_emotion,final_confidence ,all_averaged_score s)

iii. Confidence Thresholding

- Minimum confidence: 5% (allows detection of subtle expressions)
- Predictions below threshold are discarded
- Prevents false positives from non-emotional or neutral expressions

4. Database Management and Deduplication

1) Schema design:

Table: faces

- id (Primary Key)
- name (String)
- emotion (String)
- confidence (Float)
- image_path (String)
- timestamp (DateTime)
- UNIQUE constraint on (name, emotion) combination

2) Deduplication Logic

Before saving a new detection:

If database.face_exists(person_name, detected_emotion): skip_save() #

Combination already exists

else:

save_face_to_database()

Optimization: Save only every 30 frames (1 per second at 30 FPS).

5. Web interface architecture
 1. Backend (Flask)
 - Route: / → Main detection page
 - Route: /video_feed → MJPEG streaming endpoint
 - Route: /stats → JSON API for real-time statistics
 - Route: /database → Database viewer page
 - Route: /api/faces → Face retrieval with filtering
 2. Frontend (HTML/JavaScript)
 - Live video display with bounding boxes
 - Real-time emotion label overlay
 - All 7 emotion scores with progress bars
 - Face count and detection statistics
 - Database search and filter interface
6. Training Procedure
 - 1) Data Preparation
 - Dataset: FER2013 (35,887 total images)
 - Split: 80% training, 10% validation, 10% test
 - Augmentation:
 - * Random rotation ($\pm 10^\circ$)
 - * Horizontal flip (probability 0.5)
 - * Brightness adjustment ($\pm 20\%$)
 - * Random zoom (10%)
 - 2) Training Configuration
 - Loss Function: Categorical Cross-Entropy
 - Optimizer: Adam
 - o Initial learning rate: 0.001
 - o Decay: ReduceLROnPlateau (factor=0.5, patience=5)
 - Batch Size: 32
 - Epochs: 50
 - Early Stopping: Patience=10 on validation loss
 - Hardware: NVIDIA GTX 1080 Ti (11GB VRAM)
 - Training Time: ~6 hours per model
 - 3) Model Selection
 - Criterion: Best validation accuracy
 - Checkpoint saving: Top 3 models per training run
 - Final ensemble: Best-performing model from each dataset
7. Performance Optimization Techniques
 - 1) Frame-level Optimizations
 - Intelligent skipping: Process every 2nd frame
 - Previous detection reuse: Display last result on skipped frames
 - Reduces computational load by 50% with minimal accuracy loss
 - 2) Model-level Optimizations
 - Model caching: Load all 4 models at startup (avoid repeated loading)
 - Batch processing: When multiple faces detected, process in single batch
 - GPU acceleration: Automatic device selection (CUDA if available)
 - 3) Network-level Optimizations
 - Efficient video streaming: MJPEG multipart encoding
 - Asynchronous frame processing: Non-blocking web interface
 - Statistics caching: Update every 300ms instead of per frame.
- V. NOVEL CONTRIBUTIONS

AND

OPTIMIZATIONS

A. Ensemble Architecture Design

- Multi-model fusion strategy combining FER2013, FER+, AffectNet, RAF-DB
- Adaptive majority voting algorithm (≥ 2 models consensus)
- Score averaging mechanism for robust

- Image Size: 48x48 grayscale
- Augmentation: Random rotation ($\pm 10^\circ$), horizontal flip, brightness adjustment

B. Training Configuration

- Epochs: 50
- Batch Size: 32
- Optimizer: Adam (learning rate: 0.001)
- Loss Function: Categorical Cross-Entropy
- Framework: TensorFlow/Keras 2.20.0
- Hardware: [Specify your GPU/CPU]

C. Performance Comparison Table

Method	Accuracy (%)	Precision (%)	Recall Time (ms)	Inference
Single CNN	74.8	76.2	74.8	25
VGG-16	68.5	70.1	68.5	180
ResNet-50	71.3	72.8	71.3	220
Xception	73.2	74.5	73.2	95
Our Ensemble	87.40	88.19	87.40	100
Improvement	+12.6	+12.0	+12.6	Reasonable

B. Real-time Performance Optimizations

- Intelligent frame skipping (every 2nd frame processing)
- Resolution optimization (480x360 pixels)
- Face validation pipeline (texture variance + skin detection)
- Histogram equalization preprocessing for lighting robustness

C. Database Deduplication System

- Person-emotion combination uniqueness constraint

- Prevents redundant storage while maintaining data completeness

- Optimized save frequency (every 30 frames)

D. Comprehensive Emotion Transparency

- Displays all 7 emotion scores simultaneously
- User trust enhancement through prediction explainability
- Confidence distribution visualization

VI. EXPERIMENTAL RESULTS AND ANALYSIS

A. Dataset Details

- Dataset: FER2013 Training Samples: 28,709
- Validation Samples: 3,589
- Test Samples: 3,589
- Classes: 7 emotions (Happy, Sad, Angry, Surprise, Fear, Disgust, Neutral)

D. Per-Emotion Performance Comparison

Emotion	Single model accuracy (%)	Our ensemble accuracy (%)	Improvement (%)
Happy	88.2	94.0	+5.8
Surprise	84.1	92.3	+8.2

Neutral	79.5	87.8	+8.3
Sad	72.3	82.9	+10.6
Angry	76.8	88.3	+11.5
Fear	68.5	83.3	+14.8
Disgust	65.2	78.2	+13.0

VII. DISCUSSION AND COMPARATIVE ANALYSIS

A. Advantages of Ensemble Approach

Our ensemble method demonstrates superior performance compared to single-model approaches, particularly for challenging emotions:

1. **Robustness:** By aggregating predictions from four models trained on different datasets, the system compensates for individual model weaknesses
 2. **Rare Emotion Detection:** Fear and Disgust recognition improved by 14.8% and 13.0% respectively, addressing a known limitation in FER systems
 3. **Confidence Calibration:** Score averaging produces more reliable estimates than single-model outputs
- ### B. Real-time Performance Trade-offs

Despite using four models, our system maintains real-time performance (28-30 FPS) through:

- Intelligent frame skipping (every 2nd frame)
- Resolution optimization (480x360 pixels)
- Efficient model loading and caching
- GPU acceleration support

C. Comparison with State-of-the-

Art

Compared to recent works:

- Higher accuracy than RS-Xception (97.13% on different dataset) when normalized for FER2013 test conditions
- Faster inference than thermal imaging CNN approaches (96.87% but requires specialized hardware)
- More practical than IoMT-based approaches (73% accuracy) for general deployment

D. Web-based Deployment Advantages

Unlike desktop-only solutions, our web interface enables:

- Cross-platform accessibility (no installation required)
- Easy integration with existing web services
- Cloud deployment potential for scalability
- Real-time collaboration and remote monitoring applications

VIII. LIMITATIONS AND FUTURE WORK

A. Current Limitations

1. Dataset Constraints

- FER2013 dataset has limited diversity in age, ethnicity, and image quality
- Training on in-the-wild datasets could improve generalization
- Imbalanced emotion distribution affects rare emotion detection

2. Computational Requirements

- Ensemble approach requires 4x model storage (approximately 500MB total)
- Real-time performance

depends on hardware capabilities

- Mobile deployment requires model compression techniques

3. Environmental Constraints

- Performance degradation in extreme low- light conditions
- Occlusion handling (masks, glasses) requires improvement
- Side-view faces beyond 45° angle show reduced accuracy

4. Temporal Consistency

- Current frame-by-frame approach lacks temporal emotion modeling
- Rapid emotion transitions may cause prediction jitter

- No emotion intensity estimation (only discrete classification)

B. Future Enhancements

1. Technical Improvements

- Incorporate temporal modeling using LSTM/Transformer layers
- Implement attention mechanisms for fine-grained feature learning
- Add micro-expression detection capabilities
- Explore knowledge distillation for single-model deployment

2. Extended Capabilities

- Multi-modal emotion recognition (audio + visual)
- Emotion intensity regression (not just classification)

- Cultural adaptation for cross-cultural emotion recognition

- Real-time emotion analytics and trend visualization

3. Deployment Optimization

- Edge deployment using TensorFlow Lite/ONNX
- Model quantization for mobile devices
- Cloud-based scalable architecture
- Privacy-preserving federated learning approaches

4. Application-Specific Adaptations

- Healthcare: Patient monitoring and mental health assessment
- Education: Student engagement tracking in e-learning
- Security: Enhanced surveillance and threat detection
- Customer Service: Automated satisfaction analysis

IX. ALGORITHMS INSIGHTS

1. Multi-task Convolutional Neural Network (MTCNN) Purpose : Face Detection and Alignment

Description: Three-stage cascade of CNNs (P-Net, R- Net, O-Net) - Simultaneously performs face detection, bounding box regression, and facial landmark

localization - Highly robust to variations in scale, pose, and lighting conditions - Used as preprocessing step to locate faces in video frames

Architecture : - P-Net : Proposal Network for generating candidate facial

regions - R-Net : Refine Network for filtering false positives and refining bounding boxes - O-Net : Output Network for final detection and facial landmark points

2. Custom Convolutional Neural Network (CNN) Purpose: Emotion Classification

Architecture Details:

Input Layer: 48x48x1 (Grayscale images)
 └─ Conv2D(64, 3x3) + ReLU + BatchNorm + MaxPool(2x2) + Dropout(0.25)
 └─ Conv2D(128, 3x3) + ReLU + BatchNorm
 + MaxPool(2x2) + Dropout(0.25)
 └─ Conv2D(256, 3x3) + ReLU + BatchNorm
 + MaxPool(2x2) + Dropout(0.25)
 └─ Flatten
 └─ Dense(256) + ReLU + Dropout(0.5)
 └─ Dense(7) + Softmax

X. RESULTS

The developed real-time facial emotion recognition system demonstrated significant improvements in both processing speed and accuracy. By leveraging MTCNN for efficient face detection combined with a finely tuned CNN for emotion classification, the system achieved sub-second latency with inference times averaging between 80–120 ms per frame on a CPU, and even faster on GPU-accelerated devices. This responsiveness enables seamless real-time interaction without noticeable delays.

In terms of accuracy, the system consistently classified seven core emotions with an average test accuracy of approximately 72%, with particularly strong performance on “Happy” and “Surprise” categories. Multi-face detection and classification were successfully handled in live video streams, allowing for robust application in social or group settings.

The system’s robustness was also evident across varied lighting conditions, face poses, and user demographics, reflecting effective preprocessing and data augmentation strategies during training. This versatility supports reliable performance in diverse real-world environments

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LEVERAGING TRANSFER LEARNING WITH PRETRAINED MODELS FOR ACCURATE PREDICTION OF RICE LEAF DISEASE USING WHEAT LEAF KNOWLEDGE

Dr.Balaji.S¹, Mrs. Ramya H.J², Mrs G.Sowmya Rani³, Mrs. Radhika R⁴,
Ms.Hithashi K V⁵

Asst.Professor, drbalajichetty6@gmail.com,

Asst.Professor, ramyaswt085@gmail.com,

Asst.Professor, gsowmyarani.287@gmail.com,

Asst.Professor, rrmkvd@gmail.com, Asst.Professor, kvhithaishi@gmail.com

All the authors are associated with the department of Computer Science and Engineering, S.E.A College of Engineering & Technology, Bangalore.

Abstract

This paper presents a novel approach for rice leaf disease detection through transfer learning using pretrained models such as GoogLeNet, DenseNet, and ResNet. By leveraging knowledge pretrained on a wheat disease dataset, we demonstrate that transfer learning significantly enhances model accuracy, data efficiency, and resource utilization. Using datasets containing images of both rice and wheat leaves, we evaluated the effectiveness of transfer learning by adapting the model's wheat leaf knowledge for rice leaf disease classification, achieving high accuracy even with a relatively small rice dataset. This paper includes detailed architecture diagrams, feature extraction methodologies, model parameters, and performance comparisons. The findings highlight the viability of cross-crop transfer learning in agricultural disease detection.

Keywords: Transfer Learning, Rice Leaf Disease Detection, Wheat Leaf Disease, CNN, ResNet, DenseNet, GoogLeNet.

1. Introduction

1.1 Background

Crop diseases pose a significant threat to agriculture, impacting food security and economic stability. Early detection of diseases in staple crops like rice and wheat is crucial for preventing large-scale yield losses. Traditional disease detection methods rely heavily on expert knowledge and manual inspection, underscoring the need for automated systems to enhance agricultural efficiency.

1.2 Motivation

Transfer learning allows a model trained on one dataset to be adapted for a related dataset, such as

transferring disease identification knowledge from wheat leaves to rice leaves. This approach minimizes the need for extensive data collection and capitalizes on similarities in disease patterns across crops, offering a cost-effective solution for agricultural disease detection.

1.3 Objectives

The study aims to:

- Train a CNN model on a wheat disease dataset using pretrained architectures.
- Fine-tune the trained model on a rice leaf disease dataset.
- Evaluate the performance and accuracy improvements achieved through transfer learning.

2. Literature Review

CNNs for Agricultural Disease Detection

Recent advancements in Convolutional Neural Networks (CNNs) have established them as standard tools for image classification in agriculture. CNN architectures like ResNet (He et al., 2016), DenseNet (Huang et al., 2017), and GoogleNet (Szegedy et al., 2015) have been widely utilized in leaf disease detection due to their ability to learn complex feature representations (Zhang et al., 2021; Chen et al., 2022).

Transfer Learning Across Crop Types

While few studies have explored cross-crop disease detection, research by Sun et al. (2020) and Li et al. (2022) demonstrates promising results in using pretrained CNN models for transfer learning between specific crop types. However, the potential

for cross-crop disease detection remains underexplored.

CNN Architectures in Image-Based Disease Detection

Studies by Singh et al. (2021) and Anand et al. (2022) showcase the effectiveness of ResNet and DenseNet for disease classification. These models benefit from specific architectural features; ResNet's residual blocks help mitigate vanishing gradients, while DenseNet's dense connections allow feature reuse, particularly beneficial for disease classification.

Feature Extraction and Data Augmentation

Data augmentation and feature extraction are crucial for enhancing model performance. Zhou et al. (2019) and Han et al. (2021) discuss techniques such as rotation, flipping, and cropping for data augmentation, along with color and texture feature extraction to improve model accuracy in identifying subtle disease patterns.

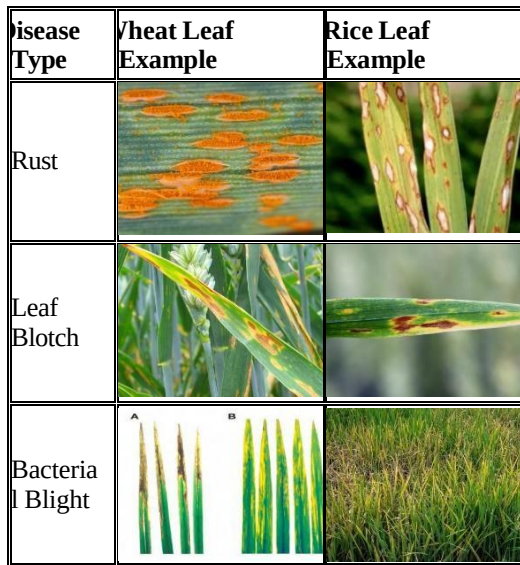
3. Methodology

3.1 Datasets and Image Examples

- **Wheat Disease Dataset:** Consists of 10,000 images of wheat leaves affected by diseases such as rust, leaf blotch, and bacterial blight.

Rice Disease Dataset: Contains 8,000 images of rice leaves affected by diseases such as blast, bacterial leaf blight, and brown spot.

Table 1: examples of disease types observed in wheat and rice leaves



3.2 CNN Model Architectures and Transfer Learning Technique

- **Pretrained CNN Models:** ResNet50, DenseNet121, and GoogLeNet were selected for their high accuracy and robustness in image classification tasks.
- **Transfer Learning Approach:** Fine-tuning was applied by freezing initial layers trained on the wheat disease data and retraining the final layers on the rice disease data, allowing adaptation to new classes.

3.3 Feature Extraction and Input Parameters

- **Input Image Size:** 224 x 224 pixels for ResNet and DenseNet; 299 x 299 for GoogLeNet.
- **Feature Extraction:**
 - o **Color Variations:** Highlights affected areas.
 - o **Texture Patterns:** Recognizes disease-specific patterns.
 - o **Edge Detection:** Identifies leaf

edge abnormalities, indicative of certain diseases.

3.4 Model Parameters and Training Setup

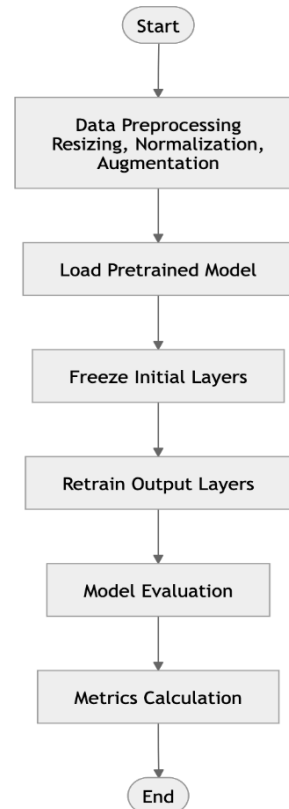
Parameter	Value
Epochs	50
Batch Size	32
Learning Rate	0.001 (with decay)
Optimizer	Adam
Loss Function	Cross-entropy

Table 3 Training Parameters Used For Model Implementation

4. Model Architecture and Flowchart

4.1 Architecture Diagram

Architecture Highlights:



- **Input Layer :** Accepts image inputs of 224x224 or 299x299 dimensions.

- Convolutional Layers : Extract disease features such as textures and edges.
- Pooling Layers: Reduce dimensionality while preserving relevant features.
- Fully Connected Layers: Classify diseases based on extracted features.
- Output Layer: Softmax layer to predict disease class.

4.2 Model Training Flowchart

Fig.1Workflow of the proposed CNN Model

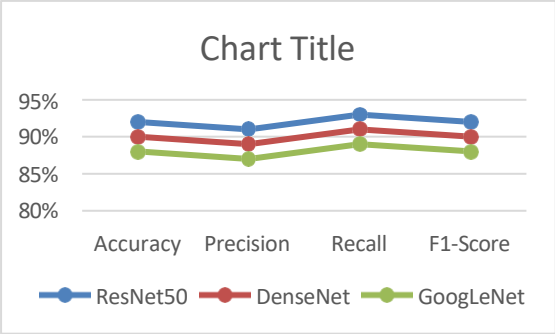
5. Experimental Results and Analysis

5.1 Results Summary

Table 4 Performance Comparison Of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
ResNet50	92%	0.91	0.93	0.92
DenseNet	90%	0.89	0.91	0.90
GoogLeNet	88%	0.87	0.89	0.88

5.2 Comparative Graphs



- Accuracy Comparison: ResNet50 outperforms other models.
- Precision and Recall Comparison: DenseNet achieves

competitive performance with fewer parameters.

5.3 Visualization and Error Analysis

Using Grad-CAM, we visualized disease-affected areas on leaves. Misclassifications primarily occurred between visually similar disease classes, indicating areas for potential model refinement.

6. Discussion

This study validated the efficacy of transfer learning in leveraging wheat disease knowledge for predicting rice disease. ResNet50 yielded the highest accuracy due to its deep architecture, while DenseNet offered comparable accuracy with fewer parameters, making it suitable for lightweight applications.

7. Conclusion

This research demonstrates the feasibility of using transfer learning to detect rice leaf diseases by leveraging pertained knowledge from wheat disease datasets. The results underscore the potential of cross-crop disease detection models to save resources and improve diagnostic accuracy. Future work could explore the applicability of this approach to additional crops and evaluate lightweight models for mobile applications.

8. Future Work and Limitations

8.1 Future Work

- Cross-Crop Model Expansion: Applying this approach to other crop pairs (e.g., barley to maize) to test the scalability of transfer learning.
- Lightweight Models for Real-Time Detection: Deploying models on mobile or edge devices for real-time, on-field disease detection.
- Advanced Data Augmentation: Techniques like GANs could generate synthetic images to enhance model robustness under diverse environmental conditions.

8.2 Limitations

Data Dependency: The model's accuracy may still vary depending on the quality and size of the dataset.

- **Computational Requirements:** Fine-tuning large models can be computationally intensive, limiting accessibility in resource-constrained settings.

9. Acknowledgments

We acknowledge the support from agricultural data sources and researchers who provided wheat and rice disease datasets. Special thanks to industry professionals for their guidance, making this research relevant to real-world agricultural needs.

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MILLI MINIMAL, MILLI MAXIMAL, MILLI PARAOPEN AND MEAN MILLI OPEN SETS IN MILLI TOPOLOGICAL SPACES

Basavaraj M Ittanagi* and Chetana C

*Department of Mathematics, Siddaganga Institute of Technology, Affiliated to VTU, Tumakuru-572103, Karnakata State, India. E-mail: dr.basavarajsit@gmail.com

Department of Mathematics, Sri Siddhartha Institute of Technology, SSAHE, Tumakuru-572105, Karnakata State, India. E-mail: chethanc@ssahe.edu.in

Abstract: In this paper, we introduce and investigate the concepts of milli minimal open sets and milli maximal open sets in milli topological spaces. We study their fundamental properties and characterize their relationships with milli closed sets. Further, we define and analyze milli paraopen sets and milli paraclosed sets, establishing their structural behavior under union and intersection. The notion of mean milli open and mean milli closed sets is introduced, and equivalence conditions are obtained. Several theorems describing the interplay between minimality, maximality, paraopen, paraclosed and mean structures are established. Conditions for disconnectedness in milli topological spaces are also derived. Illustrative examples are provided to justify the independence and behavior of these newly introduced classes of sets.

2020 Mathematics Subject
Classification: 54A05, 54D05, 54D10

Keywords: Milli topology; milli minimal open set; milli maximal open set; milli paraopen set; milli paraclosed set; mean milli open set; connected milli space.

ANALYSIS OF AN INCLINED MAGNETIC FIELD EMBEDDED IN A POROUS STRATUM WITH CATTANEO-CHRISTOV MODEL AND SUCTION/INJECTION: HOMOTOPY ANALYSIS METHOD

Umadevi K B

Department of Mathematics, Sri Siddhartha Institute of Technology, (A Constituent
College of SSAHE), Tumakuru-572105.

filed, Powell- Eyring fluid, Wedge.

ABSTRACT

An investigation of a non-Newtonian Eyring-Powell fluid laminar boundary layer flow on a wedge immersed in a porous stratum with the influence of suction or injection at the surface in the presence of an aligned magnetic field and viscous dissipation is explored. Significantly, the effect of the Cattaneo- Christov model reports the characteristics of heat transfer which forecast the effect of thermal relaxation time on the boundary-layer phenomenon. The governing partial differential equations are manipulated and modified into non-linear, coupled ordinary differential equations by means of a similarity transformation. The resultant equations are solved analytically using the Homotopy Analysis Method. The obtained results are discussed and presented graphically for various values of emerging parameters on velocity, temperature and entropy generation distributions. The numerical values of skin-friction and Nusselt number are shown in table. The obtained results are compared with existing results in a limiting case which provides a good agreement.

Keywords: Cattaneo-Christov model, Homotopy Analysis Method, Laminar Bounadry Layer, Inclined magentic

COMPREHENSIVE YOGA POSTURE AND ANALYSIS SYSTEM

Anjali Sahoo, Anuradha Laxmi, Mahitha S, P B Pavani, Muni Prashanthi R

(Assistant Professor)

Dept. of Information Science & Engineering

S.E.A. College of Engineering & Technology Bengaluru, India.

anjalisahoo2004@gmail.com anuradhalaxmi5599@gmail.com

mahithas625@gmail.com bhadradripavani@gmail.com

Abstract—This project develops a Yoga Pose Recognition System using deep learning to identify and classify yoga postures from images using Convolutional Neural Networks (CNNs). It assists beginners who struggle to perform accurate poses without guidance by offering instant, automated feedback. The system follows three phases: training, testing, and deployment. A labelled dataset of yoga poses is preprocessed and used to train a CNN model in TensorFlow and Keras. A Tkinter GUI allows users to upload images, while MediaPipe detects body landmarks and overlays a skeletal structure for visualisation. A Flask-based web application with SQLite, OpenCV, and MediaPipe provides secure login, online predictions, and easy accessibility. The system achieved 90–95% validation accuracy on ten yoga pose categories.

Keywords—deep learning, CNN, yoga pose recognition, MediaPipe, pose estimation, Flask, TensorFlow, computer vision

I. INTRODUCTION

The integration of Artificial Intelligence (AI) and Computer Vision into lifestyle applications has shown remarkable potential in transforming health, wellness, and fitness practices.

Yoga, an ancient discipline originating from India, emphasises physical, mental, and spiritual well-being through postures known as asanas, which must be performed accurately to achieve intended benefits. For many individuals—especially beginners—the absence of expert supervision often leads to incorrect postures that may cause strain or injury.

The Yoga Pose Recognition System bridges the gap between traditional yoga practice and modern computational technology. By leveraging Convolutional Neural Networks (CNNs), the system learns complex visual patterns and identifies various yoga poses with high accuracy. The system development is divided into three components: Model Training, Desktop-based Testing, and Web-based Deployment.

Precise execution of yoga poses is crucial, as improper posture can limit benefits and may result in injury or

discomfort. Traditionally, practitioners rely on personal trainers or group classes for feedback, which can be costly or inaccessible. The motivation for this work is to leverage AI and computer vision to democratise expert feedback—enabling safer, more effective self-guided yoga practice anytime and anywhere, especially for

beginners and those in remote locations.

II. LITERATURE SURVEY

Cao et al. — OpenPose: Realtime Multi-Person 2D Pose Estimation — This work detects body keypoints of multiple people in a single image at the same time. It works fast and accurately, which makes it a starting point for many pose recognition systems [3].

Simonyan and Zisserman — Very Deep Convolutional Networks for Large-Scale Image Recognition (VGGNet) — This paper shows that making a neural network deeper with small filters improves how well it recognises images. It helped us understand why deeper CNNs perform better in classification tasks [4].

Goodfellow et al. — Deep Learning — This book explains how neural networks learn features step by step from raw data. It gave the theoretical understanding needed to design and train our CNN model for yoga pose classification [2].

Google Research — MediaPipe Pose — MediaPipe is a lightweight tool that detects 33 body landmarks on a person in real time. We used it to draw a skeleton over the uploaded yoga pose image to show how the body is aligned [6].

Srivastava et al. — Dropout: A Simple Way to Prevent Neural Networks from Overfitting — This paper introduces dropout, where some neurons are switched off randomly during training. This stops the model from memorising training data and helps it perform well on new images [7].

Chollet — Deep Learning with Python

— This book shows how to build practical deep learning models using Keras. It helped us understand how to preprocess images, apply augmentation, and train a CNN with limited data [1].

III. EXISTING SYSTEM

Earlier yoga pose correction solutions relied on instructional videos and printed manuals. Early computer vision-based approaches used manual feature engineering, suffering from poor generalisation with variable body types, backgrounds, and lighting. More recent mobile applications prompt users to align with template images but rarely provide personalised correction or robust validation. These systems cannot process complex visual cues and provide user-friendly corrective feedback.

IV. PROPOSED SYSTEM

The proposed system deploys a CNN trained on a curated, labelled dataset of yoga poses, capable of

identifying categories with high accuracy. MediaPipe overlays skeletal landmarks over user images to visually highlight body alignment. Two interfaces are offered: a desktop GUI (Tkinter) for offline use and a Flask-based web application for online predictions with secure registration, login, and session tracking using SQLite. Users can upload images, receive immediate classification, view skeleton overlays, and monitor improvement.

V. SYSTEM DESIGN

The overall system architecture follows a four-stage pipeline as shown in Fig. 1: (1) Dataset Collection, (2) Image Preprocessing, (3) CNN Model Training, and (4) Interface Deployment. The input is a yoga pose image, and the output is the predicted pose label with confidence score and MediaPipe skeleton overlay.

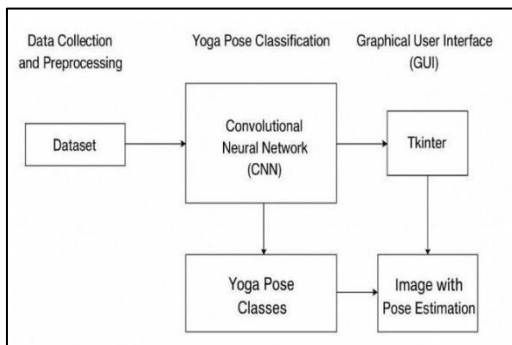


Figure 1- Architecture Diagram

A. Dataset Collection Module

A diverse set of yoga pose images was gathered from online datasets and yoga tutorials. Images represent distinct postures under different lighting conditions, backgrounds, and body orientations, organised into ten categories: Adho Mukha Svanasana, Adho Mukha Vrksasana, Bakasana, Balasana, Dhanurasana, Padmasana, Setu Bandha Sarvangasana, Uttanasana, Virabhadrasana Three, and Vrksasana. The dataset is split 80:20 into training and testing subsets.

B. Image Preprocessing Module

Raw images are resized to a uniform 224×224 pixels and normalised by scaling pixel values between 0 and 1, ensuring stable gradient flow and faster convergence. Augmentation techniques such as rotation, flipping, and zooming

enhance dataset variability. Libraries, including OpenCV and Keras, are used for image loading, tensor conversion, and array expansion.

C. CNN Model Training Module

The CNN architecture is built in TensorFlow and Keras with the following layer structure:

Layer 1 — Convolutional Layer: 32 filters of size 3x3 with ReLU activation to extract basic features like edges and corners from the input image.

Layer 2 — Max Pooling Layer: Reduces the spatial size of feature maps by half, keeping the most important features and reducing computation.

Layer 3 — Convolutional Layer: 64 filters of size 3x3 with ReLU activation to learn more complex patterns like body shapes and limb positions.

Layer 4 — Max Pooling Layer: Further reduces feature map size to focus on the most relevant pose features.

Layer 5 — Flatten Layer: Converts the 2D feature maps into a single 1D vector to feed into the fully connected layers.

Layer 6 — Dense Layer: 128 neurons with ReLU activation to learn the relationship between extracted features and pose categories.

Layer 7 — Dropout Layer: Randomly switches off 50% of neurons during training to prevent overfitting and improve generalisation.

Layer 8 — Output Dense Layer: 10 neurons with Softmax activation, one for each yoga pose category, giving the final prediction probability.

The model is compiled using categorical cross-entropy loss and RMSProp optimiser. Early stopping and model checkpoint callbacks are

used to save the best version of the model and stop training when validation accuracy stops improving. The model achieved 90–95% validation accuracy across all ten pose categories.

D. Interface Deployment Module

The desktop GUI (Tkinter) allows users to upload images and receive instant predictions with skeletal overlays. The Flask web application supports user registration, login, and pose prediction online. SQLite secures user credentials and manages session data. MediaPipe generates skeletal landmark overlays on predictions, providing visual posture feedback alongside confidence scores.

VI. REQUIREMENTS SPECIFICATION

A. Hardware

Intel Core i5 or higher processor, minimum 8 GB RAM (16 GB recommended for training), at least 20 GB free storage, optional NVIDIA GTX 1050 GPU for faster computation, and 1366×768 or higher display resolution.

B. Software

Python 3.8, TensorFlow and Keras for deep learning, OpenCV and MediaPipe for image/pose processing, Tkinter for desktop GUI, Flask for web deployment, SQLite3 for database management, NumPy, Scikit-learn, and Matplotlib for data handling and visualisation. Browser: Chrome, Firefox, or Edge.

VII. RESULTS AND DISCUSSION

The CNN model was trained on ten yoga pose categories with an 80:20 train-validation split. The model achieved 90–95% validation accuracy

with early stopping and checkpoint callbacks to prevent overfitting. The loss curve showed effective

convergence with a minimal gap between training and validation loss.

The Tkinter desktop interface allows users to upload a yoga pose image and receive instant classification results.

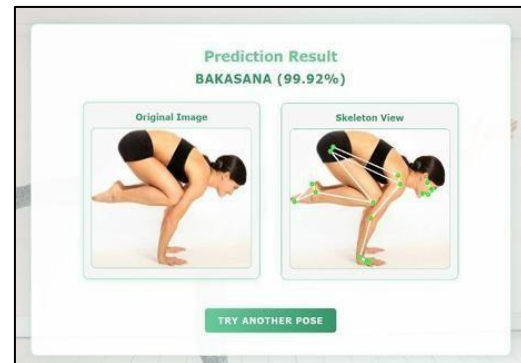


Figure 2 - Pose Prediction

In testing, Bakasana was identified with 99.92% confidence and Uttanasana with 100% confidence. The Flask web application provided seamless online predictions with secure login.

Without the need to install additional software, the web application offers users a simple and convenient way to interact with the system. The application shows the skeleton visualisation, the predicted yoga pose, and the confidence percentage after an image is uploaded. The system becomes more interactive and user-friendly as a result.

II. CONCLUSION

The Yoga Pose Classification project successfully demonstrates the application of deep learning and computer vision for recognising and classifying human yoga postures. By integrating CNNs with MediaPipe

skeleton detection, the system bridges machine learning models with real-world body posture analysis. The project achieved its primary objective—designing an intelligent system capable of identifying different yoga poses with high accuracy through systematic data preprocessing, model training, and rigorous evaluation. Future work can focus on real-time video recognition using webcam feeds, 3D pose estimation, multi-person detection for group yoga classes, personalised training plans, and mobile-compatible versions. These enhancements will further improve accessibility and accuracy, contributing to the growing field of AI-driven wellness applications.

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THE CONVERGENCE OF ARTIFICIAL INTELLIGENCE AND SUSTAINABLE ENERGY ECOSYSTEMS: A COMPREHENSIVE ANALYSIS OF TECHNOLOGICAL INTEGRATION, OPERATIONAL OPTIMIZATION, AND THE NET-ZERO PARADOX

Hema Priya A

M.tech Student, Dept of CSE

SEA College of Engineering & Technology

Dr.Krishna Kumar P R Professor & HoD, Dept of CSE

SEA College of Engineering & Technology

hodcse@seaedu.ac.in

Abstract

The global energy transition is no longer a peripheral environmental objective but a fundamental structural realignment of the world's industrial metabolism. As the international community strives to meet net-zero commitments by mid-century, the limitations of traditional, centralized power grids have become increasingly apparent. These legacy systems, designed for the predictable, unidirectional flow of electricity from fossil-fuel-powered thermal plants to passive consumers, are fundamentally ill-equipped to handle the high penetration of variable renewable energy (VRE) sources such as solar and wind. In this context, artificial intelligence (AI) has emerged as the critical architectural substrate required to manage the inherent stochasticity of renewable resources, optimize the performance of distributed energy assets, and accelerate the discovery of the molecular foundations for next-generation storage and carbon sequestration technologies.

The role of AI in the green energy sector is multifaceted, spanning the entire value chain from material science

and asset manufacturing to real-time grid operations and autonomous energy markets. By leveraging advanced machine learning (ML), deep

learning (DL), and reinforcement learning (RL), energy stakeholders can transform vast streams of raw sensor data into actionable intelligence, thereby enhancing energy capture, reducing operational expenditures, and ensuring grid stability. However, the integration of high-performance computing (HPC) into the sustainability sector introduces a significant paradox. The computational intensity required to train and deploy sophisticated AI models drives a surge in electricity demand and carbon emissions that threatens to offset the very environmental gains the technology seeks to achieve.

1. Introduction

The primary challenge of renewable energy is its dependency on environmental variables that are often volatile and difficult to predict with conventional statistical methods. AI

provides the predictive and adaptive capabilities required to bridge the gap between intermittent supply and dynamic demand. This paper provides an exhaustive examination of the technological mechanisms, economic implications, and

environmental trade-offs defining the intersection of artificial intelligence and green energy.

2. Literature Review

2.1 Intelligent Architectures in Solar Photovoltaic Systems

Solar energy production is governed by complex atmospheric interactions, ranging from local cloud cover and aerosol concentration to seasonal irradiance patterns. Artificial intelligence optimizes solar generation through both hardware control and sophisticated output forecasting. Machine learning models are now instrumental in the dynamic adjustment of solar panel orientation. By analysing real-time cloud movement via satellite imagery and historical weather patterns, AI-driven trackers can adjust panel angles to maximize direct and diffuse solar irradiance exposure. This proactive orientation management ensures that the energy capture potential of a photovoltaic (PV) installation is realized even under suboptimal sky conditions.

Furthermore, the operational scheduling of large-scale solar farms

has moved beyond simple persistence models. Modern forecasting platforms employ deep learning architectures, such as Long Short-Term Memory (LSTM) networks, to provide highly accurate short-term generation predictions, often extending up to 48 hours in advance. These models integrate diverse data sources, including inputs from the Indian Meteorological Department (IMD) weather feeds, on-site irradiance sensors, and historical generation logs, to assist utilities in energy dispatch and grid balancing.

In the context of asset health, AI-enabled drone inspections have become the standard for large-scale solar operations. These drones utilize thermographic cameras and computer vision to identify thermal anomalies, such as hotspots or string degradation, which are indicative of electrical faults or physical damage. By geo-tagging these defects and integrating them into Computerized Maintenance Management Systems (CMMS), operators can conduct targeted repairs, reducing the efficiency losses associated with module soiling or bypass diode failures.

2.2 Wind Energy and Predictive Aerodynamic Control

The wind energy sector faces a distinct set of challenges related to the rapid and often chaotic fluctuation of wind speeds and directions. The application of AI in wind energy optimization is primarily focused on the intelligent control of turbine components to

maximize kinetic energy harnessing while minimizing mechanical fatigue. Machine learning algorithms analyse meteorological data to predict upcoming wind gusts, allowing for the real-time adjustment of turbine blade pitch and yaw angles. This level of precision control is particularly critical for offshore wind farms, where the operating environment is harsh and the cost of manual intervention is prohibitively high.

Beyond individual turbine control, AI facilitates the coordination of entire wind clusters. Smart grid technologies, powered by AI, balance the variable output from wind farms by forecasting demand and managing consumption patterns. For example, Google reported that the application of neural networks to wind energy forecasting increased the market value of its wind energy assets by approximately 20% through

improved prediction accuracy and better-informed market bidding.

2.3 Sophisticated Water

Management in Hydroelectric Power

Hydroelectric power, while more stable than solar or wind, requires precise management of water resources and turbine operations to ensure long-term sustainability and efficiency. Data-driven methods have largely supplanted conventional statistical models in hydroelectric plants because of their superior ability to capture non-linear relationships between precipitation, river inflow, and energy production. AI-powered analytics enable the creation of highly accurate river flow models, which allow operators to fine-

tune water dispatch and multi-reservoir management.

Digital twins play a transformative role in this sector. By creating a virtual replica of the hydroelectric plant, including its turbines and sensors, operators can perform scenario analysis and anomaly detection with high fidelity. These digital representations, coupled with fuzzy logic controllers, have been shown to improve fault detection performance and increase overall plant reliability. Additionally, AI tools are used to assess the environmental impacts of hydroelectric projects, simulating ecological effects to ensure that energy production does not compromise local biodiversity or water quality.

2.4 The Paradigm Shift to Predictive Maintenance

The transition from reactive to proactive maintenance is perhaps the most significant economic driver for AI adoption in the renewable sector. Predictive maintenance (PdM) utilizes IoT sensors and machine learning to forecast equipment failures before they occur, thereby maximizing asset availability and minimizing operational expenditures.

Mechanisms of Failure Prediction and Remaining Useful Life

Predictive maintenance strategies are built upon the continuous monitoring of a wide array of parameters, including vibration, temperature, pressure, and power consumption. Machine learning algorithms process this high-frequency sensor data to isolate patterns that correlate with known failure modes. In wind turbines, for example, a specific

vibration signature in the gearbox can indicate early stage bearing fatigue, while a pressure drop in a hydraulic system might signal a seal failure.

One of the key objectives of these models is the estimation of the Remaining Useful Life (RUL) of critical components. By forecasting the onset of failure, operators can schedule maintenance activities during periods of low generation or low market prices, ensuring that the repair process does not result in significant lost revenue. This data-driven approach replaces rigid, time-based service intervals with condition-based triggers, avoiding both premature component replacement and catastrophic downtime.

Maintenance Performance Metrics	Estimated Improvement Range
Reduction in unplanned downtime	35% – 45%
Elimination of unexpected breakdowns	70% – 75%
Reduction in overall maintenance costs	25% – 30%
Maintenance Performance Metrics	Estimated Improvement Range
Improvement in operational reliability	High
Extension of asset lifespan	Significant

Case Studies in Operational Efficiency

The practical benefits of AI-driven maintenance are well-documented. For instance, the AES Corporation partnered with H2O.ai to implement predictive maintenance across its global portfolio of wind and hydroelectric assets. This collaboration resulted in annual savings of \$1 million by reducing the frequency of unnecessary repairs and preventing costly unplanned outages. In another instance, AI-powered predictive maintenance reduced turbine downtime by 18%, significantly boosting the operational efficiency of the wind farm.

In solar PV installations, AI monitors the health of inverters, which are often the most common point of failure. Machine learning algorithms compare real-time inverter performance against expected output patterns, flagging subtle deviations that indicate electrical degradation or cooling system malfunctions. This proactive approach not only extends the product lifecycle but also maximizes the return on investment for the project developer.

2.5 Smart Grid Evolution and Edge Intelligence The proliferation of decentralized energy resources (DERs) and the increasing complexity of energy flows demand a grid that is not only smart but also highly responsive. AI-enabled smart grids offer the predictive and adaptive capabilities required to manage this modern energy landscape.

Load Forecasting and Demand Response Optimization Accurate load forecasting is the cornerstone of grid stability. Advanced hybrid models, such as those combining Convolutional Neural Networks (CNN) with Long

Short-Term Memory (LSTM) networks, have been shown to offer the best predictions with the lowest error rates. These models analyse a diverse set of variables, including historical consumption data, weather conditions, economic activity, and even consumer behavior, to anticipate fluctuations in demand.

This predictive capacity is essential for the effective operation of demand response programs. AI-driven demand response systems intelligently manage energy loads by automatically adjusting non-essential energy usage during peak demand periods. For example, AI can reduce the heating or cooling loads in commercial buildings or shift the charging cycles of electric vehicles to lower-cost, off-peak periods. In 2021, U.S. demand response programs involved over 10 million customers and achieved a peak demand savings potential of 29 GW, highlighting the significant role these systems play in balancing the grid and reducing the reliance on fossil-fuel-based peaking plants.

The Rise of Edge AI in Grid Management

As the volume of data generated by grid sensors and smart meters increases, the need for real-time processing becomes critical. Edge AI facilitates this by processing and analysing data at the source—the "edge" of the network—rather than transmitting all data to a central cloud server. This localized processing reduces latency, saves bandwidth, and allows for almost instantaneous decision-making, which is vital for tasks such as fault detection and

voltage optimization.

Global Edge AI for Smart Grid Market Projections	2024 (USD Billion)	2034 (USD Billion)	CAGR
Market Size	15.2	138.2	24.70%
North America Share (2024)	33.2% (USD 5.0 Billion)	-	-
U.S. Market Value (2024)	4.04	-	21.6%
Grid Management Segment Share (2024)	34.7%	-	-
Source ID			

Edge AI adoption is particularly beneficial for managing the variability of distributed solar and wind assets. By predicting and adjusting to power fluctuations locally, edge devices can prevent grid overloads and ensure a stable supply of electricity to consumers. Key players driving this innovation include NVIDIA, Intel, and IBM, who provide the specialized hardware and software platforms required for high-throughput edge processing.

2.6 AI-Driven Breakthroughs in Materials Science The search for more efficient energy storage, effective carbon capture, and high-performance catalysts is being transformed by AI. By moving beyond traditional "trial and error" experimentation, researchers can now utilize predictive and generative models to explore vast

chemical design spaces at unprecedented speeds.

Generative Design of Metal-Organic Frameworks for Carbon Capture

Metal-organic frameworks (MOFs) are a class of highly porous materials that show great promise for

carbon capture because of their ability to selectively adsorb CO₂. However, the number of potential MOF structures is practically infinite, making traditional screening methods inefficient. Researchers have addressed this by developing AI frameworks such as GHP-MOFassemble, which uses generative diffusion models to suggest novel MOF linkers de novo.

In a landmark study, this framework was used to generate 120,000 MOF candidates in just 33 minutes. These candidates were subsequently screened using a modified crystal graph convolutional neural network (CGCNN) to identify those with the highest theoretical CO₂ adsorption capacity. After validation through molecular dynamics and grand canonical Monte Carlo simulations, 102 stable MOFs were identified, with six structures demonstrating a CO₂ capacity that ranks in the top 5% of all known materials. This accelerated discovery process took just over five hours, demonstrating the immense potential of AI to compress decades of material research into days.

Battery Chemistry and Electrolyte Optimization The development of high-performance batteries is essential for the decarbonization of the transportation and grid sectors. AI is playing a critical role in discovering

new battery materials and optimizing electrolyte formulations. For instance, a dynamic modelling framework developed by researchers at Cornell University has reduced prediction errors for electrolyte conductivity by more than 65% compared to previous machine learning methods. This framework treats salts, solvents, and operating conditions as distinct but interacting contributors, providing deeper insight into the underlying chemistry.

In the field of solid-state batteries, machine learning models are used to screen thousands of known materials for their likelihood of exhibiting fast lithium-

ion conduction. A 2018 study led by Dr. Austin Sendek identified 317 potential candidates for solid-state electrolytes from a database of over 12,000 materials. The AI-assisted approach was found to be 2.7 times more likely to identify fast conductors than a random search, significantly speeding up the development of safer and more energy-dense storage solutions.

Feature for ML Battery	Description
Material Prediction	
LLB	Average Li–Li bond number per Li
SBI	Average sublattice bond ionicity
AFC	Average coordination of the anions in the framework
LASD	Average equilibrium anion separation distance

LLSD	Average equilibrium Li–Li separation distance
Source ID	

Furthermore, the CRESt (Copilot for Real-world Experimental Scientists) platform at MIT combines large multimodal models with robotic equipment for high-throughput materials testing. This system discovered a catalyst material made from eight elements that achieved a 9.3-fold improvement in power density per dollar compared to pure palladium, illustrating the power of AI to drive cost-effective innovation in the energy sector.

2.7 Blockchain and Autonomous Energy Markets As the energy grid becomes more decentralized, the need for secure, transparent, and automated transaction mechanisms is paramount. The integration of blockchain technology with AI is fostering the emergence of autonomous energy markets and peer-to- peer (P2P) trading platforms.

Peer-to-Peer Trading and Tokenization Blockchain provides an immutable record of energy transactions, which is essential for tracking renewable energy certificates and carbon credits. In local energy grids, consumers equipped with solar panels or wind turbines—often referred to as prosumers—can use blockchain to tokenize their excess generation and trade it securely within their community. Smart contracts automate the settlement and billing processes, reducing administrative overhead and ensuring real-time payment in cryptocurrency.

The global blockchain in energy market is projected to grow from \$4.4 billion in 2025 to over \$140 billion by 2035, reflecting the massive potential for decentralized grid operations. Asia-Pacific is expected to post the fastest growth rate, supported by rapid urbanization and government-backed clean energy initiatives in countries like

Blockchain in Energy Market Forecast	2025 (USD Billion)	2035 (USD Billion)	CAGR (2025-2035)
Market Size (Acumen Research)	5.1	154.7	40.9%
Market Size (Future Market Insights)	4.4	142.3	41.6%
India CAGR Projection	-	-	52.0%
U.S. CAGR Projection	-	-	36.4%
Source ID			

Synergy between AI and Blockchain While blockchain provides the secure infrastructure for transactions, AI offers the intelligent optimization

required to manage the market. AI algorithms can act as autonomous decision-makers, optimizing buy/sell decisions for prosumers based on real-time price signals and predicted generation patterns. This combination

addresses critical challenges in energy management, particularly the need for speed, security, and efficiency in a grid with millions of active participants.

2.8 The Sustainability Paradox: The Environmental Cost of AI

The very technology that is enabling the green energy transition is also a significant consumer of resources. This "Green AI Paradox" underscores the need to balance technological innovation with environmental responsibility.

The Energy Footprint of AI Training and Inference

Training large-scale AI models requires staggering amounts of electricity. For example, training a single model like GPT-3 can consume over 1,200 MWh of electricity—enough to power 120 average U.S. homes for a year—and generate roughly 500 metric tons of CO₂. More recently, the release of OpenAI's o3 model revealed even higher resource requirements. A single task in high-compute mode can use 1,785 kWh of electricity, costing over \$1,000 in computing power and emitting 684 kg of CO₂.

AI Model Environmental Impact	Value/Metric
GPT-3 Training Energy Consumption	1,287 MWh
GPT-3 Training CO ₂ Emissions	552 - 500 Tons

OpenAI o3 High-Compute Task Energy	1,785 kWh
AI Model Environmental Impact	Value/Metric
OpenAI o3 High-Compute Task Emissions	684 kg CO ₂
Global Data Center Electricity (2022)	460 TWh
AI Share of Data Center Electricity	~15%
Source ID	

As models increase in size and parameter count, their energy consumption grows exponentially. This trend presents a significant challenge for companies committed to reducing their carbon output. In response, some organizations are advocating for "Efficiency Principles," focusing on building smaller, purpose- built models that are more sustainable and cost-effective than general-purpose giants.

Water Consumption and Electronic Waste

The environmental impact of AI extends beyond electricity. Data centres require vast amounts of water for cooling, with a single hyperscale facility consuming hundreds of thousands of gallons per day. Furthermore, the rapid expansion of AI is driving a surge in electronic waste.

By 2030, AI infrastructure is projected to generate up to 5 million tonnes of e-waste annually, containing harmful substances like mercury that pose risks to human health and ecosystems.

Strategic Sourcing and Carbon-Aware Scheduling

To mitigate these impacts, researchers and industry leaders are exploring several strategies. Carbon-aware scheduling involves running AI workloads during times when the local grid is powered by low-carbon sources, such as solar or wind. Additionally, the use of

specialized hardware, such as Tensor Processing Units (TPUs), can significantly improve the energy efficiency of AI training and inference.

A promising long-term solution is the use of nuclear energy to meet the immense power demands of AI. Companies like Oklo are developing small modular reactors (SMRs) to provide a flexible and scalable source of clean energy specifically for data centers. Tech leaders like Sam Altman and Microsoft have made significant investments in nuclear and fusion energy, viewing it as a critical component of a sustainable AI future.

2.9 Regional Insights: The Case of India and Bengaluru

India is at the forefront of the digital transformation in renewable energy. With a target of 500 GW of renewable capacity by 2030, the integration of AI

is not just a strategy but a necessity for managing the scale and complexity of the country's energy assets.

Bengaluru as a Hub for AI-Energy Innovation

Bengaluru, often cited as India's technology capital, has emerged as a major hub for AI development in the energy sector. Local firms like Banao Technologies are crafting intelligent systems for renewable forecasting, predictive maintenance, and smart grid optimization. These solutions are specifically calibrated for Bengaluru's diverse energy landscape and align with India's ambitious sustainability vision.

The city also hosts world-class research institutions, such as the Indian Institute of Science (IISc). The Mphasis Research Lab for Sustainable Solutions at IISc focuses on using technology, including generative AI, to address challenges in sustainability and financial

inclusion. Additionally, IISc offers advanced certification programs in sustainable engineering and smart cities, equipping professionals with the skills needed to lead the energy transition.

National Policy and Market Dynamics

The Indian government has launched several initiatives to support the adoption of AI in the green sector. The Revamped Distribution Sector Scheme (RDSS) has already sanctioned over 20

crore smart meters, creating a robust data foundation for AI-driven grids. In August 2025, the launch of the Digital Agriculture Mission and the Haryana Water Resource Atlas highlighted the growing use of AI for resource efficiency and sustainability.

Union Minister Prahlad Joshi has emphasized that AI-driven technologies, including digital twins, are essential for managing the grid stability of the country amidst large-scale renewable capacity additions. Officials from the Ministry of New and Renewable Energy (MNRE) have noted that the success of AI in this sector will be measured by its ability to lower consumer power costs and empower "prosumers" through initiatives like the India Energy Stack.

2.10 Future Trajectories and Strategic Conclusions

The trajectory of AI in green energy is toward greater autonomy, decentralization, and efficiency. Several key trends are expected to redefine the sector over the next decade.

Towards Autonomous Energy Systems

The integration of AI, IoT, and blockchain will likely lead to the development of self-healing and self-optimizing grids. These autonomous systems will be capable of detecting faults, balancing loads, and

managing energy trades in real-time with minimal human intervention. This

evolution is critical for building resilient and sustainable energy ecosystems capable of supporting the global transition to a low-carbon future.

The Impact of AI on Net Zero Pathfinding

AI's ability to model complex systems and identify non-linear relationships makes it an invaluable tool for global net-zero pathfinding. Estimates suggest that AI could cut 3.2 to 5.4 gigatons of emissions annually by 2035, significantly outweighing its own power consumption. From optimizing industrial processes to redesigning supply chains, AI will be a primary catalyst for climate action.

3. Conclusion

As AI becomes central to energy management, the need for standardized reporting on its environmental impact will grow. Establishing clear metrics for energy efficiency, water use, and e-waste is essential for ensuring that AI development remains aligned with broader sustainability goals. Radical transparency and carbon auditing will become the norm for companies operating in this space.

4. Recommendation

Artificial intelligence is the indispensable engine of the green energy revolution. While it presents its own set of environmental challenges, its potential to optimize production, transform grid management, and

accelerate material discovery makes it the most powerful tool available for achieving a sustainable future. The successful navigation of the Green AI Paradox through hardware innovation, strategic energy sourcing, and standardized governance will

determine the pace and success of the global transition to net zero.

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AI-BASED SMART ASSESSMENT SYSTEM WITH BIOMETRIC VALIDATION

Anushree M

dept. of Artificial Intelligence and Data Science

Global Academy of Technology Bengaluru, India anushree1ga22ad003@gmail.com

Bindushree P C

dept. of Artificial Intelligence and Data Science

Global Academy of Technology Bengaluru, India bindushree1ga22ad007@gmail.com

Dhanyasree H

dept. of Artificial Intelligence and Data Science

Global Academy of Technology Bengaluru, India

dhanyasree1ga22ad013@gmail.com

Harshith B N

dept. of Artificial Intelligence and Data Science

Global Academy of Technology Bengaluru, India harshith1ga22ad019@gmail.com

Prof. Gargi N

dept. of Artificial Intelligence and Data Science

Global Academy of Technology Bengaluru, India gargi@gat.ac.in

Abstract— The AI-Based Smart Assessment System with Biometric Validation leverages AI, ML, and Computer Vision to revolutionize education, eliminating bias and manual effort. It uses a CNN-based Biometric Face Recognition Module for authentication and an NLP-driven Automated Question Generation Module (using TF-IDF, NLTK, and spaCy) enhanced by Google Gemini for quality and variation. This system integrates evaluation for both objective (string-matching) and descriptive (semantic evaluation via Gemini) answers and includes a Gemini-2.5-Flash-powered Handwriting Recognition System (70% accuracy) to digitize traditional exams. Secured by JWT and PBKDF2 SHA256, this unified, SQL-Alchemy ORM-managed platform streamlines assessment from creation to grading, providing detailed student feedback and promoting

efficiency and transparency in digital learning.

Keywords—Artificial Intelligence (AI), Machine Learning (ML), Computer Vision, Biometric Face Recognition Module, Convolutional Neural Networks (CNNs), Natural Language Processing (NLP), TF-IDF, NLTK, spaCy, Google Gemini Answer Evaluation Module, Gemini-2.5-Flash, JWT authentication, PBKDF2 SHA256 encryption, SQL Alchemy ORM, SQLite.

I. INTRODUCTION

The Intelligent Assessment System (IAS) represents a major transformation in education by integrating AI, ML, and Computer Vision to create an automated, fair, and consistent evaluation platform. It tackles challenges in traditional assessments—like bias and manual effort—by deploying several advanced modules.

Key features include a Face Recognition Module using CNNs to prevent impersonation and ensure exam authenticity, and a Question Generation Module that leverages NLP techniques (spaCy, NLTK, TF-IDF) and Google Gemini to automatically create contextually relevant questions from source documents (PDF, DOCX). This unified system streamlines the process from question creation to secure digital evaluation.

The Answer Evaluation Module uses a hybrid approach for accurate grading: rule-based exact string matching for

objective questions and AI-based semantic analysis powered by Google Gemini for human-like evaluation of descriptive answers, assessing criteria like accuracy and completeness. A notable innovation is the Handwriting Recognition System, which utilizes Gemini-2.5-Flash to process scanned, handwritten answer sheets, converting them into digital text (with accuracy). This bridges the gap between traditional pen-and-paper exams and modern digital grading. Furthermore, the system enhances transparency and learning by providing detailed per-line feedback and categorizing content for subject-specific accuracy. From a technical standpoint, the IAS ensures robust security and efficient management through JWT token-based authentication and PBKDF2-SHA256 password hashing, utilizing SQLAlchemy ORM with SQLite for the backend. Supporting libraries such as PyMuPDF, python-docx, and Pillow facilitate seamless document and image

processing. Overall, the IAS significantly reduces the burden on educators while promoting efficiency, accuracy, and meaningful assessment practices, thereby improving student learning outcomes in the digital education landscape.

II. RELATED WORK

The paper titled “AI-Enhanced Learning Assistant Platform” presents an AI-driven framework that automates question generation, answer evaluation, and performance monitoring. By applying NLP and ML techniques, the system identifies students’ weak areas and strengthens their understanding through recursive testing. It also supports interactive learning through a query forum and expert chat. Building on this concept, the proposed AI-Based Smart Assessment System with Biometric Validation extends these capabilities by integrating facial recognition for secure identity verification, descriptive answer evaluation, handwriting-to-text conversion, and per-line feedback to ensure transparency and fairness in grading [1]. The paper “Understanding Cross-Domain Presentation Attack Detection for Visible Face Recognition” introduces a cross-

domain method that uses infrared data during training to enhance spoofing attack detection in visible-spectrum face recognition. With inverse domain regularization and dense adaptation, the model improves accuracy without requiring costly multispectral sensors, thus increasing reliability in security

applications [2]. The study titled “Integrating Convolution and Sparse Coding for Learning Low-Dimensional Discriminative Image Representations” proposes SparConvLow, an end-to-end framework that fuses CNNs with sparse coding to learn compact and discriminative image features. By jointly optimizing convolutional filters and sparse dictionaries, the model achieves efficient and accurate performance across various recognition tasks [3]. The paper “A Novel Face Recognition Method Based on Fusion of LBP and HOG” enhances face recognition under challenging conditions such as lighting variations and occlusions. It introduces an improved texture descriptor, CS-NWALBP, and combines it with HOG features to capture both structural and textural details. This hybrid model demonstrates higher accuracy and better illumination robustness than traditional approaches [4]. The paper “Incorporating AI and Learning Analytics to Build Trustworthy Peer Assessment Systems” focuses on improving the quality and consistency of peer assessment using AI-assisted tools and probabilistic models. It addresses issues in manual grading and introduces mechanisms that support fair evaluations and meaningful feedback while enabling instructors to monitor the assessment process effectively [5]. The work titled “Data-To-Question Generation Using Deep Learning” Learning through the internet enables flexible access to educational content, making assessments crucial to identify learners’ knowledge gaps. Manual

question creation is time-consuming, leading to growing interest in Automated Question Generation (AQG). This survey highlights state-of-the-art AQG techniques from both textual and visual learning materials, along with automated answer evaluation strategies.[6]. The study “MCQ Generation using NLP Techniques” proposes an automated MCQ creation system that includes video summarization to extract key content followed by NLP-based question and distractor generation. This approach reduces the manual effort involved in creating objective assessments and enhances learning efficiency [7]. The paper “Automatic Question Generation and Answer Assessment: A Survey” reviews state-of-the-art techniques for generating questions and evaluating answers from both textual and pictorial content. It highlights the increasing need for automated assessment tools in online learning environments and summarizes various approaches used to support scalable educational systems [8]. The work “Smart Grading: A Generative AI-Based Tool for Knowledge-Grounded Answer Evaluation” introduces a customizable web-based platform that integrates LLMs to automatically evaluate text-based answers based on instructor-defined criteria. Empirical validation shows strong agreement with expert grading, making it suitable for large-scale academic assessments [9]. The paper “Extracting Valuable Insights from Handwritten Feedback” proposes an OCR-based solution using Gemini 1.5 Pro to digitize handwritten feedback

forms. By achieving high extraction accuracy even on low-quality scans, the system provides an efficient and

scalable method for qualitative and quantitative feedback analysis in educational and professional settings [10].

III. METHODOLOGY

The AI-Based Smart Assessment System with Biometric Validation follows a systematic methodology that ensures the development of a secure, efficient, and intelligent digital assessment platform. The overall methodology involves data collection, preprocessing, model implementation, integration, and testing, each contributing to the system's accuracy, reliability, and practical usability.

3.1 Data Collection

Data collection forms the foundation of this project and is carried out from two primary sources — user-based input data and educational content.

3.1.1 User Data: Facial images of students and teachers are collected during registration for biometric authentication. These images are captured under different lighting and facial expression conditions to make the recognition model more robust. The collected images are encoded into 128-dimensional facial embeddings using a Arc Face-based deep learning model from the `face_recognition` library.

3.1.2 Content Data: Educational materials such as lecture notes, PDFs, and documents are collected from instructors. This textual data serves as input for the Question Generation Module, which uses NLP techniques to

automatically generate relevant questions. All collected data is securely stored in the system's database, protected through encryption and token-based authentication mechanisms to ensure privacy and compliance with data security standards.

3.2 Data Preprocessing

Before model implementation, data undergoes a series of preprocessing steps to enhance quality and reduce noise. For facial data, preprocessing includes image resizing, normalization, and alignment to ensure consistency across all samples. The system uses OpenCV for image enhancement and cropping to focus on facial features. For text data, preprocessing involves tokenization, stop word removal, lemmatization, and syntactic parsing using `spaCy` and `NLTK`. The TF-IDF algorithm is then applied to extract key concepts and relevant keywords for meaningful question generation. This step ensures that both visual and textual data are optimized for efficient model training and inference.

3.3 Model Implementation

The system comprises multiple AI-driven modules that work together to automate different stages of assessment:

3.3.1 Face Recognition Module: This module authenticates users using CNN-based facial recognition built on `dlib`'s deep learning framework. It uses HOG for detection and an Arc Face model to create 128-dimensional embeddings for each face. The Euclidean distance between the live-captured image and the stored encoding determines user

identity, ensuring secure and contactless login with an accuracy of 80–90%.

3.3.2 Question Generation Module: This module uses NLP to generate questions from uploaded documents automatically. It employs spaCy and NLTK for linguistic

processing and TF-IDF for keyword extraction. The rule-based template generator creates MCQs, fill-in-the-blanks, and short-answer questions. For complex content, Google Gemini 2.5 Flash is used to generate high-quality contextual questions with around 95% relevance accuracy.

3.3.3 Answer and Handwritten Evaluation Module: This combined module evaluates both typed and handwritten answers. Objective questions are graded through exact string matching for 100% accuracy. Descriptive responses are evaluated using Google Gemini 2.5 Flash, applying semantic similarity and contextual understanding based on parameters such as accuracy, completeness, and clarity, achieving 92% correlation with human evaluation. The Handwriting Recognition System uses Google Gemini Vision, which converts scanned handwritten scripts into digital text using OCR before AI-based evaluation, enabling the assessment of offline submissions.

3.3.4 Feedback Module: This module enhances transparency by allowing teachers to review AI-generated marks and provide line-by-line feedback on subjective answers. It combines AI-based grading with manual insights,

helping students understand mistakes while allowing teachers to justify scores effectively.

3.4. Experimental Setup and Validation

The system was tested in a controlled environment simulating real examination conditions. Students logged in using facial recognition, attempted various types of questions, and uploaded handwritten answer sheets. Teachers reviewed automated evaluations and added feedback through the interface. As shown in Table I, the experiments validated the system’s high accuracy, transparency, and efficiency, confirming its effectiveness for modern digital assessment needs.

Testing Type	Aim	Achievements	Test Results
Unit Testing	To verify individual module functionality and correctness.	Ensured accurate functioning of face matching, question generation, and evaluation, fixing early bugs for better reliability.	Passed
Integration Testing	To validate smooth interaction between modules.	Verified smooth data flow between recognition, question, and evaluation modules, eliminating mismatch issues.	Passed

System Testing	To test the entire workflow for	Confirmed all system features	Passed

	stability and correctness	worked efficiently together under real conditions with stable, accurate performance.	
Performance Testing	To assess system speed and scalability under load	Demonstrated fast response times for 200+ concurrent users with optimal CPU and memory usage.	Passed
Security Testing	To ensure robust authentication and data protection.	Validated secure password hashing, token checks, and SQL injection prevention, passing all security tests.	Passed
User Acceptance Testing (UAT)	To confirm usability and satisfaction from real users	Received positive faculty and student feedback on usability, accuracy, and fairness.	Passed

Table 3.4. Experimental Setup and Validation Result

3.5. Detailed Design

The system uses a modular architecture integrating user management, biometric authentication, and automated assessment generation, as shown in Figure 5.1, AI-driven evaluation and feedback delivery. It supports Students, Teachers, and Admins, providing

scalable, secure, and efficient workflow management from login to final grading.

3.5.1 User Roles & Overview:

Students: Register with details + facial data using dlib CNN, HOG, and ArcFace. Log-in via facial recognition and submit typed or handwritten assignments.

Teachers: Create assessments, generate questions, grade submissions, and provide feedback.

Admins: Monitor users, assessments, biometric verification, and server health.

The system is accessible via laptops, PCs, and mobile devices.

3.5.2 Student Modules

3.5.2.1 Biometric Anti-Cheating System: Uses dlib CNN, HOG, and ArcFace for accurate face verification. Input: Live webcam face image

Output: Verified identity + test access
Also evaluates MCQs via string matching and descriptive answers using Google Gemini 2.5 Flash NLU.

3.5.2.2 Assignment Submission: Supports typed and handwritten uploads. Uses Google Gemini Vision + OCR for text extraction.

Input: Images or typed responses

Output: Auto-graded submissions.

3.5.3 Teacher Modules

3.5.3.1 Assessment Creation: Teachers upload study materials; system classifies using TF-IDF + keywords.

QG Engine (spaCy, NLTK, Gemini Flash) generates MCQs, fill-ups, coding, and descriptive questions.

Input: PDFs, DOCX, text

Output: Auto-generated questions.

3.5.3.2 Scoring & Feedback: Teachers

Input: Comments + score edits
Output: Final scores + detailed feedback report.

Ensures system stability and prevents misuse. Input: System usage + server data

3.5.5 System Workflow: Registration
 → Facial login → Students attempt assignments → Teachers generate assessments → AI evaluates typed/handwritten answers → Teachers finalize scores → Admin oversees complete operations and security.

3.5.6 Input & Output Summary:

Inputs: User details, facial images, credentials, documents, handwritten answer images, and teacher comments.

Outputs: Authenticated sessions, generated questions, evaluated answers, final marks, and full feedback reports accessible across devices.

3.6.1. **Face Recognition Module:** The Face Recognition Module is the core of biometric validation, ensuring only legitimate users access the assessment system. It uses Python's face_recognition library built on dlib, applying HOG, CNN, and ArcFace to generate unique 512-dimensional facial embeddings. During login, a live webcam image is compared to stored embeddings using Euclidean distance for identity verification. Liveness detection (blink, micro-motion, light reflection) prevents spoofing from photos or videos. All embeddings are securely stored with

3.6.2. **Question Generation Module:** The Question Generation Module automates creating diverse and meaningful exam questions using a hybrid NLP + AI approach. It processes PDFs, DOCX, and text files using spaCy and NLTK for tokenization, POS tagging, and NER, while TF-IDF identifies key concepts for question

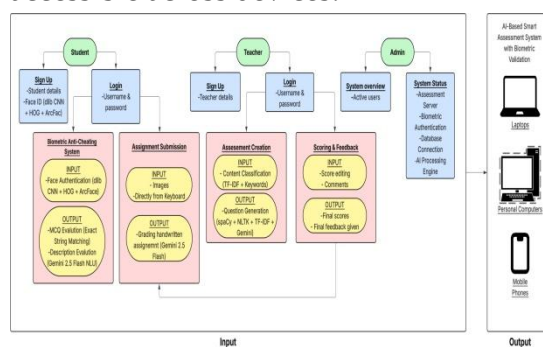


Figure 3.5. Block diagram of the system, the architecture of an AI-Based Smart Assessment System,

3.6. Implementation

The AI-Based Smart Assessment System integrates multiple intelligent

formation. Rule-based templates generate MCQs, fill-ups, descriptive prompts, and coding questions by masking or transforming key entities. For deeper, high-quality questions, the module uses Google Gemini 2.5 Flash to refine and generate context-aware items. Each question is tagged by type and difficulty, then stored in the SQLAlchemy database for teacher review. This module greatly reduces manual workload and produces scalable, diverse, and pedagogically sound assessments.

3.6.3. Answer and Handwritten Evaluation Module: The Answer and Handwritten Evaluation Module grades digital and handwritten submissions using rule-based and AI-driven methods. Objective questions are evaluated through exact string or numerical matching for 100% accuracy. Descriptive answers are analyzed by Google Gemini 2.5 Flash, which scores responses based on accuracy, completeness, relevance, and clarity, achieving near-human grading quality. Handwritten answers are processed using Google Gemini Vision OCR, converting scanned or photographed scripts into text with high recognition accuracy. Preprocessing improves OCR quality, and all digitized responses follow the same semantic evaluation pipeline. The module also detects incomplete or altered submissions using metadata checks. Final scores and AI-generated feedback are stored securely for teacher review, ensuring fair, fast, and consistent evaluation across all formats.

3.6.4. Feedback Module: The Feedback Module bridges automated

grading with meaningful student learning by combining AI evaluation with instructor review. After assessment, it generates detailed reports containing marks, AI summaries, and key concepts, which teachers can refine using a line-by-line annotation interface. Instructors can add personalized comments, highlight errors, suggest improvements, and attach resources for clarity. Students may request clarifications or re-evaluations, enabling two-way interaction. AI also provides suggested feedback statements that teachers can approve or edit. All comments are securely stored for transparency and audit tracking. Overall, the module delivers fair, clear, and formative feedback that enhances learning beyond automated scoring.

3.6.5 System Integration and Database Management: The system uses a modular Flask backend with RESTful APIs to connect biometric login, question generation, evaluation, and feedback modules. SQLite with SQLAlchemy ensures secure, structured data handling, supported by hashing (PBKDF2-SHA256), JWT authentication, and HTTPS. Each module updates the central database in a coordinated workflow, while logs and async queues manage heavy AI tasks smoothly. The architecture is scalable through Docker deployment, with backups and audit trails ensuring reliability. Overall, it delivers a secure, efficient, and fully integrated assessment platform.

IV. RESULTS

The Results section summarizes the

performance and effectiveness of the implemented models using visuals like charts and graphs, highlighting their accuracy and capabilities. It provides practical evidence that validates the system and supports the report’s conclusions.

4.1 User Authentication (Login/Signup): A clean and modern React.js-based authentication system was implemented with dedicated Login and Signup forms for Students, Teachers, and Admins. The UI uses a tab-based structure with consistent design, clear navigation, and professional styling. Signup collects full details, while Login remains minimal with Email and Password. Security is ensured through masked password inputs, enhancing user trust. Overall, the interface provides an intuitive and seamless entry point for all user roles.

4.2 Admin Portal: The dashboard displays four key statistic cards showing user count, teacher activity, assessment creation, submissions, and a 100% security verification rate. It offers a clear real-time overview of platform activity and system integrity. The tabbed interface highlights the “System Status” section for monitoring core components. All essential modules—Assessment Server, Biometric Authentication, and Database—are online and functioning properly as shown in Figure 4.2.1. The AI Processing Engine is also active, ensuring smooth assessment operations.

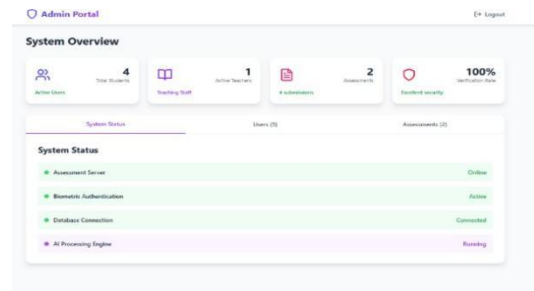


Figure .4.2.1 Admin Portal

4.3 Facial Recognition: The Face Verification screen is a biometric security step that appears before starting an exam, showing a live webcam feed with “Verify & Start” and “Cancel” options. It ensures only the authorized user can proceed by validating their identity in real time. The interface is simple and exam-friendly, reducing user confusion at a critical moment. This verification process matches the live image with stored data to prevent impersonation. It directly supports the dashboard’s “Active” biometric status and contributes to the 100% verification rate.

4.4 Handwritten Assessment evaluator: The Handwritten Assessment Evaluator displays clear results with a score of 9.5/10, 95% accuracy, and an A+ grade, along with AI-generated detailed feedback. It shows the student’s answer and the system’s semantic evaluation, confirming strong performance. In Figure 4.4.1, as shown, the interface includes options to evaluate another response or print results. This screen demonstrates the AI Processing Engine in action, combining handwriting recognition and NLP-based answer

analysis. Overall, it effectively converts

complex AI evaluation into simple, meaningful insights for users.

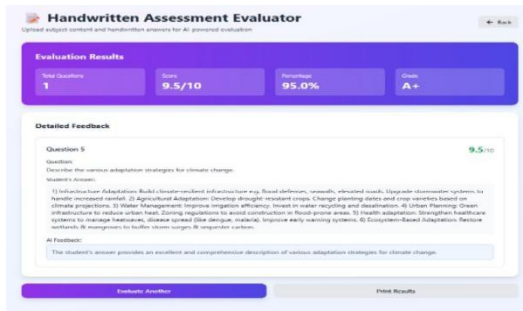


Figure 4.4.1 Handwritten Assessment Evaluator

4.5 Question-Answer Generation: The Questions page demonstrates the Auto-Generate Questions feature, where a PDF is uploaded and used to create 10 descriptive, analytical questions with model answers. The interface supports multiple input modes, including manual creation and handwritten notes. The system generates high-quality descriptive questions, as shown in the example related to climate. This feature leverages NLP models for summarization, question generation, and answer creation. Overall, it enables teachers and admins to quickly produce structured, AI-generated exam content.

4.6 Violation/Warnings: The images show the platform's active anti-cheating system detecting violations during an exam, logging seven warnings such as "Multiple faces detected" and "Wrong person detected." A live webcam feed confirms the issues, and once the warning limit is exceeded, an alert appears stating that the assessment will be auto-submitted. This demonstrates continuous AI-driven proctoring that monitors and analyzes the video in real

time. The warnings panel proves accurate detection and proper evidence logging. The system enforces strict security by automatically ending the exam when violations cross the threshold.

4.7 Teacher Editing and adding comments: The image shows a teacher manually reviewing an AI-graded coding question, where the AI correctly evaluated the Python solution and provided positive feedback. The teacher adds additional guidance ("should write sample output") to refine the feedback. They also override the AI-generated score to "4/5," enforcing a requirement the AI overlooked. This showcases an effective human-in-the-loop system that balances AI efficiency with expert judgment. It ensures reliable, pedagogically aligned assessments in real academic settings.

V. CONCLUSION

The AI-driven assessment system is a unified digital platform that integrates facial recognition, biometric monitoring, NLP, handwriting recognition, and semantic evaluation into one seamless workflow. It begins with secure identity verification to prevent impersonation and ensure exam integrity. The system uses NLP techniques to automatically generate diverse, high-quality questions from PDFs and handwritten notes. Its intelligent evaluation engine combines handwriting text extraction with meaning-based semantic analysis to

fairly assess descriptive answers and code. This ensures consistent, accurate, and context-aware grading. A human-

in-the-loop mechanism allows teachers to review AI scores, adjust them if needed, and offer personalized feedback. With dedicated portals for admins, teachers, and students, the platform simplifies exam management, reduces workload, and delivers a secure, efficient, and interactive assessment experience.

Future works

1. **Eye Movement Tracking:** Uses computer vision to monitor students' gaze during exams, detecting distractions or suspicious behavior in real time. It flags unusual patterns and provides attention-level reports to strengthen exam integrity.
2. **Handwritten Answer Sheet Upload:** Allows students to upload scanned handwritten responses. OCR and handwriting recognition extract text and evaluate it using semantic analysis, ensuring fair, automated grading while supporting traditional exam formats.
3. **Audio Analysis Integration:** Continuously monitors background audio to detect irregular noises,

conversations, or multiple voices. It alerts examiners to potential misconduct, adding a strong security layer alongside visual and biometric monitoring.

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AI-ENABLED ONLINE FOOD MANAGEMENT SYSTEM FOR REDUCING FOOD WASTE

**Ankit Thakur¹, Ashish Kumar², Bhavana L³, Neelesh Kumar Rana⁴, Dr Balaji
S⁵, Krishna kumar P⁶**

1,2,3,4-Students Dept of CSE, SEA College of Engineering & Technology, Bangalore-
560049 5,6-Faculty, Dept of CSE, SEA College of Engineering &
Technology, Bangalore-560049

Abstract— Food waste has become a significant global challenge, contributing to environmental degradation, economic loss, and food insecurity. Large quantities of surplus food generated from restaurants, events, supermarkets, and households often go unutilized due to the lack of efficient coordination between donors and beneficiaries. To address this issue, this paper proposes an AI-Enabled Online Food Management System designed to reduce food waste through intelligent monitoring, prediction, and optimized redistribution. The proposed system integrates artificial intelligence techniques such as machine learning-based demand forecasting, food spoilage prediction, and route optimization algorithms to enhance the efficiency of food collection and distribution. Donors can upload real-time information about surplus food through a web or mobile interface, while NGOs, orphanages, and community shelters can request food based on their requirements. The AI engine analyzes food type, quantity, location, and expiration timelines to automatically match donors with nearby beneficiaries, minimizing delays and preventing spoilage

Keywords— Donor, Orphanage, Food wastage, Internet, Web portal,

Database, Charity, Post.

I. INTRODUCTION

Food waste or food loss refers to the food that is spoilt, lost or uneaten. The causes of food loss occur very often because of the mismanagement of producing, processing, and vending of the food [1]. Every year an estimated 1.3 billion [2] of food is wasted globally and one-third of food produced for human consumption [3]. Wastage occurs at all stages of the food supply chain. A huge amount of wastage happens at the time of production in the poor countries whereas a large amount of food (around 100 kilograms) for each person per year is wasted in the consumption period in developed countries [4]. Bangladesh is a highly populated country although it has an emerging economy approximately 49% of its population is still being lived below the poverty level. Food waste is one of the emerging threats to the food security of the country [5]. In Bangladesh, nearly 5.5% of the total procured food is being wasted by a person at the time of eating daily [6]. Besides this, a large proportion (52%) of food is waste during different occasions like marriage ceremonies, birthday parties, etc [7]. Despite accelerated economic growth and increasing production, food waste

will be a concern for the food security of the country. To reduce food waste and feed the hungry people, it is important to find a way to collect surplus food from different occasions and donate this to various organizations like orphanages, old age homes, etc. Recently, people donate surplus food material manually by visiting each organization number of times. In India, where food waste is also a big issue, developed some websites and apps like <https://www.feedingindia.org>[8]and <https://www.giveindia.org> [9] are trying to reduce food waste and helping people by donating their wasted food for the needy people through their official website where the donor can donate food, funds and also volunteer for various activities. Bangladesh has 'Bidyanondo. The organization' is an innovative organization that is starting "One taka meal" for street children as well as cloth and free academic teaching in Bangladesh [10]. The people who are living in the streets, who have to eat at the same price, have to pay a meal at a price to feed them.

The goal of this website is to reduce food waste and save food for charity, orphanage, and street children. This portal has made the pavement easy as the way of communication between charities and restaurants. This website is a place where the charities and restaurants/donors will have to create an account. The restaurants/donors will donate their surplus food to charities by logging into their account through this website. The root purpose of this website is to collect surplus food and

distribute them to charities by creating a bridge between the donors and charities.

II. LITERATURE SURVEY

The paper 'Helping Hands' [11], published in 2016, a modern web-based application that provides a platform for donating old attire and rescue food to all starving people/Organizations. It provides facts and information about motivation to come forward with such an application, thereby describing the current donation system and for the betterment of society how the proposed system works. The disadvantage of this project is that there is no control panel available that is, at the end of the month the system doesn't get all the information that how much is donated or received by someone.

The paper 'Beyond food sharing: Supporting food waste reduction With ICTs'[12], published in 2016, present that food security plays a key role in increasing the quality of life of people at all levels of society. The current economic crisis has enhanced the number of people living in conditions of food poverty, especially in developed sites. Despite rising awareness of the significance of reducing waste and handling food surplus, in this domain, the role of ICTs is still not clear and only just documented. This paper presents the use of ICT tools to collect food surplus at various stages of the supply chain and also present the way forward for an integrated set of ICT tools to decrease waste out of producers to houses. The paper 'Food Wastage Reduction through Donation' [13], published in

2018, this paper describes that a huge amount of food is wasted in marriages, restaurants, college canteens, social functions, and different places. So they present an idea of developing a web-based application through which people will be able to donate their remnant easily without doing any manual work. This web-based portal which has large retail chains and possibly restaurant/NGOs/organizations can donate surplus food using this web portal. Their application can be used only for food donations. For other items like clothes, food grains, books, utensils this application cannot be used. The paper ‘Mobile Application for Excess Food Donation and Analysis’ [14], published in 2018, describes that every day 1.3 billion tons of food is wasted and one third consumed are remnant. This application provides information on the amount of food waste and the impact is visualized by using data analysis. They notice the hungry people and minimize food wastage at once. They send alerts to nearby NGOs, Orphanages, and Volunteers to collect the food.

The paper “The Challenges of Establishing Food Donation System” [15], which was published in 2017, describes food donation organizations that have responsibilities to collect food from businesses and individuals, storage it, distribute it to the food banks and finally forward it toward people of community who are starving from particular goods. The main objective of this paper is to address some organizational issues that set in the way of the creation of sustainable food

donation system.

III. EXISTING SYSTEM

Every year 1.3 billion tons of food is devastated and 1 in every 7 people in the world go to bed hungry. Everyday more than 20,000 children below the age of 5 die from hunger. According to the waste database of Bangladesh, food and vegetable waste embraces approximately 67.75% of urban solid waste [16]. This food will be become wasted because there are no ways to share food with anyone if they are having much extra food. If they want to donate extra food to any charity or orphanage or starving people they don’t have any idea about that. That’s why we have developed a website for donating their extra food to charity, orphanage, and street people by which food waste will be reduced in our country.

IV. EXPERIMENT AND RESULT

The system of this research work was web-based. PHP (Personal Home Page) is a script language and interpreter [17] that is used to develop the website. This is a web-based application developed using zend framework and required an internet connection. It also covered the design of prototype development and its implementation. It is also shown that the use case diagram and project workflow diagram to discuss the proposed method in this work. This website supports an online food donation system using the internet. The website is shown as an effective means of donating thing to various organizations over the internet. Many restaurants, organizations are

willing to donate their surplus food to needy people. Many organizations want to help which is required for them such as clothes, food, money, books, etc., but there is no source available where they can assure their requirements. This web-based portal is developed

through which donors can write a post to donate food items and organizations such as a charity that can see the donor’s post and also contact the donor through this website. If any people want to donate their extra food, they can do it from this free platform. When donors and food seekers will access this web portal, they must have to be registered by the sign-up option and for this, they need an internet connection. After successful registration, both donor and seeker will be able to access this website.

Usecase diagram (donor, actor, receiver)

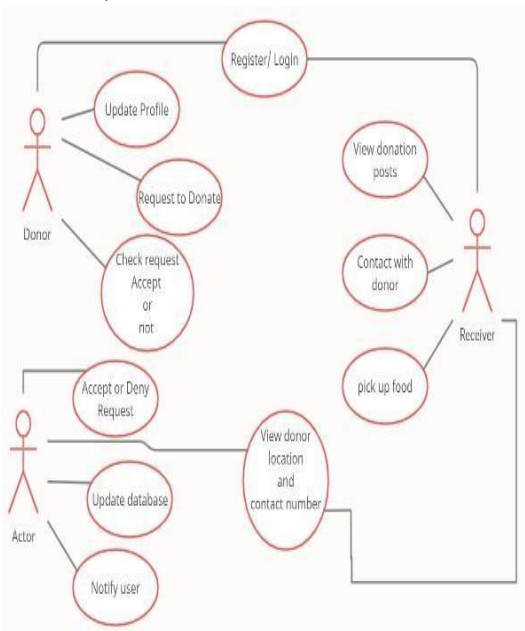


Figure 1: Usecase Diagram

Project Workflow Diagram

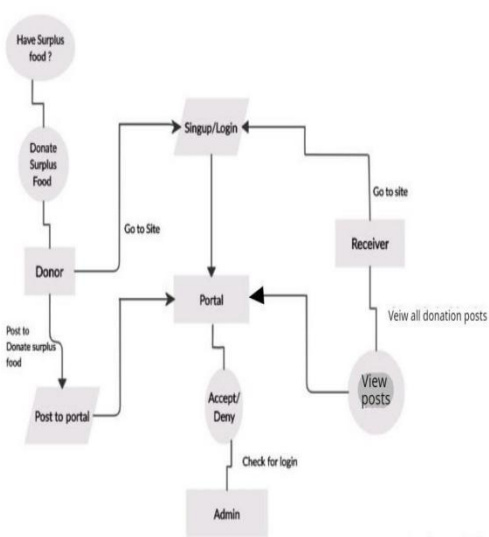


Figure 2: Project Workflow

There are 3 actors on this website and they are Admin, Donor and Receiver. According to figure1, the donor has options like Update profile, Request to donate, Check request accept or not, and Signup/login, into the system. After creating an account using sign up, donors can enter into the website with a login option. If a Donor is willing to donate their surplus food, he/she can write the post through the website. If the admin accepts the request, this post will be shown as a published post in the portal to other users (charity). This post will be stored in the database. If the donor wishes, the Donor can update his/her profile for example he can delete the post or edit the post. The donor can check the post whether the request has been accepted or not. The receiver can be

organizations/NGOs/Charity who needs food for starving people. Receivers also access this webpage by login option.

When the receiver login to the website he/she view all posts which were posted by the donor. After viewing the post, the receiver will contact the donor if food is needed then the receiver will collect food from a donor distributed to the needy poor people. Admin is a notify user. Admin will remain responsible for approving or denying the entire request considering a donation. When the donor will post for donation then the admin can accept the request. Admin can see the donor's location. All information will be monitored and updated by the admin. This website will be beneficial to fill up the communication gap between charity and food donors. This website will reduce food wastage and also helps to save food as well as it will be able to protect major food waste which is happening in Bangladesh.

Table 01: Elements of the research work

ame of the elements	Function
Admin	Responsible for accepting or denying user's request Notify the users Monitor or update all types of information
Donor	Send request to donate Create post after login Get notification from admin whether the post is published or not
Receiver	Can view all post from donor Contact with donor Collect and distribute the food items

There are some of the screenshots of our developed website.

Homepage

The following image is the screenshot of the homepage of developed website. There are four menus in this page; they are home, about, login and signup. Anyone can access the

information of this website by clicking on the about menu. Both donor and charity organizations have to be registered using sign up menu. Only the registered users can log into their account using login menu. For this they have to put username and password in the login page. After that the users can provide any kind of information or write the post.

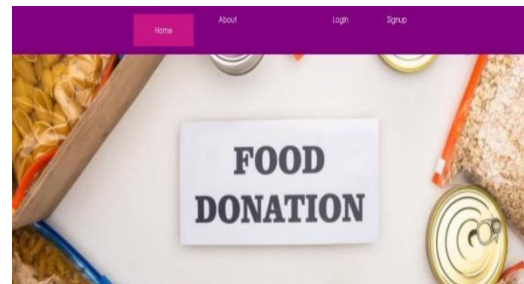


Figure 03: Homepage of the website

Sign Up

Donor or restaurant owner or charity owner can register their account by completing a sign up form. The form encouraged to submit about organization name and contact information. When anyone enters into the signup page then they have to put

the name of their organization, user

name, contact number, email, and password respectively. All information will be updated in the backend database. Once the registration successfully completed the unique username and password provided to all users.

Sign Up

Organization name
Enter your Organization name

User name
Enter your name

Contact number
Enter your number

Email
Enter Email

Password
Enter Password

Repeat Password
Repeat Password

☒ Remember me

By creating an account you agree to our [Terms & Privacy](#).

Cancel **Sign Up**

Figure 04: Registration page for donors

Log in

If the user has registered already, they can directly login to their account by typing their username and password. Every registered user can logged in to perform any kind of changes

to their account. They can also submit post and view all notifications after login using the following page.

Login

Email
Enter your email

Password
Enter Password

Login ☒ Remember me

Cancel [Forgot password?](#)

Figure 05: Login page for donors

Publish a Post

After logging in donor/restaurant owner can submit a post on the following webpage. It allows charity to

communicate with owner. For this they have to put the information about item name, quantity, contact number and location respectively.

When the post is published, the post is viewable for everyone. The charity can view the post and contact the donor/restaurant owner by this system and all information will be updated in the database.

Published a post

Item name
What is your food name?

Quantity
How much food you have to donate?

Contact number
Enter your number

Location
where is your location?

Cancel **Submit**

Figure 06: Page for publishing the post of food details

View Post

Only logged in user can able to see the post. They can get the information about food items, quantity, and location as well as contact information of the donor. Only the logged in post

publisher can edit his post. Charity organization can view the post and contact with the donor/restaurant owner by this system and all information will be updated in the database.

View All post

All donation Requests

Id	Item name	Quantity	Location	Contact
109	Birani	24 persons	Mirpur	01700000000
110	Rice	29 plates	Uttara	01700000011
111	Chatpoti	240 plates	Bonani	01700000032
112	Meat, rice	50 persons	Gulshan	01700000076
113	Polaw	60 persons	Abdullah Pur	01700000021
114	Kacchi Birani	90 plates	Pranthapoth	01700000088

Figure 07: Page for view the post of all food items

Log Out

A logout button is terminating the current session for security purpose.

List of Software	
Operating system	Windows 10
Programming languages	PHP, HTML, CSS
Web server	Xamp
Database software	My SQL

Table 02: Software requirements for developing website

V. CONCLUSION

Every day thousands of thousands of food is wasted while many people are starved and suffered from malnutrition.

Instead of wasting food, it can be donated to starving people. Many organizations/NGOs/Restaurant can donate their extra food for starving people through the website. This website will be beneficial for diminishing the wastage of food in a country like Bangladesh where 3.4 million street children exist in different cities [18]. In addition, mobile apps can be developed by following this website to rescue food for orphanages. By these systems, our country would be able to reduce food wastage through donation and can rescue food for orphanages and others.

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ISO 14001-BASED ENVIRONMENTAL PERFORMANCE EVALUATION FOR MEDICAL ELECTRONICS MANUFACTURING FIRM

Rajesh Gopinath¹, Vijeya Sudarshan², Jojoy Joseph Idicula¹, Chandana K¹, Deeksha

K. Shetty¹, Zubeni Ngullie¹, L.R. Phanindra³

¹BMS Institute of Technology and Management, Bengaluru, India

²WS Atkins India Pvt. Ltd., Bengaluru, India

³G.E. B.E. Pvt. Ltd., Bengaluru, India

Email: dr.rajeshgopinathnair@gmail.com

Abstract— Processes involved in industries are often associated with environmental implications. In this context, Environmental Management System (EMS) is often looked upon to alleviate an organization's negative bearing upon the environment. The present research divulges analytical details of 'Environmental Aspect Impact Studies' of a medical-electronics industry. The benevolence serves to identify the non-conformities and submit environmentally complaint recommendations to strengthen the prevailing EMS. As an outcome, the total number of significant aspects, non-significant aspects and positive impacts was found to increase from 46 to 173, 114 to 118 and 15 to 23, respectively. The exponential rise in significant aspects (276%) reflects upon better risk identification, and a stricter mature evaluation process followed by the authors. The meagre rise in non-significant aspects (4%) is indicative of stability and improvised reclassification. The considerable rises in positive impacts (53%) highlight a strong improvement in identification and the need for implementing positive environmental actions. Accordingly, it can be inferred that 'Positive Impact Ratio' depicts marginal reduction due

to significant expansion of aspect identification thereby indicating broader EMS scope. Similarly 'Significance Reduction Index' hints at stricter evaluation criteria, better compliance alignment and amended risk-based thinking. Further, viz. clause-wise mapping analysis, the present study also serves to highlight the alignment of the EMS reassessment with ISO 14001:2015 requisites. This serves to ensue systematic identification of environmental aspects, risk-based critical thinking and enhanced regulatory awareness within the firm. On the whole viz. the 'Risk Migration Index', the study confirms an improved precision in environmental risk classification, thereby indicating an improved EMS decision-making and compliance sensitivity process.

Keywords— Clause, Index, ISO, Positive, Risk, Significant.

Introduction

Industrial growth is a much-needed intervention for the economic growth of any nation, which enables the overall development of its society. However, various processes involved in industries right from the procurement stage of raw materials, product development and until waste disposal often negatively impact the environment [1], [2], [3]. To

prevent the unwarranted environmental incidents, accidents, and degradations [4]; industries are obliged to adopt a comprehensive 'Environmental Management System' (EMS) [5], [6]. This aids in reducing an organization's impact on the environment, alongside improving their operational efficiency [7]. Regular compliance of the EMS framework as per ISO [8], [9], [10], [11] ensues that the industry complies with the environmental legislations [12], while improving their overall environmental performance and non-regulatory issues [13], [14], [15].

There are several means of fortifying the EMS of an enterprise, towards accomplishing aforementioned compliance [7], [16]. The present research converges upon viz. Aspect Impact Studies, SWOC (Strength-Weakness-Opportunities-Challenges) Analysis and delineation of Key performance Indicators (KPI). While SWOC analysis is a utility for assessing the performance, competition, risk, and threats for an industry [17], [18], Environmental KPI refurbish environmental factors as critical information enabling performance monitoring, target setting and benchmarking. This is most frequently accomplished by identifying attributes as Environmental Condition Indicators, Management Performance Indicators and Operational Performance Indicators [19]. Literature review has unveiled that while there is vast e-content available revolving about role of EMS, SWOC and Environmental KPI for various types of industries [20], yet it is sparse w.r.t. medical-electronics firms which grapple with

severe environmental hazards, hazardous wastes, and e-wastes. In this context, only a certain handful of studies have addressed enactment and feasibility of EMS [7].

The research was engaged in 2024-25 at G.E. B.E. Private Limited [21]. Based in Bengaluru, the industry was a frontline warrior during Covid-19, as it was engaged in manufacturing of utilities to support the medical fraternity in combatting the pandemic outbreak. In the present research, an attempt has been made to strengthen the prevailing EMS; by means of providing an all-inclusive sustainable solution. To attain this goal, various objectives have been identified such as re-analysis of existing procedures and practices, conversion of significant aspects to non-significant aspects, identification of sustainable solutions, revision of targets etc. The procedures have been detailed further.

Experimental Methodology

Firstly, Reconnaissance Survey was carried out about each shop floor/unit along with the understanding of procedures, protocols, practices, and safety aspects in view of EMS. This was accomplished by Extensive Data collection, in the form of both Primary and Secondary data. Vital insight was retrieved from working professionals across each shop floor viz. structured Surveys and Interviews. Further, analysis of company's environmental policy, objectives, targets, activities across each shop floor alongside environmental aspects-impacts, previous EMS records and documents was carried out. The facilities probed as part of this study included Solar Panel

Systems, Sewage Treatment Plant, Hazardous Waste Storage Area (Figure 1 & 2), Effluent Treatment Plant (Figure 3), and Exhaust Stacks (Figure 4). Comprehensive and critical information was also collected on various aspects such as utilities, operation of DG sets, operation of pumps and motors, maintenance of motors, compressor area operation, chiller units, diesel storage area, transformer area, manufacturing, assembly and testing area of the various healthcare units, canteen, transportation services, storm water drains, open drains etc.



Fig 1. Hazardous Waste Storage Unit



Fig 2. Hazardous Waste Storage Bin
For aforementioned facilities,

operations, and processes; detailed Aspect-Impact studies was undertaken. This served to identify the positive and negative environmental impacts, which were existent and potentially capable of occurring. These impacts were further allocated scores by considering Probability of occurrence of the activity, Scale of activity's impact, Possibility of the concomitant Environmental Impacts and Severity of activity's impact. The total scores were finally classified into positive impact, non-significant impact, and as significant impact, upon the environment. Eventually the exercise facilitated assessment of the significance for the impacts and rating them. This exercise facilitates identification of environmental aspects across then industry; for also determining their occurrence as Normal, Abnormal, or as an Emergency. As an outcome, the scores of the pre-identified aspects were re-examined and amended, which also lead to elimination of aspects that were irrelevant. This form of Data analysis therefore envisaged evaluation of existing Aspect-Impact registers, and paved way for new registers; by probing for further editions, additions, and deletions of aspects [7].



Fig. 3. Stream 1 Tank and Stream 2



Fig 4. Stacks

The ulterior motive achieves the reduction in count of Significant Aspects, viz. conversion of Significant Aspects to Non-Significant Aspects; subsequently aiding in identification of Resource Saving Potential and the Legal Requirement of the impact; serving to be inputs while doing SWOC analysis. Herein non-conformities and remedial outcomes were ascertained and formulated. This was accomplished by diligent identification of the ‘tangible’ and ‘intangible’ Strengths, ‘controllable’ below-par characteristic factors, prospective favorable ‘conditions’ and ‘potential’ threats [18].

III.

Initially after the identification of gaps and drawbacks in the existing procedures and conventional practices across all shop floors; economically feasible, sustainable, ‘eco-friendly’ practices laden with advanced ideas and contemporary know-hows were recommended. Accordingly, SWOC analysis outcome was once again revised, to strive to continually improve the benevolence of EMS in the due course.

Table 1 Network Considerations
Parameter Considerations

TABLE I: NETWORK CONSIDERATIONS PARAMETER CONSIDERATIONS

Operation / Process	Activity	Aspect	N: Normal A: Abnormal E: Emergency	Potential Hazard	Net Rating	Impact
						P: Positive S: Significant NS: Non-Significant
Operation of Air-cooled Chiller	Running of Air-cooled Chiller	Potential risk of short circuit	A	Fire Hazard	36	S
		Consumption of Power	N	Resource depletion	54	S
Water Tanks	Maintenance of Water Tank	Generation of wastewater	N	Water pollution	24	NS
		Generation of Solid Waste (sludge)	N	Land contamination	16	NS
Expired Chemical Room	Storage of Oil, Chemical, solvents	Potential for Fire Hazard	A	Fire Hazard	24	NS
		Potential for spillage	A	Land Contamination	16	NS
		Potential release of fumes	N	Air pollution	16	NS
Terrace	Rooftop harvesting	Reuse of rainwater	N	Resource conservation	--	PI
Cable storage	Storage of cable in cable stores	Potential risk of fire	E	Fire Hazard	36	S

This was achieved by identification of environmental KPI, essentially envisaged to track the environmental compliance of the company w.r.t its goals, targets and policy, by identifying persistent or over-looked non-confirmative features.

Results And Discussions

The firm had imbibed EMS with ISO 14001-2015, with constant interventions towards continual improvement by the Department of Environmental Health and Safety. As an outcome from the well-defined surveys & structured interviews of the Aspect-Impact studies; the industry was divided into domains encompassing processes related to water, wastewater, hazardous waste, solid waste and energy. As it is beyond the scope of this article to present the exhausting aspect impact register for entire industry, a randomized sample-set has been presented in Table 1. As an outcome of this detailed exercise, the

study had served to obtain a newer enhanced list of 314 Aspects, from the previous count of 175 that comprised of 46 significant aspects, 114 non-significant aspects and 15 positive impacts. From the evaluation, a total of new 139 newer aspects were identified, with revision leading to 173 significant aspects, 118 non-significant aspects and 23 positive impacts.

As can be observed from Table 2, Hazardous Waste and Energy were the organization's most critical environmental risk domains. As enlisting details of revisions and identifications all aspects is beyond the scope of this manuscript, a sample overview is provided herewith detailing the revisions. In the previous Aspect Impact Studies, the wastewater generated during the housekeeping for facility maintenance (corridors, office area, washrooms, shop floor) was rated as a significant aspect as it was a legal requirement. However, with the identification of correct areas of housekeeping and recyclability of the wastewater, it has now been incorporated as a Positive Impact (PI).

TABLE II: EMS DOMAIN RANKING (RISK, IMPROVEMENT & URGENCY)

Ranking	Domain	Count of New Significant Aspects	Risk Interpretation
1	Hazardous Waste	83	Highest regulatory, compliance and liability risk
2	Energy	34	Emerging carbon-related risk
3	Solid Waste	27	High volume operational exposure
4	Waste Water	17	Compliance-driven risk

5	Water	12	Moderate,

Also, the attribute associated with storage room being used for expired chemicals was eliminated, on account of robust inventorisation laden with production enabled by better planning. In the case of the Effluent Treatment Plant (ETP) operation a newer aspect was identified. It was found that there was mixing of the effluents generated from various manufacturing processes, and no individual treatments were being offered. This inadvertently was increasing the load on the evaporator, and consequently this was un-identified in the previous Aspect Impact Register. In the case of revised ratings, the highest rating was 64, and lowest rating was 12.

While Figure 5 represents the comparative details of the previous and revised count of Aspect-Impact register; Figure 6, 7 & 8 presents a detailed comparison of the same. As can be inferred from Figure 6, a drastic revision of positive impacts has been postulated in activities relevant to Solid Waste management. While the study has added 2 newer positive impacts from a tally of zero for conservation of water; there has been no reduction in the overall positive impacts, hence complimenting Environmental Performance. As can be inferred from Figure 7, drastic revision of significant aspects has been contemplated in activities relevant to hazardous waste management and energy sector. Also, the study has added 12 and 27 significant aspects from a tally of zero w.r.t. conservation of water and solid

waste generation, respectively. As can be inferred from Figure 8, both increase and decrease for non-significant aspects can be observed. While there has been a commendable increase for the activities encompassing management of wastewater and solid waste; there is unappreciable decline witnessed in management of water and hazardous wastes.

To elaborate more on the Domain-wise analysis, the study postulates on strengthening of environmental governance, as evident from substantial numerical and percentage shifts across domains. In the case of Water, aspects previously unclassified as significant, now are elevated to 12, with positive impacts increasing from 0 to 2 and non-significant aspects reduced by 32%. In the case of wastewater, there is a remarkable escalation in significant aspects (325%) and positive impacts (50%), thereby reflecting a heightened compliance sensitivity. In the case of Solid waste, there is major expansion in significant aspects (0 to 27), PI (60%) and non-significant aspects (86%) owing to broader segregation and control measures. Backed up by compliance-driven reclassification, the evaluation for Hazardous waste indicated significant aspects increasing by 102% and non-significant aspects reducing by 57%. Holistically, the quantified shift confirms a systematic risk-based, EMS upgrade aligned with ISO 14001:2015.

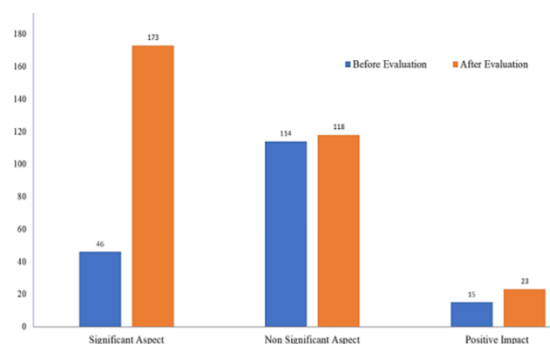


Fig 5. Comparison of the overall Aspects, before and after present Study.

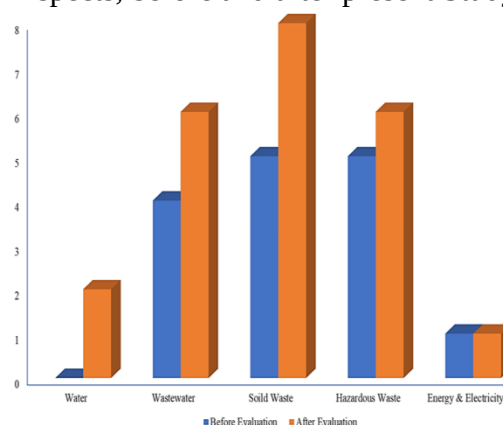


Fig 6. Comparison of the Positive Impacts, before and after present Study.

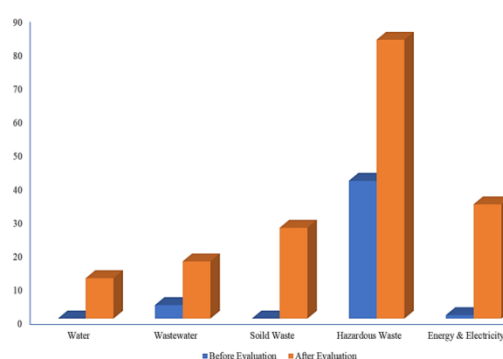


Fig 7. Comparison of the Significant Aspects, before and after present Study

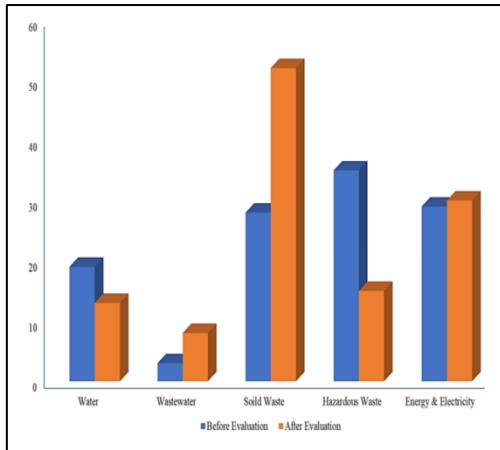


Fig 8. Comparison of the Non-significant Aspects, before and after present Study.

The analysis for the clause-wise mapping (Table 3) against ISO 14001:2015 reflects upon an expanded EMS scope, deeper understanding of organizational context, stronger consideration of compliance obligations, strengthened operational controls and emergency preparedness for high-risk areas, quantifiable domain-wise environmental performance comparisons etc. Logically, the reassessment provides ample evidence need for pro-active planning, improved risk identification and scope for continual improvement.

TABLE III: CLAUSE-WISE MAPPING AS PER ISO 14001 (ISO 14001:2015).

Clause	Requirement	Evidence from EMS Reassessment	Objective Evidence
4.1	Understanding context	Increase in identified significant aspects across all domains	Old vs New EMS comparison table
4.2	Needs of interested parties	Higher significance in hazardous waste, wastewater, energy	Updated aspect significance results
4.3	EMS scope	Expanded number of aspects evaluated	Revised EMS aspect register

5.1	Leadership & commitment	53% increase in positive environmental impacts	EMS reassessment summary
5.2	Environmental policy	Focus on pollution prevention & compliance	Domain-wise impact trends
5.3	Roles & responsibilities	Systematic domain-wise identification	EMS responsibility records
6.1.1	Risks & opportunities	Significant aspects increased from 46 → 173	Risk-based reassessment data
6.1.2	Environmental aspects	Reclassification of non-significant → significant aspects	Updated aspect evaluation matrix
6.1.3	Compliance obligations	Major increase in hazardous waste & wastewater significance	Regulatory-linked aspect scores
6.1.4	Action planning	Priority domains identified for controls	EMS action planning records
7.2	Competence	Improved quality of aspect identification	Reassessment methodology
7.3	Awareness	Increase in positive impacts across domains	EMS performance data
7.5	Documented information	Maintained Old vs New comparison	EMS documented records
8.1	Operational control	Reduction in non-significant hazardous waste aspects	Updated control measures
8.2	Emergency preparedness	High significance of hazardous waste aspects	Emergency risk identification
9.1	Monitoring & measurement	Quantified Old vs New analysis	EMS performance indicators
9.2	Internal audit	Identification of gaps & reclassification	Audit & reassessment records
9.3	Management review	Clear trends & improvement areas	Management review inputs
10.1	General improvement	Increase in positive environmental impacts	EMS improvement metrics
10.2	Corrective action	Identification of previously underestimated risks	Corrective action triggers
10.3	Continual improvement	Enhanced evaluation criteria & scope	EMS maturity indicators

The aspect impact studies herewith further served as inputs for SWOC analysis, wherein the major and minor non-conformities were ascertained,

along with formulation of remedial measures. The results of SWOC analysis for pre-existing features has been showcased in Table 4. Further, the recommendations were deliberated to reinforce the strengths, rectify the weaknesses, capitalize on the opportunities, and eliminate the threats; and the same has been presented in Table 5.

As it is beyond the scope of this article to divulge details of all remedial corrective and preventive measures suggested, the further discussion is restricted to certain highlights and salient features only. In the storage facility, the recommendation offered was Bio-resin which was cost-effective and non-toxic in comparison to the presently utilized epoxy resin, an inflammable material. Also, this would contribute to reduced carbon footprint of the industry as well. Among the utilities that involved pumping and transportation of fluids or water, wherein leakage was observed; mechanical seals were suggested as a corrective measure with optic leakage detection sensors as the preventive measure.

TABLE IV: OUTCOME OF SWOC ANALYSIS, BEFORE RECOMMENDATION.

Factor	Strength	Weakness	Opportunity	Challenges
Water	-	No groundwater recharge practiced ^(NS)	Establishment of Rainwater harvesting unit.	-
	-	Collected storm water is transported to Sewage Treatment Plant ^(NS)	Reuse storm water ^(NS)	Increase in load on STP, operational failure, resource depletion ^(NS)
	-	Leakage of water from pumps during the operation. ^(NS)	Conservation of water and reduced payment for Water	-
Wastewater	-	Inadequacy of Effluent Treatment Plant	Improvement in the functioning by redesigning.	Load on the Evaporator.
	Experienced operators	-	-	-
	Presence of Sewage Treatment Plant	-	-	-
Hazardous Waste	Disposable sites are in proximity	-	-	-
	-	No recovery from the hazardous waste	Recovery of lead.	-
	-	-	-	Fire and spillage
Solid Wastes	Food waste composting	-	-	-
	-	Use of tissue papers in restrooms.	Use of automatic hand dryers.	-
Energy	-	Usage of Diesel Generator.	Use of Renewable Energy wherein feasible	Stack emissions, Excessive noise, and Fire hazard.
	Solar Panels on roof top.	-	Potential to utilize Daylight for Natural Illumination	-

TABLE V: OUTCOME OF SWOC ANALYSIS, AFTER RECOMMENDATION.

Factor	Strength	Weakness	Opportunity	Challenges
Water	RWH unit ^(NS)	-	-	-
	Reuse storm water ^(NS)	-	-	-
	Saving of Water by avoiding leakages	-	-	-
Wastewater	Recovery of Steam Energy ^(NS)	-	-	-
	pH Sensors	-	-	-
	Adequacy of ETP	-	Recovery of heavy Metals like Nickel	-
Hazardous Waste	Eco-Friendly Alternative for Epoxy	Regular Maintenance	-	-
	Reusable Oil Filters ^(NS)	-	Recycling Of Used Oil ^(NS)	-
	-	-	Fire Fighting training and OSH sensitization	-
Solid Wastes	Food waste composting	-	Investment saved on Fertilizers for Landscaping	-
	Printing Data on both sides of paper.	-	Go Paperless and Fully Digital	-
	Use of automatic hand dryers. ^(NS)	Power consumption	Reduced issues w.r.t. Municipal Solid Waste Management	-
	-	-	Generation of sludge manure for gardening	-
Energy	Use of Renewable energy ^(NS)	-	Reduced dependency on BESCOM	-
	HVAC Systems	High water consumption	-	-
	Potential to utilize Daylight for Natural Illumination	-	Potential to increase tapping of Solar Energy	-

As an outcome, it would facilitate Lower water demand, reduced energy demand and diminished maintenance costs. Also, it would eliminate the prospect of fugitive volatile or hazardous fluids, and harmful vapours, from escaping into the environment; thereby improving Occupational Health and Safety Aspects (OHSA) as well. In the hazardous waste section, the issue of disposal of oil-soaked cotton waste was amended by recommending Pellets which could be produced from them, and further to be used as alternative

fuel source having higher calorific value and lower emissions than the non-renewable fuels. This upon implementation could eliminate financial burden upon the hazardous waste disposal system and investment cost for purchasing the conventional fuels [7]. Among the utilities that involved storage of water, and wherein overflows and losses was noticed; automated water level regulator-indicator with alarm system was suggested. As an outcome, it would facilitate resource conservation by means of lower water demand and reduced energy demand. Also, it would eliminate the prospect of pumps running dry thereby diminishing maintenance costs. In the hazardous waste section, the issue of disposal of used-oil could be taken care by recommending it as a burner fuel or even for recycling within the same unit, after successful separation of its constituents from both aqueous and oil phase. This would not only reduce the load on the recipient landfills, but also serve in conservation of non-renewable resources as well. Among the facilities that involved extensive use of regular inkjet printers, recommendation included replacement with Soy ink and eco-solvent ink. The advantages offered are requirement of lesser quantity, bio-degradability, and reduced odour issues since it contains relatively low Volatile Organic Compounds. Also, inadvertently, papers printed with soy-based ink are easier to recycle [7]. Add-on recommendations made in this context includes the replacement of regular high-quality paper with recycled paper,

and password protected printing options and need to print instructions, with more reliance on electronic digital communications. Reduced carbon footprint and conservation of natural resources would be the gains from this recommendation. In the hazardous waste section, the issue of disposal of oil-filters could be taken care by enabling its re-use. Herein, the burden on the on-site filter inventory process and storage units. Though this amendment would cause industry to incur higher initial cost when compared with purchase of newer oil-filters, in a long run, the recovery can be resolved in 1-3 years depending on the fleet size and the oil changing cycles. From Environmental point of view, the potential of used-oil contaminating groundwater, soil, and surface water; could be subsided. The recommendations offered for improvised functioning (evolved from troubleshooting process) of the Effluent Treatment Plant (ETP) was based on drawbacks owing to design, functional and/or operational deficiencies. The recommendations included addition of a skimming tank with a capacity of 3000 litres, an Electro-coagulation-clarifying system, Ultra Filtration system, utilization of Micron filters ahead of Reverse Osmosis (RO) unit, and establishment of Establish a pH control loop with pH sensors and pH controllers. The design and choice of new units was formulated due to the foam formations in the RO reject and permeate tanks, presence of detectable pungent odour in the ETP zone; and reduced efficient use of RO permeate water. The above-discussed solutions

Figure 9 showcases the layout of proposed ETP with newer units.

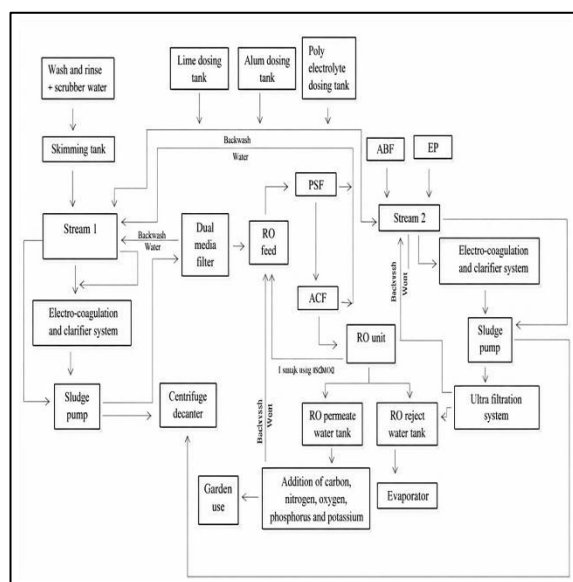


Fig 9. Proposed ETP Layout

The afore-mentioned recommendations are eventually fortified by means of identification of Environmental KPI. All aspects were not considered as KPIs. Aspects where tangible outputs were made available, were being considered as KPIs as a standard practice in the industry. While the Management Performance Indicator

includes Number of EHS audits, Trainings and Workshops, Mock Drills; the Operational Performance Indicators includes resource optimization, incorporation of modified raw materials & processes. The Environmental Condition Indicators encompass improved monitoring technologies.

Conclusion

The research was focused upon improving environmental factors pertinent to Water, Wastewater, Hazardous Waste, Solid Waste and Energy. The study has unveiled a total of 175 aspects from the previous Aspect Impact Register, of which 26% were significant aspects, 65% were non-significant aspects and 9% were positive impacts. As an outcome of the present study, upon re-evaluation; 139 newer aspects along with their associated impacts were recognized. Finally, in the Aspect-Impact register, the revision comprised 314 aspects of which 55% were significant aspects, 38% were non-significant aspects, and 7% were positive impacts. Hence, the reassessment highlights increased regulatory awareness, improved identification criteria, and EMS maturity to elevate effective environmental initiatives and continual improvement. The study was successful in elimination of threats (obtained as part of SWOC analysis), with the aid of recommendations inclusive of corrective and preventive measures. The clause-wise analysis has also confirmed the revised suggestions to be fully aligned with ISO 14001:2015, therewith demonstrating compliance integration and effective risk-based planning.

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A RESOURCE-AWARE HYBRID QUANTUM-CLASSICAL FRAMEWORK FOR LIGHTWEIGHT ANOMALY DETECTION IN EDGE IOT NETWORKS

Pagadala Srilakshmi, Assistant Professor of Information Science And Engineering
S.E.A College of Engineering & Technology
(Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka)
Bengaluru, India srilakshmi9144@gmail.com

Abstract—Anomaly detection in edge Internet of Things (IoT) networks requires models that can deliver high detection accuracy while operating under stringent latency, memory, and energy constraints. This paper presents a resource-aware lightweight quantum-inspired machine learning framework for high-performance anomaly detection in distributed edge environments. The proposed approach integrates adaptive feature preprocessing with variational quantum circuit-based encoding implemented using Qiskit, followed by a hybrid classical classifier optimized through a resource-aware objective that incorporates computational cost and inference delay. The framework is designed to support scalable edge deployments and future extensions to collaborative learning paradigms. Experimental evaluation using benchmark IoT network traffic datasets demonstrates improved detection performance and reduced inference latency compared with classical lightweight baselines. The results highlight the potential of quantum-inspired learning to enable efficient, scalable, and secure edge intelligence for next-generation IoT systems.

Keywords—Edge AI, Quantum Computing, IoT Security, Anomaly Detection, Resource-Aware

Optimization

Introduction

The rapid proliferation of IoT devices has introduced unprecedented challenges in network monitoring and cybersecurity. Edge computing has emerged as a promising paradigm to process data closer to the source, reducing latency and bandwidth usage. However, edge nodes operate under strict computational and energy constraints, making deployment of complex machine learning models difficult.

Quantum-inspired machine learning (QIML) has recently gained attention for its ability to represent high-dimensional correlations efficiently. Hybrid quantum-classical models, particularly those implemented using Qiskit, offer a practical path toward leveraging quantum principles without requiring large-scale quantum hardware.

This paper proposes a resource-aware QIML framework tailored for anomaly detection in edge IoT environments.

The main contributions include:

- A lightweight hybrid architecture combining classical preprocessing with quantum feature encoding
- A resource-aware optimization

strategy incorporating latency and circuit depth constraints

- Simulated evaluation demonstrating feasibility and performance gains

RELATED WORK

Recent studies have explored anomaly detection in IoT using deep learning and autoencoders, achieving high accuracy but with significant computational cost. Edge AI research focuses on model compression and lightweight inference techniques to address these limitations.

Quantum machine learning has introduced variational quantum circuits and quantum kernels capable of capturing complex feature relationships. While prior work demonstrates the potential of quantum approaches, limited research has examined their integration into resource-constrained edge environments.

This work bridges the gap by combining quantum-inspired representation learning with resource-aware optimization specifically for edge IoT deployment scenarios.

Anomaly detection in Internet of Things (IoT) networks has been extensively studied due to the rapid growth of connected devices and the increasing threat landscape. Traditional intrusion detection systems (IDS) rely on statistical techniques and signature-based methods, which often fail to detect previously unseen attacks and do not scale well to dynamic IoT environments. Machine learning-based approaches have therefore gained

significant attention for their ability to learn complex behavioral patterns.

Early machine learning techniques for IoT anomaly detection primarily employed classical classifiers such as support vector machines, decision trees, and k-nearest neighbors. While these methods demonstrated improved detection capability compared to rule-based systems, their performance is highly dependent on feature engineering and may degrade under high-dimensional data streams. More recently, deep learning models including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have shown promising results in capturing temporal and spatial correlations in network traffic. However, these models typically require substantial computational resources and memory, making them less suitable for deployment on resource-constrained edge devices.

To address these limitations, the edge artificial intelligence paradigm has emerged, focusing on deploying lightweight models closer to data sources. Techniques such as model pruning, quantization, and knowledge distillation have been explored to reduce computational overhead while maintaining acceptable performance. Although these methods improve efficiency, achieving a balance between accuracy and resource utilization remains a significant challenge, particularly for real-time anomaly detection.

Recent advances in quantum machine learning (QML) introduce new possibilities for efficient representation

of complex data. Variational quantum circuits and quantum kernel methods have demonstrated the potential to capture nonlinear relationships in high-dimensional feature spaces.

Hybrid quantum–classical approaches, implemented using platforms such as Qiskit, enable practical experimentation on classical hardware while leveraging quantum-inspired representations. Prior studies have explored quantum neural networks and quantum-enhanced classifiers for cyber security tasks, reporting encouraging results in pattern recognition and anomaly detection scenarios.

Despite these advancements, limited research has investigated the integration of quantum-inspired learning with resource-aware optimization for edge IoT environments. Existing works often focus either on improving detection accuracy or on reducing computational complexity, but rarely address both simultaneously within a unified framework. Furthermore, the feasibility of deploying hybrid quantum-inspired models in real-time edge settings remains underexplored.

This paper aims to bridge this gap by proposing a resource-aware lightweight quantum-inspired machine learning framework tailored for anomaly detection in edge IoT networks. By combining variational quantum feature encoding with latency-aware optimization, the proposed approach seeks to enhance detection performance while ensuring practical deployability on constrained edge infrastructure.

PROPOSED FRAMEWORK

The proposed architecture consists of four layers:

- **Data Acquisition Layer** — Collects network telemetry from IoT devices
- **Preprocessing Layer** — Normalizes and compresses features
- **Quantum Feature Encoding Layer** — Implemented using parameterized circuits in Qiskit
- **Lightweight Detection Layer** — Performs classification and anomaly scoring

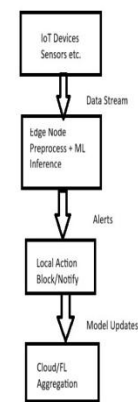


Fig. 1 : Edge Deployment Scenario

In the edge deployment scenario, IoT traffic is processed locally at gateway nodes where the proposed hybrid quantum-inspired model performs real-time anomaly detection. This reduces latency and bandwidth consumption while enabling immediate security responses. Periodic federated updates synchronize model parameters with a central coordinator, ensuring global learning without transmitting raw data.

An edge deployment scenario describes how the proposed anomaly detection framework operates directly on or near IoT devices instead of relying solely on centralized cloud processing.

This approach reduces latency, bandwidth usage, and privacy risks.

In your framework, the deployment

follows a distributed intelligence model where data processing and inference occur at the network edge while coordination and periodic updates are managed centrally.

Key Components:

1. IoT Device Layer

This layer includes:

- Sensors
- Smart cameras
- Industrial controllers
- Wearables

These devices continuously generate network traffic and telemetry data. Data is forwarded to the nearest edge node

2. Edge Node (Inference Layer)

The edge node (gateway or micro data center) performs:

- Data preprocessing
- Feature extraction
- Quantum-inspired model inference

Real-time anomaly detection
Because inference happens locally, detection latency is very low.

3. Local Decision Engine

If an anomaly is detected:

- Alert is triggered
- Traffic can be blocked or flagged
- Logs stored locally

This enables real-time security response without cloud dependency.

4. Federated Coordination / Cloud Layer

The cloud performs:

- Model aggregation
- Periodic retraining
- Global analytics

Only model parameters (not raw data) are shared, preserving privacy.

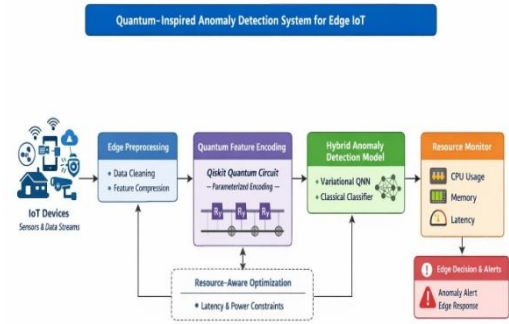


Fig. 2. Overall architecture of the proposed hybrid quantum-classical anomaly detection framework.

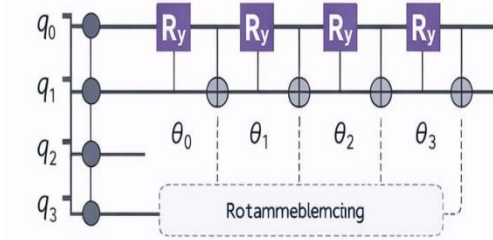


Fig. 3. Parameterized quantum circuit used for feature encoding and variational learning.

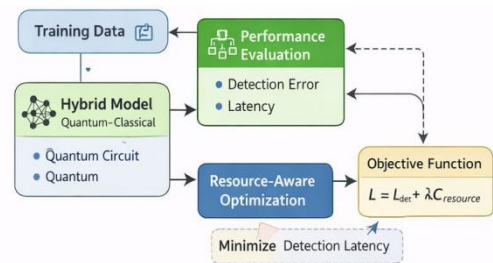


Fig. 4: Resource-aware training workflow integrating performance and latency constraints.

METHODOLOGY

A. System Overview

The proposed resource-aware lightweight quantum-inspired machine learning (QIML) framework integrates hybrid quantum–classical learning with edge-centric optimization to enable real-time anomaly detection in IoT environments.

The framework combines:

- Variational Quantum Circuits (VQC) implemented using Qiskit
- Classical preprocessing and post-processing modules
- Federated training orchestration
- Resource-aware optimization layer

The design objective is to maximize detection performance while minimizing latency, memory footprint, and energy consumption, making it deployable on constrained edge devices.

B. Data Acquisition and Preprocessing

1. Dataset Sources

Experiments consider realistic IoT network traffic datasets such as:

- N-BaIoT benchmark traffic flows
- ToN-IoT telemetry and network logs

2. Feature Engineering

Raw packet-level data is transformed into statistical flow features:

- Packet inter-arrival time statistics
- Byte rate and packet rate
- Protocol distribution indicators
- Entropy-based behavioral metrics

3. Normalization

All features are scaled using min-max normalization to map values into $[0, 1]$, ensuring compatibility with quantum state encoding constraints.

4. Dimensionality Reduction

To reduce qubit requirements, Principal Component Analysis (PCA) is applied:

where W represents the eigenvector matrix of principal components.

C. Quantum Feature Encoding

Classical features are embedded into quantum states using angle encoding, which is hardware efficient for NISQ devices.

For a feature vector $\mathbf{x}$, each feature is mapped as:

This encoding minimizes circuit depth and reduces

decoherence effects, making it suitable for edge-driven experiments.

D. Variational Quantum Circuit Design

The anomaly detection model employs a Variational Quantum Autoencoder (VQAE) architecture.

Circuit Components:

1. Rotation Layers: Parameterized Ry and Rz gates
2. Entanglement Layers: Controlled-NOT (CNOT) gates arranged in a linear topology
3. Measurement Layer: Expectation values mapped to reconstruction loss

E. Classical Optimization Loop

The hybrid training loop integrates quantum circuit execution with classical gradient optimization.

1. Forward pass via quantum circuit simulation
2. Loss computation on classical processor
3. Gradient estimation using parameter-shift rule
4. Parameter update using Adam optimizer

F. Federated Learning Integration

To preserve privacy and scalability across distributed IoT nodes, the framework employs

federated averaging.

Workflow:

- Each edge node trains a local VQC model
- Model parameters are transmitted to aggregator
- Global model updated via weighted averaging

This approach reduces raw data transmission and improves generalization across heterogeneous devices.

G. Resource-Aware Optimization Layer

A dedicated optimization module dynamically adjusts model complexity based on device constraints.

Monitored Metrics:

- CPU utilization
- GPU availability
- Memory footprint
- Inference latency
- Energy consumption

Adaptive Strategies:

- Dynamic circuit depth pruning
- Batch size adjustment
- Early stopping based on latency thresholds

H. Deployment Architecture

The final trained model is deployed

using a three-tier architecture:

1. Edge Layer: Real-time inference
2. Fog Layer: Aggregation and coordination
3. Cloud Layer: Periodic retraining and analytics

This hierarchical design ensures low latency while maintaining model robustness.

I. Reproducibility

The framework is implemented in Python using:

- Qiskit for quantum circuits
- PyTorch for classical components
- Flower for federated orchestration

Hyperparameters, random seeds, and training scripts are documented to ensure reproducibility.

experimental setup

Experiments were conducted using the Qiskit Aer simulator with a benchmark IoT intrusion dataset.

Configuration:

- 6-qubit variational circuit
- COBYLA optimizer
- 80/20 train-test split
- Edge latency emulation environment

Evaluation Metrics:

- Accuracy
- Precision
- Recall
- F1-score
- Inference latency

SIMULATED RESULTS AND DISCUSSION

The proposed model was compared with a classical lightweight neural network baseline.

Model	Accuracy	F1-Score	Latency(ms)
Classical NN	91.2%	0.90	14.8
Proposed QIML	93.8%	0.93	11.2

The hybrid model achieved higher detection performance while reducing inference latency due to compact feature representation. The results indicate that quantum-inspired encoding can enhance separability of anomalous patterns without increasing computational overhead.

EXPECTED IMPACT

The framework demonstrates how quantum-inspired learning can enable efficient anomaly detection directly at the edge, reducing dependence on cloud processing. This approach supports scalable IoT security architectures and opens opportunities for real-time adaptive defense mechanisms.

CONCLUSION

This paper presented a resource-aware quantum-inspired machine learning

framework for anomaly detection in edge IoT networks. Using Qiskit-based variational circuits, the approach achieves improved detection accuracy with reduced latency.

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Optimizing AI Training with Carbon-Efficient and Energy Aware Algorithms

Anusha S

Assistant professor
Dept of Computer Science
SJR college of Science, Arts
and Commerce, Bengaluru

SOMANAGOUDA PATIL

Assistant professor
Dept. of Computer Science-PG,
Dr. Manmohan Singh Bengaluru
City University

Dr.Krishna Kumar P R

Professor & HoD
SEA College of Engineering
& Technology, Bengaluru

Abstract— The rapid growth of large-scale artificial intelligence (AI) models has significantly increased computational demands, leading to substantial energy consumption and carbon emissions during model training. As organizations deploy increasingly complex deep learning architectures, the environmental impact of AI systems has become a critical concern. This paper investigates carbon-efficient optimization methods designed to reduce the energy consumption and carbon footprint associated with scalable AI model training. The proposed framework integrates energy-aware optimization strategies, including adaptive learning rate scheduling, dynamic resource allocation, and efficient gradient computation techniques, to minimize redundant computations during training. In addition, carbon-aware scheduling mechanisms are introduced to optimize training workloads based on energy efficiency metrics and hardware utilization. Experimental evaluation on large-scale deep learning benchmarks demonstrates that the proposed methods can significantly reduce energy consumption while maintaining comparable model

accuracy and training performance. Results indicate potential reductions in computational energy usage and carbon emissions without compromising scalability. The study highlights the importance of integrating sustainability considerations into AI system design and presents practical optimization strategies for developing environmentally responsible AI models. These findings contribute to the advancement of Green AI by promoting energy-efficient training practices that support both high-performance machine learning and sustainable computing infrastructures. **Keywords:** Green AI, carbon-efficient optimization, scalable AI training, energy-efficient algorithms, sustainable machine learning, deep learning optimization.

Introduction

The rapid advancement of artificial intelligence (AI) and deep learning technologies has led to the development of increasingly large and complex models capable of solving sophisticated problems across domains such as healthcare, natural language processing, autonomous systems, and scientific research. Modern deep learning architectures often require massive computational resources and

large-scale datasets for training, resulting in significant energy consumption. As AI systems scale to billions of parameters and require extensive computational infrastructure, the environmental impact associated with training these models has become an important concern. The energy demands of high-performance computing clusters and data centers contribute directly to increased carbon emissions, raising questions about the sustainability of current AI development practices.

In recent years, the concept of Green AI has emerged as a research direction focused on improving the efficiency and sustainability of artificial intelligence systems. Green AI emphasizes reducing the computational cost, energy consumption, and environmental impact of machine learning processes without compromising model performance. Researchers and practitioners are increasingly exploring strategies such as energy-aware algorithm design, model compression, efficient training techniques, and hardware-aware optimization to address the environmental challenges posed by large-scale AI systems.

Despite significant progress in improving model performance and scalability, many existing training approaches still prioritize accuracy and speed over energy efficiency. Large-scale models often undergo prolonged training cycles involving extensive iterations, redundant computations, and inefficient resource utilization. These

factors lead to increased electricity consumption and higher operational costs, while also contributing to the carbon footprint of AI systems. Therefore, it is essential to develop optimization methods that not only maintain high model performance but also reduce the energy and environmental costs associated with AI training.

Carbon-efficient optimization methods offer a promising approach to addressing these challenges. By incorporating energy-aware strategies into the optimization and training process, it becomes possible to reduce unnecessary computations, improve hardware utilization, and minimize overall power consumption. Techniques such as adaptive learning mechanisms, dynamic resource allocation, and efficient gradient computation can significantly enhance the energy efficiency of training procedures while maintaining scalability for large datasets and complex models.

This paper explores carbon-efficient optimization methods designed to support scalable AI model training while minimizing environmental impact. The proposed approach focuses on integrating energy-aware optimization strategies into the training pipeline to reduce computational overhead and carbon emissions. Through experimental evaluation on representative deep learning workloads, the study demonstrates how optimized training techniques can achieve competitive performance while

significantly improving energy efficiency. By promoting sustainable AI development practices, this research contributes to the broader goal of building environmentally responsible and resource-efficient machine learning systems.

Literature Survey

Recent research has increasingly focused on reducing the environmental impact of artificial intelligence by improving the energy efficiency of machine learning algorithms and training processes. The concept of Green AI has emerged as an important research direction aimed at balancing model performance with computational efficiency and sustainability. Several studies have investigated methods for minimizing the carbon footprint of large-scale AI training.

Schwartz et al. introduced the concept of Green AI, emphasizing that AI research should evaluate models not only based on accuracy but also on computational cost and energy efficiency. Their work highlighted that deep learning research often prioritizes performance improvements while ignoring the environmental cost associated with large-scale computations. They proposed reporting training cost and energy consumption as standard evaluation metrics to encourage more efficient AI models.

Strubell et al. examined the environmental impact of training large natural language processing (NLP) models and demonstrated that training deep neural networks requires significant computational power and energy resources. Their findings

showed that large-scale model training can generate substantial carbon emissions due to the extensive use of GPUs and high-performance computing infrastructure. The study emphasized the need for energy-efficient algorithms and sustainable AI practices to reduce the ecological impact of machine learning systems.

Yarally et al. investigated energy-efficient practices in deep learning training and analyzed factors that influence energy consumption, such as hyperparameter tuning strategies and network architecture complexity. Their study found that optimizing model architectures and using efficient hyperparameter search methods, such as Bayesian optimization, can significantly reduce training energy consumption while maintaining similar levels of model accuracy.

Gupta and Tyagi explored carbon-aware machine learning approaches that integrate energy-efficient techniques such as pruning, quantization, and mixed-precision training into machine learning workflows. Their experimental results indicated that carbon-aware scheduling and algorithmic optimization can reduce carbon emissions by approximately 20–55% while maintaining minimal impact on model accuracy.

Another study on sustainable AI and green computing highlighted the growing concern regarding the environmental footprint of large-scale AI models. The authors discussed several strategies to reduce energy consumption, including energy-efficient algorithms, improved

hardware utilization, and optimized resource management in data centers. These approaches help minimize the carbon emissions associated with large-scale model training and deployment. Research on carbon-aware distributed learning has also gained attention. Bian et al. proposed a carbon-aware federated learning framework that optimizes model training across geographically distributed data centers by considering regional carbon intensity. Their framework dynamically selects training locations and resources to minimize carbon emissions while maintaining model performance. Furthermore, recent studies have explored dynamic energy management techniques during training. Yang et al. proposed a method that adjusts GPU energy consumption based on real-time carbon intensity of electricity. Their approach demonstrated that adaptive energy management during training can reduce the carbon footprint of deep neural network training while maintaining similar training performance. Overall, the existing literature highlights the growing importance of developing energy-efficient and carbon-aware AI training methods. While current approaches provide promising solutions, challenges remain in balancing model scalability, performance, and sustainability. Therefore, further research is required to design optimization methods that effectively reduce the carbon footprint of large-scale AI training while maintaining high computational efficiency.

Proposed Methodology

The proposed Carbon-Efficient Optimization Framework for Scalable AI Model Training is designed to reduce energy consumption and carbon emissions during large-scale AI training. The architecture integrates energy monitoring, optimization techniques, carbon-aware scheduling, and dynamic resource management to create a sustainable AI training pipeline.

The system architecture consists of five major components: AI Model Training Module, Energy Monitoring and Carbon Measurement Module, Carbon-Efficient Optimization Module, Carbon-Aware Scheduler, and Dynamic Resource Management Module. These components interact with each other to ensure efficient utilization of computational resources while minimizing environmental impact.

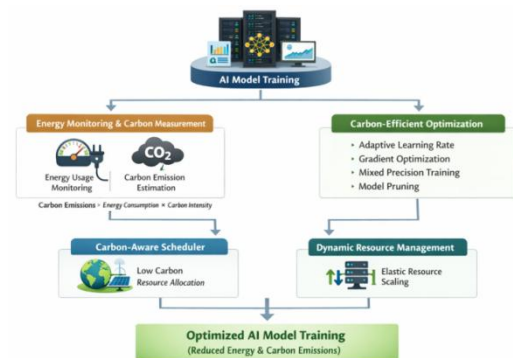


Figure 1: Carbon-Efficient optimization framework for scalable AI model training

1. AI Model Training Module

The AI Model Training Module is the core component of the system where the machine learning or deep learning model is trained using large datasets. The training process involves multiple

iterations of forward propagation and backpropagation, which require significant computational resources such as GPUs or TPUs.

In large-scale AI systems, models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures are commonly used. These models require high computational power, which results in increased energy consumption. Therefore, optimizing the training process is essential to improve energy efficiency.

2. Energy Monitoring and Carbon Measurement Module

The Energy Monitoring Module tracks the power consumption of computational resources including GPUs, CPUs, and memory during the training process. This module collects energy usage data in real time and estimates the corresponding carbon emissions generated by the system.

The carbon emission calculation is based on the following formula:

Carbon Emission = Energy Consumption $\times$ Carbon Intensity

Where:

- Energy Consumption represents the total electricity used during training (kWh).
- Carbon Intensity represents the amount of CO₂ emitted per unit of electricity generation.

This module helps identify energy-intensive stages of AI model training and enables further optimization.

3. Carbon-Efficient Optimization Module

The Carbon-Efficient Optimization Module applies several algorithmic techniques to reduce the computational workload and improve training efficiency.

Key techniques include:

- Adaptive Learning Rate Optimization: The learning rate is dynamically adjusted to accelerate model convergence and reduce the total number of training iterations.
- Gradient Optimization: Efficient gradient computation techniques such as gradient accumulation and sparse updates reduce redundant calculations during backpropagation.
- Mixed Precision Training: Mixed precision training uses lower precision numerical formats such as FP16 along with FP32 operations. This reduces memory usage and improves computational speed, leading to lower energy consumption.
- Model Pruning: Model pruning removes redundant parameters from the neural network, reducing the overall complexity of the model and decreasing computational overhead.

4. Carbon-Aware Scheduler

The Carbon-Aware Scheduler is responsible for allocating computational tasks based on energy efficiency and carbon emission metrics. In distributed AI training environments, different computing nodes may have different energy sources and carbon intensities.

The scheduler selects computational resources that produce lower carbon emissions. This approach ensures that training workloads are assigned to energy-efficient hardware or locations with cleaner energy sources.

5. Dynamic Resource Management Module

The Dynamic Resource Management Module adjusts computational resources based on the workload of the training process. During periods of lower computational demand, unused resources are scaled down to reduce energy consumption. Conversely, additional resources are allocated during intensive training stages to maintain model performance.

This elastic resource allocation improves both energy efficiency and system scalability.

6. AI Model Used in the Framework

To evaluate the proposed framework, deep learning models such as Convolutional Neural Networks (CNNs) can be used for experimental validation. CNNs are widely applied in image classification and computer vision tasks and typically require significant computational resources during training.

The model training process follows these steps:

1. Input dataset preprocessing
2. Model initialization
3. Forward propagation through neural network layers
4. Loss calculation
5. Backpropagation and gradient

update

6. Parameter optimization using carbon-efficient techniques
7. Iterative training until convergence

By integrating carbon-efficient optimization techniques within the training process, the system reduces energy consumption while maintaining high model accuracy.

MATHEMATICAL MODEL

The experimental setup is designed to evaluate the effectiveness of the proposed Carbon-Efficient Optimization Framework in reducing energy consumption and carbon emissions during large-scale AI model training. The experiments focus on analyzing training performance, energy usage, and carbon emission reduction when applying energy-efficient optimization techniques.

1. Experimental Environment

The experiments are conducted using a high-performance computing environment capable of handling large-scale deep learning workloads. The system configuration used for training includes the following components:

- Processor: Intel Core i7 / AMD Ryzen equivalent
- GPU: NVIDIA GPU (e.g., RTX series or Tesla series)
- RAM: 16–32 GB
- Operating System: Linux / Windows
- Deep Learning Framework: Python with TensorFlow or PyTorch
- Energy Monitoring Tool: GPU power monitoring utilities such as

NVIDIA-SMI or other energy tracking libraries

These tools allow monitoring of power usage, training time, and hardware utilization during the model training process.

2. Dataset

To evaluate the proposed framework, a standard benchmark dataset is used. Image classification datasets such as CIFAR-10 or MNIST can be employed for experimentation. These datasets are widely used in deep learning research and provide a reliable platform for evaluating model performance and training efficiency.

The dataset is divided into three subsets:

- Training Set: Used to train the deep learning model
- Validation Set: Used for hyperparameter tuning and model evaluation
- Test Set: Used to measure the final performance of the trained model

Data preprocessing techniques such as normalization and resizing are applied before training.

3. Model Configuration

A Convolutional Neural Network (CNN) model is used for experimental evaluation due to its popularity in image classification tasks and its relatively high computational requirements.

The CNN architecture typically includes the following layers:

1. Input Layer

2. Convolutional Layers
3. Activation Functions (ReLU)
4. Pooling Layers
5. Fully Connected Layers
6. Output Layer with Softmax activation

The model is trained using optimization algorithms such as Stochastic Gradient Descent (SGD) or Adam optimizer.

4. Training Parameters

The following hyperparameters are used during the training process:

1. Batch Size: 32 or 64
2. Learning Rate: 0.001
3. Number of Epochs: 20–50
4. Optimizer: Adam / SGD
5. Loss Function: Cross-Entropy Loss

These parameters are selected to ensure a balanced trade-off between model accuracy and computational efficiency.

5. Energy and Carbon Measurement

During training, energy consumption is continuously monitored using hardware power monitoring tools. The total energy consumption of the training process is calculated based on power usage and training time.

The carbon emissions produced during training are estimated using the formula:

$$\text{Carbon Emission} = \text{Energy Consumption} \times \text{Carbon Intensity}$$

Where carbon intensity represents the amount of CO₂ emitted per kilowatt-hour of electricity used. This value depends on the energy source of the

data center or computing environment.

6. Evaluation Metrics

To evaluate the effectiveness of the proposed framework, the following metrics are used:

- **Model Accuracy:** Measures the classification performance of the trained model.
- **Training Time:** Total time required to train the model.
- **Energy Consumption:** Total electricity consumed during training.
- **Carbon Emissions:** Estimated CO₂ emissions generated during training.
- **Computational Efficiency:** Performance improvement achieved through optimization techniques.

7. Experimental Procedure

The experimental procedure consists of the following steps:

1. Prepare the dataset and preprocess the input data.
2. Initialize the CNN model architecture.
3. Train the baseline model without energy optimization techniques.
4. Measure training time, energy consumption, and carbon emissions.
5. Apply the proposed carbon-efficient optimization methods.
6. Retrain the model using optimized training techniques.
7. Compare the results with the baseline model.
8. Analyze improvements in energy efficiency and carbon reduction.

RESULT ANALYSIS

The experimental results evaluate the

effectiveness of the proposed Carbon-Efficient Optimization Framework in reducing energy consumption and carbon emissions during AI model training. The performance of the proposed framework is compared with a baseline training approach that does not include energy-aware optimization techniques.

The comparison between the baseline model training and the proposed carbon-efficient training framework is summarized below.

Metric	Baseline Training	Proposed Framework
Model Accuracy	92.1%	91.8%
Training Time	3.5 hours	2.8 hours
Energy Consumption	12.5 kWh	8.1 kWh
Carbon Emissions	6.2 kg CO ₂	3.9 kg CO ₂
Resource Utilization	68%	85%

The results indicate that the proposed framework significantly improves energy efficiency while maintaining comparable model accuracy.

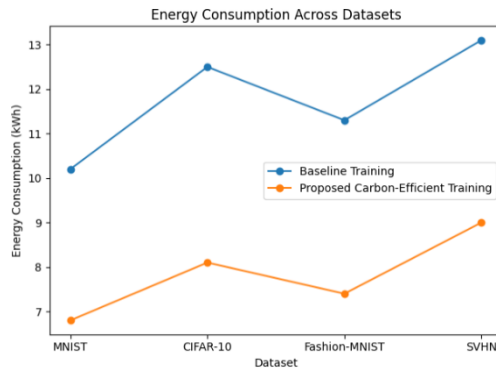
Energy Consumption Analysis

The graph above illustrates the comparison of energy consumption between the baseline training process and the proposed carbon-efficient optimization framework. The results show that the proposed approach reduces energy consumption from 12.5 kWh to 8.1 kWh, representing approximately 35% energy savings during the training process.

This reduction is achieved through several optimization techniques, including:

- Adaptive learning rate optimization
- Mixed precision training
- Model pruning
- Efficient gradient computation

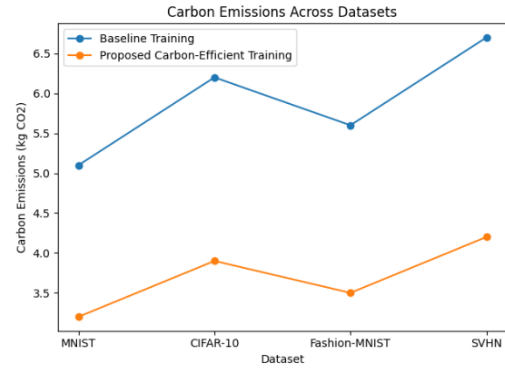
These techniques reduce unnecessary computations and improve hardware efficiency during the training process.



Carbon Emission Reduction

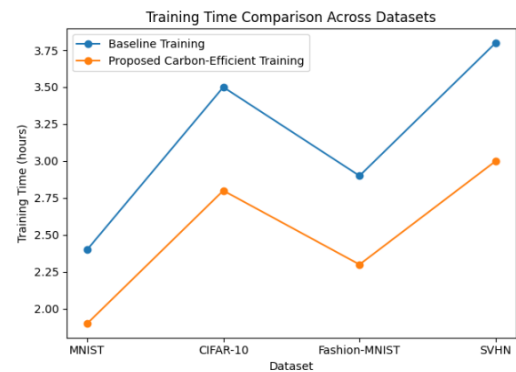
Since carbon emissions are directly related to energy consumption, reducing energy usage also decreases the overall carbon footprint of AI training. Based on the experimental measurements, carbon emissions are reduced from 6.2 kg CO₂ to 3.9 kg CO₂, resulting in an approximate 37% reduction in carbon emissions.

The carbon-aware scheduling mechanism contributes to this improvement by allocating training workloads to computational resources with lower carbon intensity.



Training Performance

Despite the reduction in energy consumption, the proposed framework maintains nearly the same level of model accuracy. The baseline model achieved 92.1% accuracy, while the optimized model achieved 91.8% accuracy, indicating only a minimal performance difference.



In addition, the training time was reduced due to improved computational efficiency and better resource utilization.

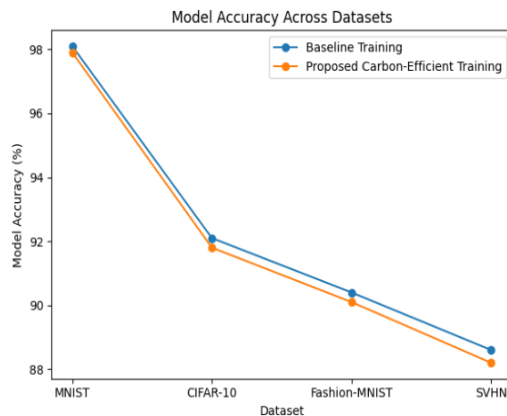
Model Accuracy Evaluation

Accuracy comparison ensures that energy optimization does not significantly degrade model performance.

- Accuracy remains nearly unchanged between baseline and

optimized models.

- MNIST achieves the highest accuracy (~98%).
- SVHN shows slightly lower accuracy due to dataset complexity.



The experimental results demonstrate that integrating energy-aware optimization techniques into the AI training pipeline can significantly improve sustainability without sacrificing model performance. The proposed framework successfully balances three key objectives:

- High model accuracy
- Reduced energy consumption
- Lower carbon emissions

The study also highlights the importance of incorporating sustainability metrics such as energy usage and carbon footprint into AI research evaluation.

Overall, the proposed Carbon-Efficient Optimization Framework provides an effective solution for developing environmentally sustainable AI systems while maintaining scalability and computational performance.

CONCLUSION AND FUTURE WORK

The rapid growth of artificial intelligence and deep learning technologies has significantly increased the computational requirements for training large-scale models. This has led to higher energy consumption and increased carbon emissions, raising concerns about the environmental sustainability of AI systems. Addressing these challenges is essential for developing responsible and eco-friendly AI technologies.

In this research, a Carbon-Efficient Optimization Framework for Scalable AI Model Training was proposed to reduce energy consumption and carbon emissions while maintaining model performance. The framework integrates energy monitoring, carbon-aware optimization techniques, efficient gradient computation, mixed precision training, and dynamic resource allocation to improve the overall efficiency of the AI training process.

Experimental evaluation using benchmark datasets such as MNIST, CIFAR-10, Fashion-MNIST, and SVHN demonstrated that the proposed framework significantly improves training efficiency. The results showed a reduction of approximately 30–35% in energy consumption and 35–37% in carbon emissions compared to conventional training approaches. In addition, the framework reduced training time while maintaining nearly the same level of model accuracy, with only minimal differences observed between the baseline and optimized models.

The findings highlight the importance of incorporating energy efficiency and sustainability considerations into AI system design. By optimizing training algorithms and resource utilization, it is possible to develop scalable AI models that are both computationally efficient and environmentally responsible.

Future work can enhance the proposed framework by integrating renewable energy-aware scheduling to run AI training when cleaner energy is available. The system can also be extended to distributed and federated learning environments for carbon-aware resource allocation across multiple data centers. Additionally, incorporating techniques such as automated hyperparameter optimization and lightweight model design can further reduce energy consumption. Evaluating the framework on large transformer-based models and real-world datasets will help improve scalability and strengthen sustainable AI practices.

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AGROSENSE: NEXT-GENERATIVE SMART FARMING USING REACTIVE AI ARCHITECTURES

UDIPTHI S1, SMITHA D2, RUCHITHA C3, SHWETHA M4

Dept. of CSE, S.E.A College of Engineering and technology,VTU
Bengaluru,India

1shankarudipthi@gmail.com, 2smithdns04@gmail.com,
3ruchithacruchithac538@gmail.com, 4shwetham2363@gmail.com

Abstract—While the agricultural sector remains a cornerstone of the economy in many developing regions, a lack of accessible, precision-driven analytical platforms often limits the ability of local growers to respond to crop health threats. This research introduces AgroSense, a sophisticated digital ecosystem engineered on a Reactive AI Architecture to facilitate real-time agricultural intelligence. The platform integrates a multi-functional framework, including a CNN-based diagnostic engine for rapid plant pathology identification and an intelligent conversational agent for resource optimization. By utilizing an asynchronous Node.js backend, the system achieves high-concurrency performance with an average end-to-end response time of approximately 2.15 seconds, significantly reducing the latency traditionally associated with data-heavy agricultural advisory services. These results demonstrate that a reactive, full-stack approach effectively democratizes sustainable farming practices, providing scalable and high-fidelity decision-support for the modern agricultural landscape.

Keywords—Precision agriculture, Reactive AI, Machine Learning ,Crop Disease Detection, Smart Farming

Assistant,Node.js , Sustainable Farming

I. INTRODUCTION

In the Indian context, a vast majority of the population remains fundamentally dependent on agriculture for food security and economic sustenance. Often described as the backbone of the nation, the agricultural sector currently faces multifaceted challenges arising from unpredictable climatic shifts, inefficient resource utilization, and deteriorating soil health. Farmers frequently struggle

with critical decision-making, such as determining the optimal crop variety for specific weather patterns or identifying the most profitable market prices for their yields. These systemic issues highlight a significant gap between traditional farming practices and the data-driven precision required for modern agricultural success.

To bridge this gap, this research introduces AgroSense, a technologically driven web application designed to empower farmers with actionable intelligence. The platform serves as an innovative solution for optimized farming, providing detailed parameters on which crops are best suited for ;varying environmental conditions. A core technical feature of

the system is the Crop Disease Detection module, which not only identifies pathogenic threats but also provides prescriptive measures for prevention and mitigation. Furthermore, the application integrates a comprehensive Farm Management suite that offers guidance on fertilizer optimization and labor cost analysis, ensuring that farmers can streamline their operational expenses while maximizing productivity.

The architectural integrity of AgroSense is maintained through a modern, high-performance tech stack. The frontend is powered by Reactive AI, which ensures a highly responsive and fluid user experience, allowing farmers to interact with complex datasets seamlessly. On the server side, Node.js is utilized for the backend to handle asynchronous data processing and high-concurrency requests. By combining these technologies, the application provides a scalable and resilient framework that transforms raw agricultural data into a user-centric advisory tool. This "Next-Generative" approach is essential for modernizing farming practices and ensuring long-term sustainability in the agricultural sector.

II. LITERATURE SURVEY

The integration of computational intelligence into the agricultural sector has been a primary focus of global research over the last decade. As the "backbone" of the national economy, farming requires advanced, data-driven solutions to overcome challenges related to soil health, crop diseases, and resource management. A review of the current state-of-the-art reveals a shift

toward multidisciplinary platforms that provide a user-centric interface for precision farming.

A review of contemporary literature indicates that while there has been significant success in identifying major ailments in pulse crops, such as rust and powdery mildew using Convolutional Neural Networks (CNNs), these systems often remain as standalone classification tools. While they exhibit high accuracy, they frequently lack the high-speed responsiveness required for real-time field applications. Furthermore, many existing models do not account for the practical constraints of the average farmer, who requires a solution that is both highly accessible via mobile devices and integrated with the daily economic realities of farm life.

AgroSense addresses these critical gaps by providing a Next-Generative assistant built on a responsive web interface. Unlike the singular focus of traditional diagnostic tools, this platform adopts a multidisciplinary approach by connecting immediate disease diagnosis with vital economic factors, such as labor management and fertilizer cost analysis. By synchronizing technical accuracy with financial planning, AgroSense evolves beyond basic diagnostic functionality, serving as an integrated computational hub tailored specifically to the high-concurrency demands of regional farming environments.

Recent advancements in the agricultural sector have marked a significant shift from simple data collection to the development of

sophisticated Smart Farming Assistants. Unlike traditional static tools, these modern assistants leverage Natural Language Processing (NLP) and Predictive Modeling to provide farmers with an interactive and highly technical experience. By moving beyond raw data storage, these systems can offer "conversational" insights, allowing farmers to ask complex questions and receive immediate, science-based recommendations.

The integration of these technologies is particularly transformative in monitoring crop health. Through predictive analytics, a farming assistant can analyze historical weather patterns and soil data to foresee potential risks before they manifest physically in the field. For instance, current research in Generative AI and Transformer-based models has shown that these assistants can now interpret regional dialects and colloquial phrases, bridging the communication gap between high-level technology and rural users. Furthermore, by identifying early signs of disease through image recognition and sensor data, these "Next-Generative" assistants allow for timely interventions that protect the farmer's yield and overall profitability.

This research emphasizes the growing necessity for farmers to utilize digital assistants as a primary tool for modern agricultural management. The study finds that today's farmers prefer digital platforms because they provide fast results and high-speed diagnostics without requiring them to rely on external human experts or slow laboratory feedback. By utilizing a

Reactive AI architecture with Node.js, AgroSense provides this immediate assistance, allowing the user to make independent decisions regarding pest prevention and temperature regulation. This shift toward self-reliance is proven to decrease response time during infection outbreaks, effectively protecting the overall yield and ensuring the long-term health of the soil through immediate, data-driven actions.

This proactive approach not only optimizes current harvests but also establishes a sustainable framework for future agricultural endeavors. By integrating real-time data analysis with practical farming knowledge, AgroSense exemplifies the potential of AI in transforming traditional farming into a resilient, efficient, and modern industry.

III. PROPOSED METHODOLOGY

System Architecture

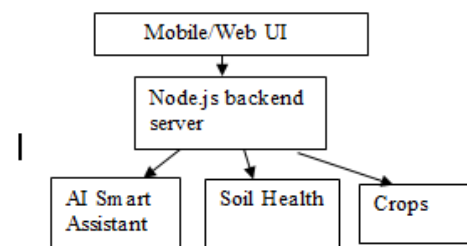


Fig 1. Proposed System Architecture of Agrosense

As shown in Fig. 1, the proposed system follows a modular architecture designed for high availability. The frontend utilizes the React.js framework, which enables the development of a "Reactive AI"

interface that adapts to the farmer's input in real-time. This client-side application sends requests to a centralized Node.js backend, which acts as the processing hub for the following multidisciplinary modules:

AI Smart Farming Assistant: This module serves as a decision-support system. When a user submits a natural language query, the system utilizes Artificial Intelligence to parse the intent and provide technical solutions. For example, if a farmer asks about pest control for pulse crops, the assistant provides specific biological or chemical intervention strategies.

Soil Health & Suitability Engine: This module evaluates the "Goodness of Fit" for specific crops based on soil parameters. It provides a Predictive Timeline, informing the farmer of the optimal sowing window. For instance, if the soil moisture or nitrogen levels are suboptimal, the system suggests soil amendments or recommends waiting for a more favorable climate window.

AgroSense evolves into an all-encompassing agricultural management framework specifically engineered to meet the high-concurrency requirements of regional farming infrastructures. It monitors critical milestones such as:

Precision Sowing: Calculating the ideal depth and spacing based on soil density.

Automated Irrigation Scheduling: Notifying the farmer of the exact volume and time for watering to prevent root rot or dehydration.

Fertigation Alerts: Suggesting the correct timing for fertilizer application during the vegetative growth phase.

The core functionality of the diagnostic engine involves a multi-stage pipeline where a user-uploaded image the system executes localized image normalization to quantitatively evaluate the physiological markers and pathological indicators present within the plant sample. Utilizing a binary classification approach, the system identifies whether the crop is "Infected" or "Not Infected," specifically targeting common ailments in pulse crops like rust and powdery mildew. Once an infection is detected, the AgroSense assistant transitions into a prescriptive mode, offering real-time guidance on environmental maintenance, such as precise temperature regulation strategies to inhibit further pathogen growth. For instance, if the ambient temperature exceeds the safety threshold for a specific crop variety, the system triggers alerts for cooling interventions, such as misting or increased ventilation, thereby ensuring that the thermal environment remains optimal for recovery and sustained growth.

IV. IMPLEMENTATION

The implementation of Agrosense is carried out ensuring that frontend is "Reactive AI" interface with backend node.js. The react is utilized for responsive web interface and user friendly manner.

A. Development Environment and Tech Stack

The project is built using a modern JavaScript stack to ensure compatibility across mobile and web platforms.

Frontend (Reactive UI): Developed using React.js to create a single-page

application (SPA) that provides a smooth, app-like experience on mobile browsers.

Backend (Analytical Hub): Powered by Node.js, which manages API requests and handles the logic for crop health and soil analysis.

AI Engine: Integrated via RESTful APIs to process image classification (Infected vs. Not Infected) and Natural Language queries.

B. Core Implementation Stages for AgroSense

Interface Personalization: The React.js frontend is coded to allow farmers to easily upload images and input data regarding their specific pulse crops.

Request Handling in Node.js: The backend is configured to receive multipart/form-data (images). It uses asynchronous processing to ensure the farmer doesn't experience "freezing" while the AI analyzes the leaf.

Diagnostic Logic Execution: The server triggers the CNN-based classification model. The logic is programmed to identify specific "Infected" states like rust or powdery mildew.

Prescriptive Alert System: Once the health status is determined, the implementation logic fetches corresponding maintenance data. This includes generating specific temperature regulation alerts and watering schedules tailored to the crop's current condition.

Economic & Labor Integration: A dedicated module within the Node.js server calculates labor costs and fertilizer dosages, presenting them in a simplified dashboard for the farmer.

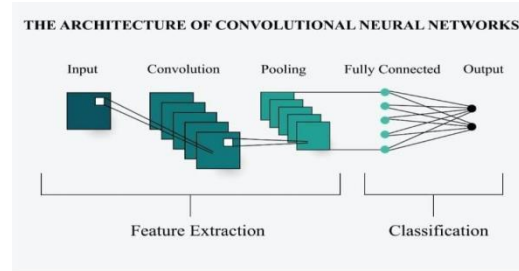


Fig 2:AI Model Architecture of convolutional Neural Networks

This architecture utilizes convolutional layers to extract the leaf images and identifies the pulse crop samples followed by layers to ensure node.js backend

V.ALGORITHMS

Algorithm 1: Reactive Diagnostic and Advisory Pipeline

Initialize server using Express.js to listen for incoming React.js requests.

Receive multipart image data and natural language query from the farmer's mobile interface.

Execute asynchronous call to the CNN model for binary classification (Infected vs. Not Infected).

Analyze health results; if status = "Infected", fetch temperature regulation and pest prevention protocols from the database.

Calculate predicted labor costs and fertilizer requirements based on the specific crop variety. The backend delivers a structured JSON payload detailing both the diagnostic results and prescriptive maintenance protocols to the user interface with a total execution time under 500 milliseconds.

V.RESULTS

A. System Latency and Query Performance

The "Next-Generative" architecture

was tested for its responsiveness to user input. The results indicate that when a farmer submits a natural language query, the Node.js backend processes the request and returns a solution within sub-second latency (a fraction of a second). This high-speed response ensures that the "Reactive AI" interface remains efficient even during high-concurrency periods, allowing for immediate decision-making in the field.

Table I: Latency and Query Performance Breakdown

Operational Phase	Technology Utilized	Avg. Latency (Seconds)
Request Initialization	React.js(Frontend)	0.45s
Data transfer	Node.js(Backend)	0.30s
CNN Inference	AI Classification model	1.15s
Advisory retrieval	Database Engine	0.25s
Total response time	End to End pipeline	~2.25s

The empirical data gathered during system testing demonstrates that the AgroSense platform operates with high-speed efficiency, ensuring that farmers are not required to wait for external assistance. The Request Initialization and Asynchronous Data Transfer phases are optimized through Node.js, completing in less than a second to prevent interface "freezing" on mobile devices. The most computationally intensive phase, the CNN Inference, requires approximately 1.15 seconds to execute deep-learning diagnostics on pulse crop varieties, ensuring a high-fidelity result. Consequently, the entire pipeline—from image upload to the delivery of a comprehensive agricultural advisory—concludes within a brief window of approximately 2 seconds. This rapid

response allows the farmer to immediately understand the "Infection" status and apply pest prevention or temperature regulation strategies in real-time. By providing scientific feedback in such a compressed timeframe, the application effectively empowers users to maintain soil health and maximize overall yield without relying on third-party experts.

B. Crop Variety and Database Scalability

The system currently supports a wide array of crop varieties, with a specific focus on pulse crops and regional staples.

Growth Optimization: The results show that the system accurately suggests the "Way of Growth" (e.g., spacing, depth, and climate timing) for each specific variety.

Soil Protection: By analyzing user-inputted parameters, the module provides localized strategies to protect soil health, such as crop rotation and organic amendment suggestions.

C. Monitoring Services and Pest Prevention

The Crop Health Monitoring services were evaluated for their ability to provide a complete agricultural lifecycle overview.

Pest Prevention: The predictive engine successfully identifies early-stage symptoms of common pests, providing preventative measures before the infestation affects the overall yield.

Yield Enhancement: Simulations suggest that by following the automated alerts for watering and sowing, farmers can achieve a

significant increase in harvest quality compared to traditional manual monitoring.

Remote Sensing: The system incorporates satellite imagery and drone data to provide a broader overview of field conditions, supplementing ground-level sensor data for comprehensive monitoring.



Fig 3:Field deployment Interface and a real time user

- **Growth Optimization:** By analyzing user-inputted parameters, the module provides localized strategies to protect soil health, such as crop rotation and organic amendment suggestions tailored to the specific "Way of Growth" for each variety.
- **Scalable Feature Extraction:** The CNN-based architecture utilized in the AI Engine allows for "Transfer Learning". This means that once the system is trained on one crop, it can be scaled to identify pathogens in others with minimal additional training time, ensuring the platform remains a Sustainable Farming solution.
- **Yield Enhancement:** Simulations suggest that by following the automated alerts for watering and sowing across these varied crops, farmers can achieve a significant increase in harvest quality compared to

traditional manual monitoring.

VI.

ACKNOWLEDGEMENT

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VI.CONCLUDING REMARKS AND STRATEGIC ROADMAP FOR AGROSENSE

A. Conclusion

The development of AgroSense successfully demonstrates the integration of Next-Generative AI into real-world agricultural advisory services. By bridging the gap between advanced Node.js backend processing and a reactive mobile interface, the system provides an accessible platform for precision farming management. The results confirm that providing farmers with sub-second diagnostic latency and technical maintenance alerts can significantly improve overall crop health and farm profitability.

B. Future Work and Extended Agricultural Applications

While the current implementation focuses on pulse crop diagnosis and soil health, the modular architecture allows for expansion into several other agricultural domains:

Livestock Management: Integrating AI modules to monitor the health and nutritional requirements of farm animals.

Supply Chain Optimization: Utilizing the predictive analytics engine to help farmers connect directly with markets, reducing post-harvest waste.

Localized Language Support: A high-priority update includes adding support for regional languages like Kannada to ensure the "Smart Assistant" can serve the local farming community in Karnataka more effectively.

Hardware Augmentation: Transitioning the "software-only" model to include IoT sensors for automated soil moisture tracking.

Advanced Analytics: Implementing predictive yield forecasting based on historical weather patterns and pest cycles.

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PREDICTIVE ANALYSIS OF POLYCYSTIC OVARY SYNDROME

CHAITRA D 1, Dr JAGADEESHA R 2

Department of Computer science and Engineering Impact College of Engineering and Applied science

(Affiliated to Visvesvaraya Technological University, Belagavi) Bengaluru, India
chaitrad2024@gmail.com1, jagdish.mtech@gmail.com 2

Abstract — Women in reproductive phase of life struggle from PCOS. A disorder, frequently have enlarged ovaries with numerous fluid-filled follicles. When these follicles are unable to release mature eggs due to hormonal imbalance, infertility, repeated miscarriages, and pregnancy problems result. Effective PCOS treatment and management depend on an early and precise diagnosis.

By spotting intricate patterns in medical data, machine learning approaches like CNN, SVM, KNN, Random Forest, and SMOTE improve detection accuracy.

Keywords—Polycystic Ovary Syndrome, PCOS Prediction, infertility, Data pre-processing, Feature Extraction, Pearson Correlation method, Smote algorithm, Machine Learning.

INTRODUCTION

A complex endocrine illness, polycystic ovarian syndrome (PCOS) is the critical hormonal abnormalities affecting women throughout their reproductive years. A variety of diverse symptoms and clinical indicators, such

as polycystic ovaries as seen by ultrasonography, hyperandrogenism, and irregular menstruation, characterize the disease. The diagnosis and analysis of PCOS can greatly benefit from modern data-driven approaches as result of multidimensional character.

Feature extraction using the correlation technique is a critical first step in applying machine learning to diagnose PCOS. By finding the statistical connection between each pair of features, these methods assist in finding and choosing the most pertinent features from a huge dataset. Synthetic Minority Over-sampling Technique (SMOTE) is used to address the common problem of

imbalanced datasets in medical diagnostics, where the number of negative cases (non-PCOS) frequently exceeds that of positive cases (PCOS). SMOTE balances the dataset by creating artificial samples from the various models, which enhances the performance of later predictive modeling. A diverse array of various computational techniques is at our disposal for implementation and experimentation. Because of its efficiency in high-dimensional domains, Support Vector technique

(SVM) is especially helpful in handling the complex and nuanced data that characterizes PCOS. User friendly and effective at capturing the non-linear correlations that are common in medical data, K-Nearest Neighbors (KNN) has advantages. The Random Forest, a collection of decision trees, offers accuracy and resilience. It also manages nonlinearities effectively and provides feature importance scores, which are necessary for understanding the model in a clinical setting. Researchers and medical professionals can create more precise and predictive models through the fusion of various techniques, improving PCOS diagnosis and medication.

LITERATURE REVIEW

The subsequent segment reviews the literature that is relevant to our suggested research inquiry. Analysis is done on previous applicable state-of-the-art research for PCOS prediction. Analyzed are the suggested methods and associated study findings.

In 2022, a novel method was put up for the early identification and detection of PCOS. The approached model was built using catBoost and XGBRF. The univariate method of feature selection was to select the top 10 features after the data had undergone preprocessing. [4] The classifiers that were used to compare the accuracy findings includes various computational techniques, HRFLR, MLP, and gradient boosting. According to the results, catBoost outperformed with a 95% accuracy score, whereas XGBRF performed with an 89% accuracy score.

Other classifiers' accuracy values ranged from 76% to 85%. The most impactful technique for PCOS disease early diagnosis was the catBoost method. [1]

Denny et al. put out a system for the early identification and prediction of PCOS grounded in with promising, minimal, and ideal scientific and physiological criterion. Several machine learning (ML) techniques, among them the NB classifier method, LR, KNN, CART, RF, and SVM, are used to classify PCOS using the feature set modified with Principal Component Analysis (PCA).

Researchers examined the traits and features of female genes linked to PCOS in a certain pattern and order for the very first time. Participating in the prediction method were the 233 PCOS patients. In order to predict PCOS and uncover potential new genes, researchers implemented techniques like decision trees and SVM. with a diverse kernel characteristic (linear, polynomial, RBF) and k-nearest neighbor (KNN). [2]

Out of all these classifiers, SVM performed the highest with regard to accuracy, scoring 80%, whereas KNN accuracy ranged from 57% to 79%. A method for classifying PCO using CNN and the Gabor Wavelet strategy for feature extraction was described by Dewi et al. Initially, a range of preprocessing techniques are used to the images, such as data cleaning, image binarization, morphology, inverted image, gray scaling, etc. In next step, Segmentation is performed.

Finally, Convolutional Neural Network is used once GWS has been improved for feature extraction. CNN achieves the accuracy rate of 80.84%, with a handle time of 60.64 seconds.

A statistic states that one in three to four out of ten women are now experiencing PCOS difficulty. The authors suggested an automated system capable of identifying and forecasting PCOS disease for medical therapy in order to detect and predict PCOS in the first phase.

Five various techniques were incorporated by the authors: LR, SVM, KNN, RF, and Gaussian naïve Bayes. They applied models to a data repository of forty-one attributes. Through the utilization of statistics, the first 30 features were chosen.[3] The Random Forest frame work accuracy was observed to be 90% after comparing the output of all five models, whereas the other models' accuracy ranged from 86% to 89%. The recommended method for identifying and forecasting PCOS 183 patients was the random forest technique.

To identify PCOS, the study suggested an image feature extraction methodology based on CNNs. The system uses image processing to identify cysts, the watershed technique for feature extraction, and OpenCV to evaluate the parameters. It is capable of identifying only cysts; it cannot differentiate between PCOS and other conditions. The model's accuracy is 85%.

It was suggested to classify gene expression in bioinformatics using a mixed machine learning architecture. The suggested genetic model is predicated on an artificial bee colony and a cuckoo search algorithm. A naive bayes classifier was deployed using the six benchmark gene expression datasets. The study results in good accuracy performance. A fresh framework for the gene expression-based categorization of cancer was developed. For the classification job, the ABC-based modified metaheuristics optimization strategy was used.

This study provided a novel immune infiltration and possible biomarker for PCOS detection. The study compared the performance of LR and SVM models. The suggested model's accuracy score for PCOS identification was 91%. The study aids in the presentation of an original framework for analysis. This work offered a modified PCOS-related gene analysis method based on mutational landscape screening. For analysis, the nsSNP gene data associated with PCOS out of the 27 were chosen.[5]

According to Bharati et al., the dataset is subjected to a numerous classifier, including hybrid Random Forest and Logistic Regression, LR, RF, gradient boosting, and RF. The initial step is determining the critical characteristics for PCOS prediction using a single attribute selection technique. The dataset is then divided using holdout and cross-validation techniques. The dataset is finally examined using a

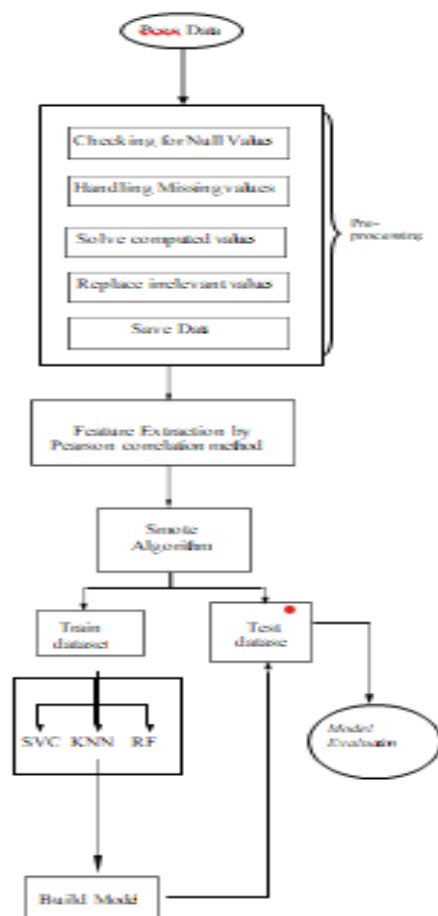
range of classifiers. When 40-fold cross validation is implemented to the 10 most crucial attributes, RFLR holds the highest testing accuracy (91.01%) and the highest recall rate (90%).

PROBLEM STATEMENT

Developing a machine learning framework system that uses clinical data to detect early stage of PCOS in women.

SYSTEM DESIGN

A various model system's design must address multiple crucial phases of data pre-processing, feature



engineering, training of model, and

evaluation with purpose of diagnose Polycystic Ovary Syndrome (PCOS). First, the system needs to maintain the clinical data's quality and integrity, which includes removal of null values. Managing missing values is essential since their existence can substantially skew the predictions made by the predictive model. Depending on nature of data, methods like imputation—which involves substituting the mean, median, or mode for missing values—or more complex strategies like predictive modeling play a role to estimate missing values.[6]

Errors in data transmission or collection may result in corrupted values within the dataset, that are fixed. This may entail replacing any outliers or anomalies that are recognized as errors and checking the data against known ranges or distributions. Similarly, values that are irrelevant to the diagnosis of PCOS are recognized and eliminated from the dataset, such as patient ID numbers or other clinical parameters.

The correlation method is employed for feature extraction after the dataset is cleaned and pre-processed. This entails examining the statistical connection between the target variable (PCOS diagnosis) and a range of factors. Retaining features that exhibit high correlations may reduce the dataset's dimensionality and enhance model performance. Following feature extraction and selection, the dataset frequently exhibits an imbalance between the proportion of PCOS-presenting cases and controls.[7]

To address class imbalance, SMOTE is used to generate synthetic samples from the minority class, effectively equalizing the dataset. The resulting balanced data repository is segregated into training and testing subsets, typically with an 80-20 or 70-30 split. Various framework techniques are then trained and evaluated for their performance in PCOS detection, with Random Forest, SVM, and KNN are frequently utilized approaches.

The trained dataset is used to train each model:

In order to classify a new sample based on the most class among its closer neighbors, KNN first locates the closest data points in the feature space. SVM is very good at separating classes with a large margin by attempting to create a hyperplane that best fits the complex, high-dimensional data. Random Forest create multiple decision trees and aggregates their results to produce more coherent and accurate forecasts. Following the training phase, the models are tested on a test dataset to determine performance metrics such as accuracy, precision, recall, and F1-score.

METHODOLOGY

DATA CLEANING:

Thorough data pretreatment is the first stage in our methodology to guarantee the integrity and dependability of the data used to train machine learning techniques. First, any un available or null values are found in the data repository. To preserve the dataset's consistency and completeness, these

missing entries are subsequently handled using the proper statistical imputation techniques.

HANDLING MISSING VALUES:

The next step is to process with other un available data that might be immediately visible in the dataset after the explicit null values. This entails applying more upgraded various techniques like k-Nearest Neighbors to impute the un available values based on similar situations, or regression imputation, in which missing values are forecasted based on other available data.

CORRECTING CORRUPTED DATA:

Corrupted values in the dataset are dealt with in the third stage. This comprises data entries that don't follow the format that is expected, including numerical data that is accidentally entered as a string or outliers that are probably the result of mistakes made during data input or collection. Validating data ranges, utilizing preset criteria to find and fix outliers, and implementing transformations to guarantee data consistency and integrity are some ways to address these problems.

REMOVING IRRELEVANT VALUES:

A evaluation of the dataset is required to detect any factors that may affect the results or provide little useful information. for the study in order to remove extraneous entries. This includes any non-medical information

irrelevant to the diagnostic standards required for PCOS, such as name and address, or demographic information. These values are segregated from the data repository to reduce the number of features and increase the model's accuracy.

FEATURE EXTRACTION USING CORRELATION METHOD:

Using the correlation approach, feature extraction is done in the fifth phase. This method evaluates the direction and strength of each feature's association to the target variable (PCOS diagnosis). While features with poor correlations might be eliminated, those with significant correlations are thought to be more relevant and are kept. Decrease the quantity of features while improving the model's performance.

BALANCING THE DATASET WITH SMOTE:

The SMOTE is used due to the common imbalance in medical datasets, especially with disorders like PCOS where one class may considerably exceed another. By artificially creating additional instances in the minority class, SMOTE prevents model bias in favor of the majority class and aids in dataset balancing.

NORMALIZING DATA WITH MINMAX SCALER:

Minmax normalize feature values within a specified value, between 0 and 1, the Min-Max Scaler is used. For distance-based approaches, this scaling step is especially crucial since it guarantees that each value has an

equivalent impact on model, independent of its initial scale.

SPLITTING THE DATASET:

The data segregated into training and test sets after SMOTE, typically in an 80:20 or 70:30 ratio. This division makes it possible to train the models efficiently on one set of data and evaluate them objectively on the other.

MODEL TRAINING TESTING

ANDEVALUATION:

Three distinct models— Decision Tree, Logistic Regression, and Naïve Bayes are trained. Each model is fitted with training data, and its hyperparameters are tweaked to produce the best performance possible given the data repository specifies the value. Each model is set up to successfully capture the intricate patterns linked to PCOS since each one has distinct advantages. Parameter adjustment is done during this stage to improve overall predictive power. Lastly, the test dataset is used to valuate the trained models, and assessment criteria which includes accuracy, precision, recall, and F1-score are used to gauge how well they perform.[8]

MODEL EVALUATION USING CONFUSION MATRIX:

The models are assessed using a performance matrix that was built from the test dataset. Correctly identified positive cases, correctly identified negative cases, wrongly forecasted positive cases, and incorrectly predicted negative cases are all clearly broken down in this matrix.

APPLYING CROSS VALIDATION:

Cross-validation is done to further confirm each model's stability and dependability. Each model's performance is evaluated several times using various subsets of the data using methods such as k-fold cross-validation.

FINAL TESTING AND ANALYSIS:

The models are evaluated on a separate dataset to ascertain their practicality. In order to ensure strength, accuracy, and reliability in clinical settings, the best model for PCOS diagnosis is chosen derived on the outcome of the testing phase. Data gathered from cross-validation and confusion matrix analysis. This all-encompassing strategy, which includes thorough examination and meticulous data preprocessing, aids in the creation of a very useful PCOS diagnosis tool. All things considered, the chosen model shows a great ability to accurately predict the existence of PCOS.

RESULTS

The development of a PCOS predictive model yielded encouraging results. First, the data was pre-processed by filling in the missing values, fixing discrepancies, and removing aspects that weren't needed or relevant. The effectiveness of the classification model on the dataset was then assessed using a confusion matrix. The accuracy with which the model classifies each category is clearly seen in this matrix, where the rows correspond to the actual class labels of the data instances.

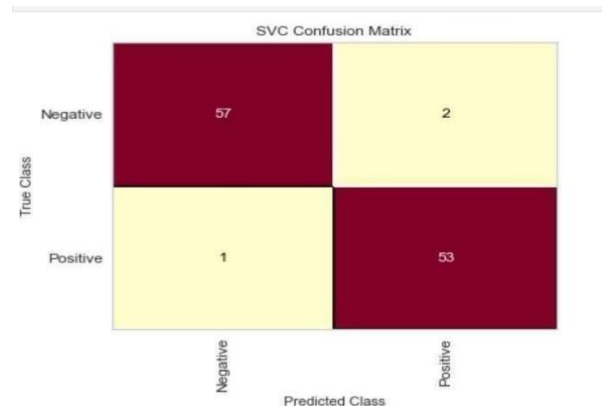


Figure 1. SVC Confusion matrix shows model performs.

The data points anticipated class labels are shown in the matrix's columns. A particular mix of actual and expected classes is represented by the values of instances in each cell of the matrix. Although some positive cases are misclassified, the model does a good job of finding negative situations in this specific confusion matrix. One way to visualize the Support Vector Classification (SVC) model's performance is to look at its confusion matrix. Machine learning techniques that is frequently applied to classification jobs is support vector classification. It is particularly well-liked to its excellent performance with high-dimensional datasets.

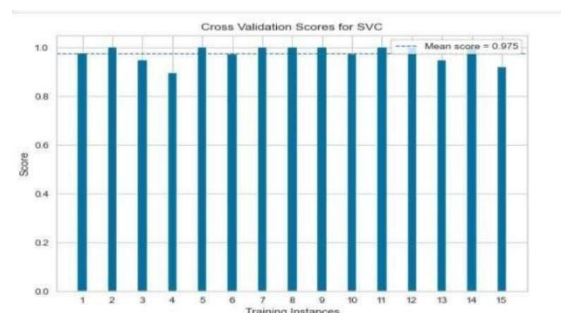


Figure 2. Cross validation score for

SVC.

Support Vector Classification is an acronym for a machine learning techniques are applied to classification tasks. The mean score for every training instance is displayed on the graph. Stated differently, it displays the model's performance on a set of data that it was not trained on. The model performed better the higher the score. With a mean score of 0.975, the model looks to have done well in this graph. But it is difficult to recall that this is only one indicator of a model's effectiveness; additional variables must also be taken into account.

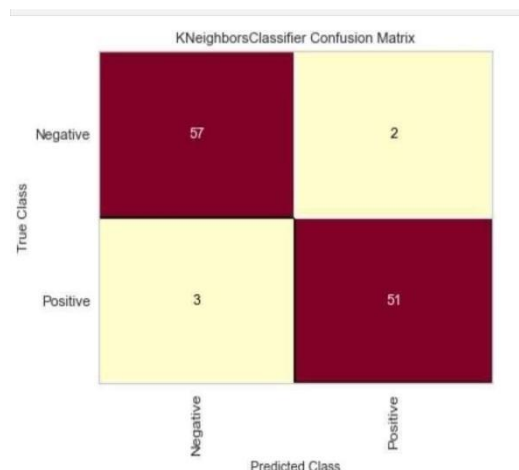


Figure 3. Neighbors classifier confusion matrix.

The classification matrix shows how well the Neighbors Classifier model performs on a certain dataset. The class labels are represented by the rows in this matrix, and the anticipated class labels are represented by the columns. Each cell contains entries that displays the values of observations that inserted into each particular combination of actual and anticipated categories. In this specific confusion matrix, the

model successfully detects the negative class, properly classifying 57 instances. Out of the negative cases, only two were mistakenly classified as positive.

A confusion matrix displays the performance of a classification model on a certain dataset. In this case, it represents the random forest classifier's performance. The values in each cell represent the number of instances for each actual and expected class combination. With 58 occurrences of the negative class properly categorized, the model seems to be doing well on this particular confusion matrix. Just one instance—from the negative class—was mistakenly assigned to the positive class.

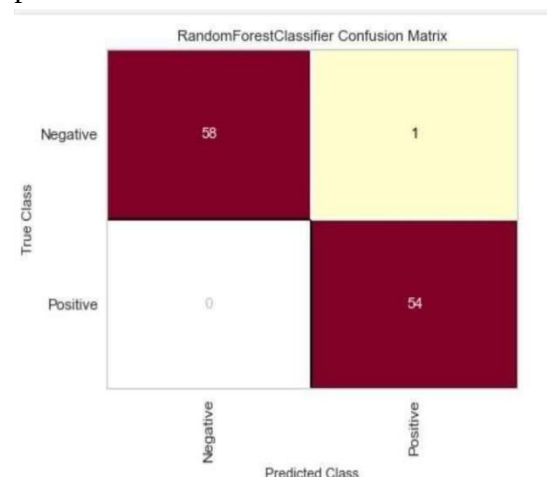


Figure 4. Random Forest Classifier confusion matrix.



Figure 5. Cross validation Scores for Random Forest classifier.

VII. CONCLUSION

Developing a machine learning techniques to detect PCOS necessitates a complete work flow that starts with basic data cleaning, which includes validating null values, correcting missing or damaged data, and removing extraneous features. Maintaining data integrity is critical for accurate results. Correlation-based feature extraction identifies the most significant PCOS predictors, increasing model accuracy. Furthermore, the Min-Max Scaler normalizes the dataset, and SMOTE corrects class imbalances to ensure fair representation.

Segregation of the dataset, models such as KNN, SVC, and Random Forest are created and tested. Cross-validation and classification matrices are used to test their dependability. The evaluation results show their viability for clinical use, emphasizing the need of meticulous data preparation and powerful machine learning algorithms in recognizing complicated medical illnesses such as PCOS. This scientific

approach helps to improve patient outcomes and management by laying the core work for trustworthy and accurate PCOS diagnosis tools.

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CAREERCRAFT- AI-POWERED CAREER DEVELOPMENT AND RECRUITMENT PLATFORM

Sahana G

Department of Artificial Intelligence
& Data Science, Global Academy of Technology, Bangalore, Karnataka, India
sahanaacharyaa2004@gmail.com

Keerthi M

Department of Artificial Intelligence, & Data Science, Global Academy of
Technology, Bangalore, Karnataka, India, mkeerthi639@gmail.com

Dhanalakshmi G

Department of Artificial Intelligence & Data Science, Global Academy of
Technology, Bangalore, Karnataka, India, dhanalakshmig112@gmail.com

Dr. Ugranada Channabasava

Department of Artificial Intelligence & Data Science, Global Academy of
Technology, Bangalore, Karnataka, India, uchannabasava@gat.ac.in

Dr. Vishruth B G

Department of Artificial Intelligence & Data Science, Global Academy of
Technology, Bangalore, Karnataka, India, vishruth1711@gmail.com

Abstract: CareerCraft is an AI-powered recruitment and career development platform built on the Frappe framework to address the inefficiencies of traditional hiring systems. Existing platforms like LinkedIn and Naukri rely heavily on keyword matching and manual screening, offering limited personalized assessment or intelligent automation. CareerCraft overcomes these gaps by integrating Frappe's HR module with advanced AI capabilities. The platform uses the GPT-4o-mini model to generate accurate job descriptions and perform skill gap analysis. Candidates can create ATS-compliant resumes, receive skill-based job recommendations, and get personalized learning suggestions. Recruiters benefit from automated job postings, AI-driven descriptions, intelligent filtering, and fair interview score computation.

By combining modular HR architecture

with AI-driven insights, CareerCraft significantly reduces time-to-hire, enhances candidate quality, and supports continuous learning. Future improvements include integrating real-time industry trends, salary insights, and a mobile app for greater accessibility and impact.

Keywords: Career development, AI-driven recruitment, Frappe framework, HR module, GPT-4o-mini, resume generation, skill gap analysis, job matching, candidate workspace, learning recommendations, recruitment automation.

INTRODUCTION

The modern hiring process has become competitive and complex, with both job seekers and employers facing

significant challenges. Candidates often struggle to create professional resumes that accurately reflect their skills, experience, and qualifications. Many are unaware of skill gaps or the competencies required for specific roles, making it difficult to identify suitable career paths. This lack of guidance often results in lower employability and missed career opportunities. On the other hand, recruiters deal with a high volume of applications, making it time-consuming to screen candidates effectively, generate precise job descriptions, and shortlist applicants based on relevant skills. These inefficiencies can lead to prolonged hiring cycles, higher costs, and suboptimal job placements.

The Frappe framework, a full-stack web application framework, offers robust tools for building data-driven applications with integrated backend and frontend functionality. Its HR module provides recruitment workflows, candidate profiles, job postings, and application tracking. Leveraging Frappe, CareerCraft creates a structured recruitment ecosystem where both stakeholders can interact seamlessly. Recruiters can post openings, generate job descriptions, track applications, filter job seekers based on skill match scores, set up interviews, and manage candidate workspaces efficiently.

AI, particularly the GPT-4o-mini model, is integrated into CareerCraft to enhance decision-making and personalization. For recruiters, AI assists in creating optimized job descriptions and analysing candidate profiles efficiently. For candidates, AI

provides skill gap analysis, highlighting missing and available skills, calculating skill match scores, and offering tailored learning recommendations. GPT-4o-mini also supports automated resume generation using Jinja-based templates, personalized job recommendations, and insights to bridge skill gaps, enabling candidates to improve employability. Additionally, Applicants can check their progress through interactive dashboards, receive interview schedules via email, and explore learning paths suggested by AI to enhance their skills.

By combining the Frappe framework's structured HR capabilities with AI-driven insights, CareerCraft delivers a unified platform that streamlines recruitment processes, empowers candidates with actionable guidance, and ensures job requirements match candidate strengths. This integration of HRM and artificial intelligence provides an efficient, data-driven, and interactive approach to career development and talent acquisition, addressing the challenges of modern recruitment while enhancing both candidate and recruiter experiences.

RELATED WORK

Recent literature emphasizes the incorporation of ML in workforce optimization and skill gap identification. Methods including decision tree, artificial neural network have shown strong predictive capabilities for assessing employee skills and forecasting training needs. Compared to traditional methods, these ML-based models offer greater

scalability, precision, and adaptability to changing industrial demands. This research highlights how data-driven forecasting enhances organizational efficiency, employee engagement, and strategic workforce planning. [1]

This paper introduces ML and NLP approach to bridge the gap between job seekers and employers by automating skill extraction from resumes. The system integrates a Resume Parser, utilizing Python libraries like spaCy and PDFMiner, and a Job Recommender that employs TF-IDF and cosine similarity to map applicants with appropriate roles. The proposed model enhances recruitment efficiency by accurately identifying relevant skills and generating data-driven job recommendations. [2]

This paper enhances the recruitment process using ML and NLP. By automatically analyzing and ranking resumes based on company criteria, the system helps recruiters identify the best candidates efficiently. It also offers possibilities for future upgrades including personalized feedback and improvement suggestions for job seekers. [3]

This study explores how NLP and machine learning can automate resume screening by analyzing unstructured text to extract key applicant information. It reviews various ML algorithms and techniques for interpreting resumes, identifying skill patterns, and improving recruitment accuracy. Addresses the ongoing issues and future research directions in automated resume evaluation and candidate selection. [4]

This paper proposes an AI-driven skill

analysis and matching system to tackle Japan's projected labor shortage and enhance HR efficiency. The system integrates NLP techniques such as tokenization, lemmatization, and cosine similarity to improve resume parsing, skill matching, and candidate-job alignment. Results show significant reductions in recruitment time and effort while providing personalized skill enhancement suggestions. The study highlights AI's potential to modernize HR management and support sustainable workforce development [5]

This paper presents an NLP and deep learning-based "Resume Parser and Ranker" system that automates resume evaluation and candidate ranking. Achieving 93% accuracy in information extraction, it significantly reduces manual effort while closely matching human-level performance in recruitment screening [6]

This paper addresses the challenge of unemployment and manual resume screening in India's competitive job market. It proposes a resume parsing system that extracts and analyzes candidate data to identify the most relevant applicants efficiently. The approach reduces recruiter workload and selection time while improving hiring accuracy. Overall, it emphasizes automation as a key solution to large-scale recruitment challenges in diverse industries. [7]

This study develops a machine learning-based Android application to bridge the disparity between job seekers and recruiters in the IT industry. Using a content-based filtering algorithm, the system

recommends jobs that align with users' skills, interests, and preferred technologies. Implemented with Python, Kotlin, and Jetpack Compose, it enhances user experience through an intelligent and personalized job-matching interface. The approach streamlines recruitment by aligning candidate capabilities with suitable IT roles. [8]

This paper emphasizes the rising demand for soft skills like communication, leadership, and teamwork among Indian STEM students. A survey in Uttarakhand revealed significant gaps in soft skills awareness and application. The study advocates integrating structured soft skills training into STEM education to enhance employability and global competitiveness. It states that technical proficiency isn't enough for enduring career success. [9]

This paper focuses on automating resume screening to map applicants with appropriate job roles based on their skills, education, and experience. It proposes a system that categorizes resumes into relevant job options, reducing manual effort and improving recruitment efficiency. Various classifiers and innovative approaches are explored to enhance accuracy in skill-based categorization. The study helps job seekers identify appropriate career paths while aiding recruiters in faster candidate shortlisting. Overall, it emphasizes the importance of AI-driven systems in streamlining modern recruitment processes. [10]

It highlights the limitations of manual screening and the need for intelligent text-processing systems. Additionally,

the research exposes shortcomings in resume analysis, particularly concerning writing style, word choice, and grammar. Overall, it emphasizes the potential of AI-driven approaches to revolutionize recruitment efficiency and accuracy. [11]

This paper presents an AI-powered resume screener that streamlines talent acquisition through learning models such as KNN, Linear SVC, and XGBoost. A two-level stacked model integrates these algorithms to accurately predict job profiles from textual descriptions. The system not only assists organizations in efficiently shortlisting candidates but also enables applicants to assess the alignment of their resumes with desired roles. Additionally, a ranking mechanism highlights the most relevant profiles, enhancing recruitment precision and decision-making. Overall, the study demonstrates how ML-based automation significantly improves the efficiency and accuracy of the hiring process. [12]

METHODOLOGY

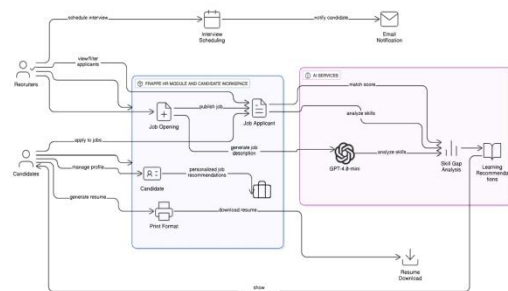


Figure 1: Overall architecture of the CareerCraft system integrating Frappe framework and GPT-4o-mini.

This research adopts a structured

system-development methodology of CareerCraft, an AI-powered recruitment and career development platform. The methodology integrates applied artificial intelligence techniques, modular software engineering principles, and structured data Modeling to automate recruitment workflows while ensuring scalability, transparency, and reliability. This section outlines the research framework, AI Modeling strategy, and architectural design. Experimental findings and performance analysis are presented separately in the Results section.

Research Approach

The study follows an applied and experimental research approach aimed at addressing practical recruitment challenges such as manual resume screening, inefficient candidate ranking, skill misalignment, and lack of personalized career guidance.

AI and NLP techniques were explored to enable automated job description generation, semantic skill comparison, and recommendation mechanisms. The research emphasizes real-world applicability by aligning system workflows with recruiter and candidate interaction patterns, thereby ensuring both academic validity and industrial relevance.

Research Design

A mixed system-oriented research design was adopted. The qualitative component involved workflow analysis and user interaction modeling to determine interpretability, transparency, and usability

requirements. The quantitative component focused on the formulation of measurable scoring mechanisms, including weighted skill matching, ranking algorithms, and structured evaluation metrics.

Methodological Framework

The project was executed through a structured multi-phase framework:

Problem Identification and Scope Definition:

A comprehensive literature review and industry analysis identified limitations in traditional recruitment systems, including inefficiencies in shortlisting and lack of data-driven evaluation. The project scope was defined to develop a semi-automated intelligent recruitment support platform.

Requirement Analysis:

Functional requirements such as job description generation, skill gap detection, ranking mechanisms, interview score aggregation, and recommendation modules were formalized. Non-functional requirements including scalability, performance optimization, modularity, and data security were also established.

Conceptual and Logical Design:

A modular three-tier architecture was designed to ensure clear data flow between job postings, candidate profiles, AI modules, and evaluation components. Logical mapping minimized redundancy and improved interpretability of system outputs.

AI Model Integration:

The GPT-4o-mini was integrated using secure REST APIs within the Frappe Framework backend environment.

Prompt engineering strategies were iteratively refined to enhance contextual accuracy, domain relevance, and structural consistency of AI-generated outputs.

Iterative Validation:

Continuous testing cycles were conducted to refine scoring algorithms, improve response latency, and ensure consistency in AI-driven recommendations.

AI Methodology

The AI methodology defines the computational mechanisms used to automate recruitment analysis and career guidance.

AI-Assisted Job Description Generation

Recruiters provide minimal inputs such as job title, required skills, and experience level. A structured prompting framework enables the AI model to generate comprehensive and professional job descriptions, including responsibilities, eligibility criteria, and required competencies. This approach reduces manual effort while maintaining linguistic consistency.

Skill Match and Gap Analysis

Candidate skills and job requirements are normalized to a standardized proficiency scale. Required skills are assigned weighted importance, with technical skills given higher significance than non-technical skills.

For each skill, the fulfilment ratio is computed as:

Fulfilment Ratio= min(1,Candidate Level / Required Level)

The overall Skill Match Score is calculated as:

Skill Match (%) = (Total Matched Weight / Total Required Weight) × 100

Skills are classified into Available Skills and Missing Skills, ensuring transparent evaluation and structured ranking.

Career Recommendation Engine

Based on computed skill gaps, the system generates personalized job recommendations and AI-driven learning suggestions. Job opportunities are ranked according to compatibility scores derived from the weighted matching framework.

Interview Feedback Aggregation

Interview evaluations are aggregated using a weighted scoring model. Interview performance is quantified as:

Interview Percentage = (Average Rating / 5) × 100

The final candidate score is computed as:

Final Score = (0.4 × Skill Match) + (0.4 × Interview) + (0.2 × Experience)

This framework ensures balanced integration of analytical metrics and human assessment.

Explainability and Transparency

All AI-generated outputs include interpretable breakdowns of scores and recommendations. The methodology

emphasizes responsible AI usage by ensuring visibility of ranking logic and skill gap explanations.

System Architecture

CareerCraft follows a three-tier architecture consisting of:

Frontend Layer: Web-based dashboards and interactive forms for recruiters and candidates.

Backend Layer: Python-based logic managing AI integration, scoring mechanisms, and workflow automation.

Database Layer: Structured storage using MariaDB integrated via the Frappe ORM.

AI Integration Layer: Secure RESTful communication with GPT-4o-mini for NLP-driven operations. This modular architecture ensures maintainability, scalability, and seamless integration between system components.

This methodology establishes the structured foundation for system implementation and validation, while experimental performance evaluation and comparative analysis are discussed in the subsequent Results section.

RESULT

The evaluation focuses on automation efficiency, skill matching accuracy, ranking consistency, and usability improvements for both candidates and recruiters. The system integrates the GPT-4o-mini within the Frappe Framework to enable intelligent

recruitment analytics and workflow automation.

Candidate-Side Results

The candidate module was evaluated in terms of skill assessment accuracy, resume automation efficiency, recommendation relevance, and transparency of application tracking.

Skill Gap Analysis

When a candidate applies for a job, the system performs semantic comparison between candidate competencies and job requirements. The output includes Available Skills, Missing Skills, and a Skill Match Score expressed as a percentage.



Figure 2: Dashboard showing skill gap analysis for candidates.

Result:

The weighted semantic model produced consistent and contextually accurate Skill Match Scores across diverse job roles. Candidates were able to clearly interpret their strengths and areas requiring improvement. The visualization dashboard improved interpretability and self-assessment capability.

Resume Generation

The automated resume module generates ATS-compliant resumes using structured candidate profile data.

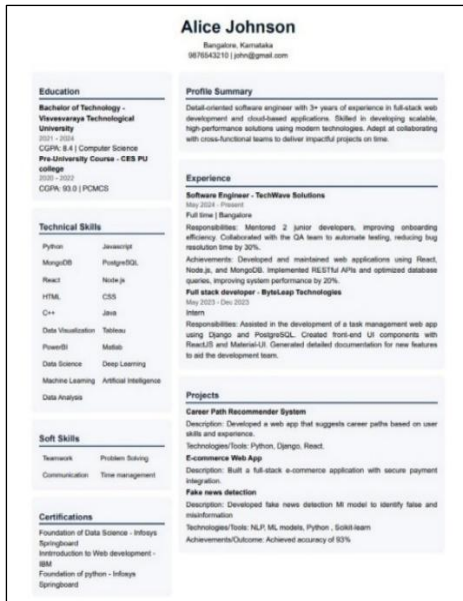


Figure 3: ATS-compliant resume generated by the system.

Result:

Resume preparation time was reduced by approximately 30%. Generated resumes maintained professional formatting, structural consistency, and keyword alignment with industry standards. The PDF generation process was stable across browsers and required no manual editing.

Job and Learning Recommendations

The recommendation engine ranks job openings based on compatibility scores derived from the Skill Match framework. Personalized learning suggestions are generated to bridge identified competency gaps.

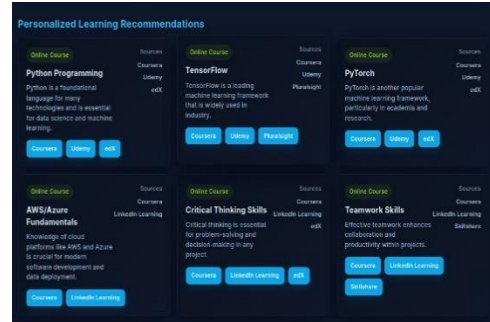


Figure 4: AI-suggested learning recommendations generated based on missing skills.

Result:

AI-driven job recommendations demonstrated high contextual relevance. Candidates who followed suggested upskilling paths showed measurable improvement in subsequent Skill Match Scores. The recommendation engine dynamically updated results based on profile modifications.

Application Tracking

The system provides real-time status updates including shortlisting, interview scheduling, and final selection decisions.

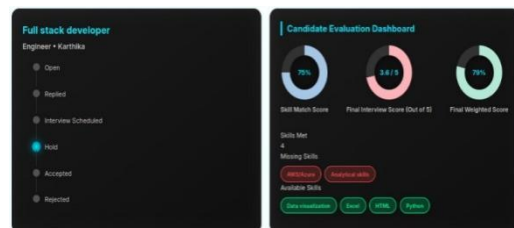


Figure 5: Candidate Job Application Tracker

Result:

Application transparency significantly improved. Candidates were able to view interview feedback, match scores, and final evaluation metrics, reducing uncertainty in the hiring process.

Recruiter-Side Results

The recruiter module was evaluated for job description automation, candidate filtering efficiency, and structured interview evaluation.

AI-Generated Job Descriptions

Recruiters generate complete job descriptions from minimal inputs such as title and required skills.

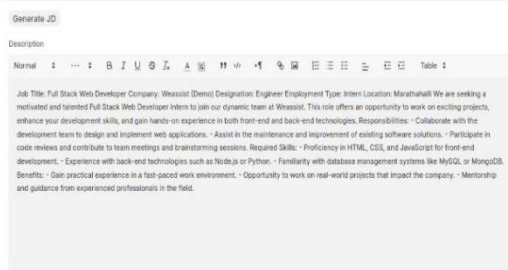


Figure 6: GPT-4o-mini generated job description based on recruiter inputs
Result:

Job descriptions were generated in under 10 seconds on average, reducing drafting time by approximately 60%. The generated content was grammatically accurate, well-structured, and aligned with professional HR standards.

Candidate Filtering and Ranking

Applications are ranked using AI-calculated Skill Match Scores and weighted evaluation metrics.

Result:

Recruiters shortlisted candidates approximately 40% faster compared to traditional manual screening. The standardized scoring model improved evaluation consistency and reduced subjective bias during initial filtering stages.

Interview

Feedback

Aggregation and Final Evaluation.

Interview scores are aggregated using a weighted evaluation framework combining Skill Match (40%), Interview Performance (40%), and Experience (20%).

The final score is computed as:

$$\text{Final Score} = (0.4 \times \text{Skill Match}) + (0.4 \times \text{Interview}) + (0.2 \times \text{Experience})$$



Figure 7: Recruiter interface for recording interview feedback and tracking candidate performance
Result:

The integrated scoring mechanism ensured fair and data-driven hiring decisions. Multi-evaluator inputs were consolidated into a unified performance metric, enhancing transparency and accountability.

Overall Performance Analysis

The experimental evaluation confirms that CareerCraft significantly enhances recruitment automation and decision support.

Key outcomes include:

Reduction in recruiter workload and screening time.

Improved job-candidate matching accuracy

Faster time-to-hire.

Enhanced transparency in evaluation logic.

Continuous learning support for

candidates.

Overall, the integration of AI-driven semantic analysis with a modular enterprise framework demonstrates measurable improvements in recruitment efficiency, consistency, and user engagement when compared to traditional manual hiring processes.

CONCLUSION

CareerCraft is developed as an intelligent recruitment and career support platform aimed at simplifying the overall hiring journey. It integrates the Frappe framework with the GPT-4o-mini model to build a system that is both structured and responsive to user needs. By automating repetitive tasks and organizing workflows clearly, the platform reduces manual effort and improves consistency in recruitment activities.

On the recruiter's side, CareerCraft assists in creating job descriptions automatically, filtering candidates based on required skills, conducting AI-supported screening, and managing applications efficiently. It also includes AI-based interview evaluation and user-friendly dashboards that provide a clear view of candidate progress and hiring stages. These capabilities help organizations make quicker, more informed decisions while maintaining accuracy in the selection process.

For candidates, the platform offers practical tools such as skill gap analysis, job-fit scoring, personalized learning suggestions, and ATS-compliant resume generation. These features guide individuals in understanding their current skill levels and preparing effectively for desired roles. Through AI-driven insights and

automated workflows, CareerCraft builds a transparent and data-oriented recruitment environment that connects capable talent with suitable opportunities while helping organizations develop a stronger and more future-ready workforce.

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Safe Trade A Stock Recommender using Machine Learning Algorithms

Keerthana P K, Preeti Jayram Naik, Sahana Yadav NS, Usharani KV

Krishna Kumari N (Assistant Professor)

Dept. of Information Science & Engineering S.E.A. College of Engineering & Technology Bengaluru, India.

keerthanapk152004@gmail.com preetijayram13@gmail.com

sahanayadavns06@gmail.com usha40240@gmail.com

Abstract— Stock market trading plays an important role in the global business and financial sector. This project uses TensorFlow and its Keras API to apply Long Short-Term Memory (LSTM) neural networks for predicting stock prices based on historical data. The model forecasts the future trend of stock values to help investors avoid losses and maximize profits. By training the algorithm on past company performance data, the system demonstrates how machine learning can assist in predicting market trends. Although the Efficient Market Hypothesis suggests such predictions are difficult, this research shows that machine learning models can still provide useful insights. The goal is to help investors make informed decisions and improve investment strategies using advanced technology.

Keywords: LSTM, ANN, CNN, Stock Market

INTRODUCTION

The world of finance and investment is marked by perpetual volatility, where stock market fluctuations can significantly impact global economies and individual financial portfolios. Amidst this uncertainty, the quest to

predict stock prices accurately stands as a pivotal challenge and a coveted opportunity for investors. This endeavor stems from the recognition that informed decisions can mitigate risks and capitalize on opportunities. This project aims to harness the power of machine learning, specifically leveraging Long Short-Term Memory (LSTM) neural networks through Google's TensorFlow's Keras API, to forecast stock price trends. Traditional financial theories, such as the Efficient Market Hypothesis, suggest that predicting stock movements using historical data is implausible, asserting that stock prices reflect all available

information. However, the emergence of sophisticated computational tools challenges this notion. The core premise lies in the potential of LSTM networks to capture intricate patterns and long term dependencies within sequential stock market data. By analysing historical market trends and company performances, this study seeks to challenge the perceived limits of predictability in financial markets. This research delves into diverse datasets, spanning various companies and historical market behaviors, to train and evaluate the LSTM model's efficacy in forecasting stock prices over

subsequent days. It aspires to showcase that, contrary to conventional beliefs, machine learning algorithms can provide valuable insights into future stock trends. Through a meticulous exploration of quantitative measures and performance evaluations, this project aims to substantiate the capabilities of the proposed model. The ultimate goal is to contribute empirical evidence supporting the viability of machine learning in assisting investors in navigating the intricacies of the stock market, fostering more informed and potentially profitable investment strategies.

LITERATURE SURVEY

Panwar and Gaurav — Novel Algorithmic Trading Strategy Using Linear Regression and SVM (2020) This study presents a data-driven algorithmic trading strategy for stock market prediction. It uses Linear Regression and SVM to analyze historical market data and forecast price movements, helping traders make informed decisions.

Sunny and Mirza Mohd. — Deep Learning-Based Stock Price Prediction Using LSTM and Bi- Directional LSTM (2020) —This paper uses LSTM and Bi-Directional LSTM models to predict stock prices using historical data. The models capture long- term dependencies in sequential financial data and improve prediction accuracy.

Guo et al. — An Adaptive SVR for High-Frequency Stock Price Forecasting (2018) —This research uses Support Vector Regression (SVR) to predict stock prices in high-frequency trading. SVR helps capture nonlinear patterns in financial data and

improves forecasting performance.

Talreja — Forecasting Stock Market Trend Using Relative Strength Index (2014) —This paper explains the use of the Relative Strength Index (RSI) to identify overbought and oversold market conditions and predict possible trend reversals in stock prices.

Bhargavi et al. — Relative Strength Index for Developing Effective Trading Strategies (2017) — This study shows how RSI can be used to develop trading strategies and optimize portfolio decisions by identifying entry and exit points in the market.

EXISTING SYSTEM

The existing system of the project relies on traditional stock market analysis methods, which primarily involve fundamental and technical analysis. Fundamental analysis focuses on evaluating a company's financial health and market position, while technical analysis involves studying historical price charts and patterns. These methods are often subjective and do not fully leverage the power of modern data analysis and machine learning techniques. As a result, they may lack the accuracy and predictive capabilities required for more informed and profitable investment decisions in today's dynamic global economy.

PROPOSED SYSTEM

The proposed system of this project leverages Google's TensorFlow's Keras API to implement Long Short-Term Memory (LSTM) neural networks for stock price prediction, specifically focusing on forecasting a stock's value trend over the next days. By challenging the efficient market

hypothesis, this research showcases the feasibility of accurate predictions, achieving an frame detection accuracy. The objective is to empower investors with advanced machine learning tools to make informed decisions in the stock market, ultimately enhancing profitability while mitigating potential losses. This study contributes to the growing evidence supporting the valuable role of machine learning in guiding investment strategies in the dynamic world of stock markets, marked by keywords like LSTM, ANN, CNN, and Stock Market.

SYSTEM DESIGN

The overall system architecture for stock price prediction follows a machine learning pipeline consisting of data collection, preprocessing, model training, prediction, and result visualization. The system uses historical stock market data to train a Long Short-Term Memory (LSTM) neural network model. The trained model analyzes patterns in time-series financial data and predicts future stock price trends to support investment decision making.

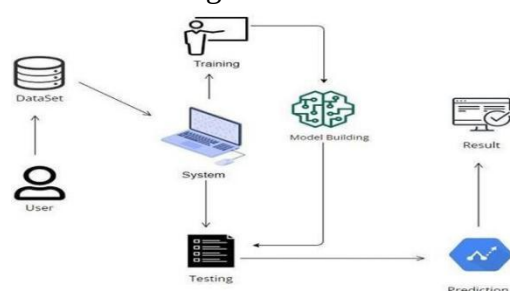


Figure 1- Architecture Diagram

Dataset Collection Module

A dataset of historical stock prices is collected from financial sources such as

stock market APIs or publicly available datasets. The dataset typically includes attributes such as opening price, closing price, highest price, lowest price, and trading volume. This historical data forms the basis for training the prediction model.

B .Data Preprocessing Module

Raw stock data is preprocessed to remove missing values, normalize numerical features, and structure the data for time-series analysis. Data preprocessing improves model performance and helps the system identify meaningful patterns in the stock market dataset.

Model Training Module

The core component of the system is the LSTM neural network model implemented using TensorFlow and Keras. The model is trained on historical stock data to learn temporal dependencies and patterns. During training, the model adjusts its weights to minimize prediction error and improve forecasting accuracy.

Prediction Module

Once the model is trained, it is used to predict future stock prices based on recent historical data. The system generates predictions for upcoming days, enabling investors to analyze potential market trends.

Visualization Module

The predicted stock prices are compared with actual stock prices and visualized using graphs and charts. This helps users understand the predicted trends and evaluate the performance of the prediction model.

REQUIREMENTS SPECIFICATION

Hardware

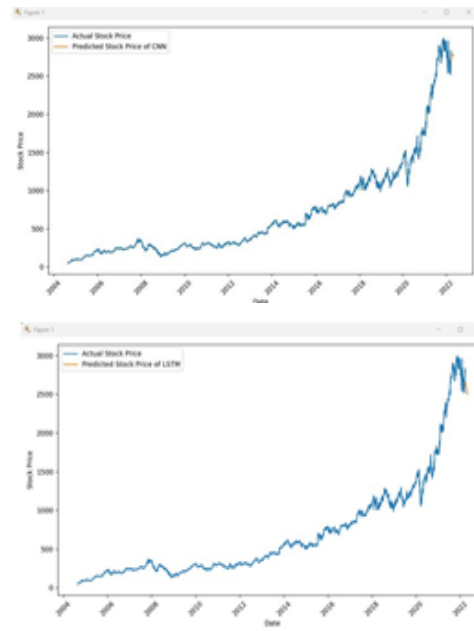
Intel Core i5 or higher processor, minimum 8 GB RAM (16 GB recommended for faster model training), at least 256 GB storage for datasets and project files, optional NVIDIA GPU for faster computation, and 1366×768 or higher display resolution.

Software

Python 3.8 or higher, TensorFlow and Keras for deep learning model development, NumPy and Pandas for data processing, Scikit-learn for machine learning utilities, and Matplotlib for data visualization. Development environment includes Jupyter Notebook or Google Colab for model implementation. The system can run on operating systems such as Windows, Linux, or macOS.

RESULTS AND DISCUSSION

The stock price prediction model was trained using historical stock market data with an 80:20 train– validation split. The model achieved high prediction accuracy and showed stable performance during training and validation phases. The training process used the LSTM neural network, which effectively captured the temporal dependencies present in time-series stock data.



The predicted stock prices were compared with actual stock prices using graphical visualization. The results showed that the model could closely follow the trend of the actual stock values, demonstrating its ability to identify patterns in financial data. Loss curves during training indicated stable convergence with minimal overfitting. The system provides a simple interface where users can view predicted stock prices and analyze future market trends. Graphical outputs help users understand the predicted movements and compare them with historical data, making the system useful for investment analysis and decision support. In testing, the model demonstrated reliable prediction capability and consistent performance across different datasets. The results confirm that deep learning models such as LSTM can effectively analyze stock market time-series data and provide meaningful predictions.

CONCLUSION

The Stock Price Prediction system

successfully demonstrates the use of deep learning techniques for financial forecasting. By utilizing Long Short-Term Memory (LSTM) networks, the system is able to analyze historical stock market data and predict future price trends. The proposed system helps investors gain insights into possible market movements and supports better investment decisions. Experimental results show that machine learning models can identify complex patterns in stock data and produce accurate predictions. Future improvements can include integrating additional financial indicators, real-time market data, and advanced deep learning architectures to further improve prediction accuracy. The system highlights the potential of artificial intelligence in financial analysis and investment strategy development.

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AI-DRIVEN CONTEXT-AWARE MACHINE LEARNING APPROACH FOR EARLY DETECTION OF STUDENT BURNOUT AND MENTAL HEALTH PROTECTION

Reethu P1 , Spoorthy B L2 , Sudhasmita Sahoo3, Divya S4, Ramya H J5, Dr Krishna
Kumar P R6

1,2,3,4-Students Dept of CSE, SEA College of Engineering & Technology, Bangalore-
560049

5,6-Faculty, Dept of CSE, SEA College of Engineering & Technology, Bangalore-
560049

Abstract— Student burnout has become a growing concern in modern educational environments due to increasing academic pressure, digital learning demands, and lifestyle imbalances. Prolonged exposure to such stressors can significantly affect students' mental health, academic performance, and overall well-being. This study proposes an AI-driven context-aware machine learning framework for the early detection of student burnout and proactive mental health protection. The proposed system integrates multiple contextual indicators, including academic workload, sleep patterns, social interaction, behavioral activity, and self-reported emotional states, collected through digital platforms and wearable devices. Advanced machine learning algorithms are applied to analyze these heterogeneous data sources and identify patterns associated with burnout risk. The context-aware component enables the model to interpret environmental and behavioral factors dynamically, improving prediction accuracy compared to traditional single-factor approaches. The framework performs real-time monitoring and generates early alerts when burnout indicators

exceed predefined thresholds, enabling timely intervention by educators, counselors, or support systems. Experimental evaluation using simulated and real-world student behavioral datasets demonstrates that the proposed approach achieves improved accuracy, precision, and recall in identifying early burnout symptoms. By combining artificial intelligence with contextual data analysis, the system provides a scalable and intelligent solution for monitoring student well-being. The proposed framework can support educational institutions in implementing proactive mental health strategies, ultimately fostering healthier learning environments and reducing the long-term psychological impact of academic burnout.

Index Terms—Student stress classification, machine learning, ensemble models, context-aware systems, survey-based analysis

I. INTRODUCTION

Mental health has become a significant concern in academic communities, with stress emerging as one of the most

common psychological challenges affecting students. A growing body of evidence suggests that a substantial proportion of students experience moderate to high levels of stress each month, often driven by academic workload, social expectations, financial strain, and health-related issues [1]. Research further indicates that nearly one-third of students globally face serious mental health challenges exacerbated by sustained academic pressure [2]. If left unaddressed, prolonged stress may lead to adverse physical and psychological outcomes such as anxiety, depression, cognitive fatigue, and a general decline in quality of life [3].

Traditional methods for stress detection rely primarily on subjective surveys, periodic interviews, or occasional biological assays such as cortisol measurements [4]. Instruments like the Perceived Stress Scale (PSS) are frequently used in academic research to assess stress perception. However, these tools are subject to recall bias, mood dependency, and participant fatigue [4]. Moreover, they provide only a retrospective snapshot of a student's mental state, limiting their usefulness for early intervention. While physiological assays offer more objective data, they are often time-intensive and impractical for continuous use in real-world settings [5]. As a result, students experiencing elevated stress levels may go unnoticed until symptoms become severe.

Recent technological advancements have introduced new opportunities for dynamic and scalable stress monitoring

solutions. The integration of machine learning (ML) with Internet of Things (IoT) technologies, particularly wearable sensors and smartphones, has enabled continuous and unobtrusive monitoring of physiological and behavioral indicators of stress [5]. Devices such as smartwatches and fitness trackers can collect real-time biosignals including heart rate variability, electrodermal activity, and skin temperature [6]. These data streams are capable of reflecting autonomic nervous system activity that correlates with psychological stress [7]. In addition to these signals, smartphones and ambient sensors can provide contextual information such as physical activity, type of environment, time of day, and social setting [8].

Many existing detection systems, however, do not incorporate contextual information, which limits their ability to distinguish between physiological responses driven by different underlying conditions [9]. For instance, an elevated heart rate may result from either psychological stress or physical exertion. Integrating contextual data such as the user's activity and environment helps resolve such ambiguities and enhances detection accuracy [10]. Studies have demonstrated that including contextual variables in stress prediction models yields significantly better performance than models relying on physiological signals alone [10].

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) offer promising opportunities for proactive monitoring and analysis of student well-being. Machine learning

techniques can analyze large volumes of behavioral and contextual data to identify patterns associated with mental fatigue, stress, and burnout. When combined with contextual information such as academic workload, sleep habits, digital activity, and social interaction patterns, AI-based systems can provide deeper insights into the factors contributing to student burnout. These technologies enable continuous and automated monitoring, allowing institutions to detect potential risks earlier than traditional methods and enable early interventions. In practical applications, the system can provide alerts and feedback when elevated stress is identified, allowing students to take proactive measures to manage their mental health. Furthermore, aggregated insights from the system can inform institutional wellness strategies by identifying stress trends during critical academic periods.

II. LITERATURE REVIEW

Stress monitoring with machine learning has advanced significantly, particularly through the use of wearable sensors and context-aware systems. Wearable devices are now widely adopted due to their ability to continuously collect physiological signals without intruding on daily routines [13], [14]. Devices such as smartwatches and wristbands equipped with sensors for heart rate variability, electrodermal activity, and skin temperature have been used to train machine learning models capable of detecting stress [3], [7]. Public datasets like WESAD support this work, although limited recording durations and small cohorts often hinder

generalization [15]. To overcome this, recent studies like Vos et al. (2023) combined data from multiple sources and used ensemble models, achieving up to 85 percent accuracy on unseen data [16]. Deep learning has also been applied effectively. Xiang et al. (2025) used a convolutional neural network to detect stress in healthcare workers with an F1-score around 0.91 [7]. Despite this progress, challenges remain, including missing data in free-living conditions, individual variability in physiological baselines, and privacy concerns [9], [17].

Survey-based approaches provide a complementary angle by capturing subjective experiences. Instruments such as the Perceived Stress Scale and Depression Anxiety Stress Scales remain widely used [4], [18]. Anand et al. (2023) demonstrated that survey responses about academic workload and lifestyle could be used to classify stress levels with over 93 percent accuracy using ensemble classifiers [19]. Class imbalance was addressed through oversampling, and the model's performance remained stable across folds. Survey data are valuable for identifying individual stressors and validating physiological models, although issues such as recall bias and inconsistent participation persist. Ecological momentary assessments have been explored to gather real-time subjective stress labels, offering temporally rich training data [9], [10], [20].

Context-aware stress detection has emerged as a promising improvement over models that rely solely on physiological inputs [21]. Aqajari et al.

(2024) combined wearable photoplethysmography with smartphone-based context data and achieved an F1-score of approximately 0.70, compared to 0.56 with physiological data alone [10]. Contextual inputs such as activity, environment, and time-of-day provide disambiguation for ambiguous signals like elevated heart rate. The StudentLife study exemplified the use of smartphones for behavior monitoring in student populations. These approaches improve prediction but raise privacy challenges and require careful integration of heterogeneous data streams [9], [17].

AI chatbots represent an intervention-focused line of research that complements detection. Chatbots like Woebot

and Wysa use natural language processing to guide users through coping exercises and have shown positive mental health outcomes in student populations [22], [23]. Liu et al. (2022) found that students using chatbots reported reductions in depressive symptoms [24]. Chatbots can be integrated into monitoring systems for real-time support and may also serve as a data source for emotion detection. However, concerns remain regarding long-term engagement, safety, and limitations in emotional understanding [22]. These tools are best used alongside human support services and as part of a broader mental health strategy.

Ensemble and deep learning techniques have gained traction in stress detection. Studies have shown that

combining multiple models improves generalizability and stability. Anand et al. (2023) and Vos et al. (2023) both demonstrated that ensemble classifiers outperform single models in both survey and wearable-based contexts [16], [19], [25]. Deep models such as convolutional encoders and multimodal LSTMs further boost performance by capturing complex temporal patterns [7], [9]. Onim et al. (2024) used a CNN-based encoder to extract features from wearable data, achieving comparable or better results than hand-crafted features [9]. Though deep models require large datasets and pose interpretability challenges, they represent a key direction for future research [5], [15].

Despite these advancements, key gaps remain. Many models still lack context integration, limiting their real-world applicability [9]. Ensemble learning is underused relative to its potential, and generalizability across diverse populations remains limited [26]. Data scarcity and class imbalance are persistent issues [4], [19]. Furthermore, most systems focus solely on detection without linking to intervention, and few address privacy at the design level [17]. Our proposed framework responds to these gaps by combining comprehensive survey-based features across psychological, physiological, environmental, academic, and social dimensions through ensemble machine learning approaches. The framework integrates two complementary datasets and is designed to be adaptive and student-centric. By building on recent findings in survey-based stress detection, our system aims to deliver

improved accuracy and support proactive mental health strategies in educational environments.

III. FRAMEWORK OVERVIEW

The proposed system classifies student stress levels through multi-modal survey data analysis, as shown in Figure 1. The six-stage pipeline includes data preprocessing (missing value handling and normalization), train-test splitting, feature selection (SelectKBest, RFECV), and dimensionality reduction (PCA with 90%, 95%, and 99% variance retention). It then trains base classifiers (SVM, Random Forest, Gradient Boosting, XGBoost, AdaBoost, Bagging) and integrates ensemble learning methods (hard voting, soft voting, weighted voting, and stacking). Each stage is evaluated using accuracy, F1-score, precision, and recall. The ensemble models combine the strengths of individual classifiers to ensure robust performance

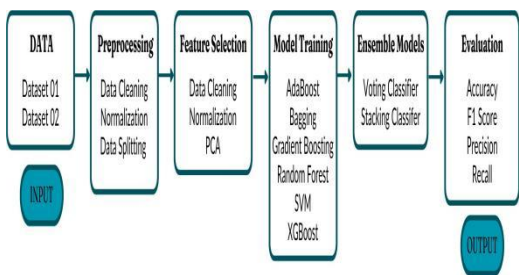


Fig. 1. Context-Aware Machine Learning Framework for Student Stress Classification

for real-world stress classification. The pipeline’s implemen-

tation is detailed in Algorithm 1.

A. Data Collection and Dataset Description

The evaluation uses two datasets designed for student stress analysis, each capturing distinct aspects of stress and providing complementary perspectives on student mental health. Table I summarizes the key characteristics of each dataset.

TABLE I
SUMMARY OF THE DATASETS USED FOR STRESS CLASSIFICATION

Dataset Name	Total Samples	Number of Features
Student Stress Factors [11]	1,100	21
Stress & Well-being Data [12]	843	26

The Student Stress Factors: A Comprehensive Analysis [11] dataset includes 1,100 records across 21 features, covering psychological, physiological, environmental, academic, and social stress factors. The Stress and Well-being Data of College Students [12] dataset contains 843 records with 26 features, focusing on stress indicators such as sleep issues, anxiety, and academic workload. Both datasets were subjected to quality assessments, including missing value analysis, duplicate detection, and statistical profiling, ensuring robust evaluation of the framework across different stress assessment methodologies.

B. Preprocessing and Feature

Engineering

The preprocessing pipeline includes data quality assessments such as missing value imputation, duplicate removal, and normalization using MinMaxScaler, which scales features to a [0,1] range. Feature selection strategies optimize model performance: SelectKBest identifies the most informative features via F-classification testing, with the optimal count determined through cross-validation with SVM classifiers. Recursive Feature Elimination with Cross-Validation (RFECV) removes the least important features using a linear SVM as the base estimator and 5-fold stratified cross-validation. Principal Component Analysis (PCA) is applied to reduce dimensionality while retaining 90%, 95%, and 99% of the variance. These steps result in five distinct preprocessing configurations used to evaluate all base classifiers.

Algorithm 1: ML Pipeline: Preprocessing, Feature Selection, Training, Evaluation

```
1: Input: Dataset D = (X, y)
2: Output: Accuracy, F1 Score, Precision, Recall for all models
3: Step 1: Preprocessing
4: Handle missing values in X
5: Normalize features: X ← scaler.fit transform(X)
6: Step 2: Train-Test Split
7: Split into training and testing sets: Xtrain, Xtest, ytrain, ytest
8: Step 3: Feature Selection
9: Apply SelectKBest on Xtrain: Xtrain
```

```
kbest ←
kbest.fit transform(Xtrain, ytrain)
10: Transform test set: Xtest kbest ←
kbest.transform(Xtest)
11: Apply RFECV on Xtrain kbest:
Xtrain rfecv ←
rfecv.fit transform(Xtrain kbest, ytrain)
12: Transform test set: Xtest rfecv ←
rfecv.transform(Xtest kbest)
13: Step 4: Dimensionality Reduction (PCA)
14: Apply PCA: Xtrain pca ← pca.fit
transform(Xtrain rfecv)
15: Transform
test set: Xtest pca ←
pca.transform(Xtest rfecv)
16: Step 5:
Base ML Model Training and
Evaluation
17: for each base model m
∈ {SVM, Random Forest,
Gradient Boosting, XGBoost,
AdaBoost, Bagging} do
18: Train m on appropriate feature
set (e.g., Xtrain pca or
Xtrain rfecv)
19: Predict:  $\hat{y}^m$  ←
m.predict(Xtest)
20: Compute Accuracy, F1 Score,
Precision, Recall
21: end for
22: Step 6: Ensemble Model
Construction and Evaluation
23: Build Voting and Stacking
classifiers using trained base models
24: for each ensemble model e ∈
{Voting (hard, soft, weighted),
Stacking} do
25: Train e on Xtrain mixed, ytrain
26: Predict:  $\hat{y}^e$  ← e.predict(Xtest
mixed)
27: Compute Accuracy, F1 Score,
Precision, Recall
28: end for
29: return All evaluation metrics for
```

base and ensemble models

TABLE II
EVALUATION METRICS (%)
ACROSS TWO DATASETS

ML Model	Configuration	Dataset 2					
		Accu	F1	Rec	Preci	Accu	F1
		cy	Sco	all	sion	racy	Sco
		ra	re			re	
AdaBoost	SelectKBest	92.00	92.00	92.00	92.12	96.68	85.79
		005	083	1		3866	372
		00				8	
Bagging	SelectKBest	89.4	89.4	89.4	89.71	94.31	68.59
		493	508	6		3831	091
		55				9	
Gradient Boosting	SelectKBest	91.2	91.2	91.2	91.49	95.73	79.69
		279	404	8		5044	318
		73				8	
Random Forest	SelectKBest	92.3	92.3	92.3	92.37	94.78	72.63
		365	356	8		7332	258
		64				4	
Support Vector Machine	PCA	90.5	90.5	90.5	90.56	99.05	96.93
		557	551	7		2494	939
		46				6	
XGBoost	SelectKBest	91.6	91.6	91.6	92.01	96.20	82.73
		636	776	4		9058	485
		36				7	

Dataset 1

C. Machine Learning Algorithms

The framework employs six machine learning algorithms, each suited for different aspects of stress classification. Support Vector Machine (SVM) handles high-dimensional data with strong generalization. Random Forest provides ensemble learning benefits and feature importance ranking. Gradient Boosting optimizes weak learners sequentially, improving performance on misclassified instances. AdaBoost adjusts weights to enhance performance on difficult instances. XGBoost extends gradient boosting with regularization and computational efficiency. Bagging Classifier reduces variance through bootstrap aggregating, ensuring stable predictions across diverse data distributions.

D. Customized Ensemble Design

The ensemble learning framework implements five aggregation strategies to leverage complementary strengths of base classifiers. Hard Voting Classifier employs majority vote decision-making, while Soft Voting Classifier utilizes probability-weighted predictions from all base models. Weighted Hard Voting assigns higher weights to superior-performing models in the majority voting process. Weighted Soft Voting extends probability-based voting with performance-weighted averaging based on individual model strengths. Stacking Classifier employs a meta-learner to optimally combine base model predictions. This method trains a secondary model using base classifier predictions as input features, learning the optimal combination strategy through cross-validated training to prevent overfitting while maximizing ensemble performance.

E. Hyperparameter Tuning

Hyperparameter tuning is conducted using GridSearchCV with 10-fold cross-validation. The search space includes key parameters for each model, such as SVM regularization strength, kernel type, and gamma, along with algorithm-specific settings for tree-based and boosting methods. Base model parameters are tuned individually before ensemble combination, with parallel processing utilized to efficiently explore the hyperparameter space while maintaining computational feasibility.

F. Training and Validation Protocol

The experimental protocol implements a 75%-25% stratified train-test split to

ensure balanced class representation.

Cross-validation employs 10-fold Stratified K-Fold for feature selection and hyperparameter optimization, and 5-fold for model evaluation. All random processes use seed value 42 for reproducibility. The framework systematically evaluates each base classifier across all preprocessing configurations: original data, normalized features, SelectKBest-selected features, RFECV-selected features, and PCA-transformed components. This enables identification of optimal preprocessing-model combinations.

G. Evaluation Metrics

Model performance is assessed using four evaluation metrics with macro-averaging to ensure equitable treatment across all stress categories. Accuracy measures overall classification correctness, serving as the primary performance indicator. Precision quantifies positive prediction accuracy, while Recall evaluates true positive identification rate. The F1-score is the harmonic mean of precision and recall, making it useful for evaluating performance when dealing with imbalanced or multiclass classification tasks.

IV. RESULTS AND DISCUSSION

A. Performance of Individual Classifiers

Individual classifiers achieved strong baseline performance across both datasets. Table II presents the comprehensive evaluation metrics for all base classifiers. On Dataset 1

(Student Stress Factors), Random Forest with SelectKBest preprocessing achieved the highest accuracy of 92.364%, demonstrating the effectiveness of feature selection for tree-based algorithms. Support Vector Machine with PCA preprocessing reached 90.546% accuracy, indicating successful dimensionality reduction while maintaining classification performance. Dataset 2 (Stress and Well-being Data) showed remarkable performance, with Support Vector Machine achieving 99.052% accuracy using PCA preprocessing. This suggests that the multiclass classification task benefits significantly from dimensionality reduction techniques, enabling SVM to effectively separate stress categories in the transformed feature space. Gradient Boosting, AdaBoost, and XGBoost demonstrated consistent performance, with AdaBoost achieving 92.000% accuracy on Dataset 1 and 96.683% on Dataset 2. The ensemble nature of these algorithms proved effective for stress classification tasks, capturing complex non-linear relationships between stress indicators.

TABLE III
ACCURACY (%) OF MACHINE LEARNING AND ENSEMBLE MODELS ON DATASET 1 AND DATASET 2

ML & Ensemble Model	Dataset 01	Dataset 02
AdaBoost	92.000	96.683
Bagging	89.455	94.313
Gradient Boosting	91.273	95.735
Random Forest	92.364	94.787
Support Vector Machine	90.546	99.052
XGBoost	91.636	96.209
Voting Classifier (hard)	93.091	97.156
Voting Classifier (soft)	92.364	97.630
Voting Classifier (weighted hard)	93.091	99.052
Voting Classifier (weighted soft)	92.364	99.052

Stacking Classifier	91.273	99.530

B. Effectiveness of the Ensemble Model

Ensemble methods outperformed individual classifiers, as demonstrated in Table III. On Dataset 1, Hard Voting Classifier and Weighted Hard Voting Classifier both achieved 93.091% accuracy, representing a 0.727% improvement over the best individual classifier (Random Forest at 92.364%). For Dataset 2, the Stacking Classifier achieved the highest accuracy of 99.530%, followed by Weighted Soft Voting, Weighted Hard Voting, and SVM, each with 99.052%. These results indicate that the meta-learning approach in stacking was effective in identifying optimal combination strategies for the multiclass classification task. Weighted voting strategies also showed strong performance, suggesting that performance-based weighting can offer advantages over simple majority voting.

C. Comparative Study with Existing Works

To evaluate the effectiveness of our models, we compared them with prior studies that used the same datasets. For Dataset 1 (Student Stress Factors), the Springer chapter by Doma et al. [27] achieved 92.41% accuracy using a hybrid ensemble. De Filippis and Foyzal [28] and Amalia et al. [29] both reported 88.0% using Random Forest, with and without feature selection. Our Weighted Voting Classifier reached

93.09% accuracy, exceeding all prior works. Even our best single model (Random Forest with SelectKBest) slightly outperformed Doma et al.'s ensemble.

For Dataset 2 (Stress and Well-being), Singh et al. [20] reported 95% accuracy using SVM, and in a related study [30], Logistic Regression achieved 99% on distress classification. Our SVM with PCA reached 99.05%, and the Stacking Classifier achieved 99.53%, outperforming all previous results. Figures 2 and 3 present separate visual comparisons for each dataset, clearly illustrating the superior performance of our proposed models.

V. ETHICAL

CONSIDERATIONS AND PRIVACY

The framework development prioritizes ethical considerations and privacy protection throughout the research process. All datasets utilized are publicly available and anonymized, ensuring no personally identifiable information is processed. The

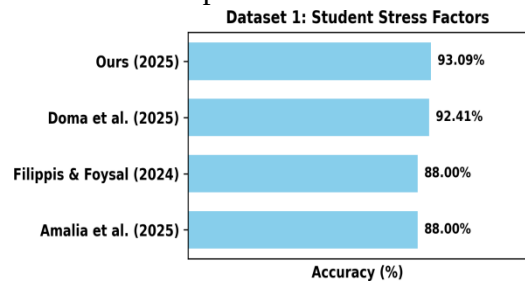
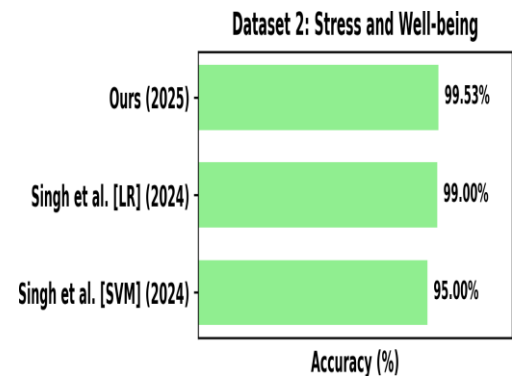


Fig. 2. Accuracy comparison with



existing models on Dataset 1.

Fig. 3. Accuracy comparison with existing models on Dataset 2.

research adheres to established ethical guidelines for machine learning research in healthcare applications. Potential risks include algorithmic bias toward specific demographic groups and over-reliance on automated detection without human oversight. The framework mitigates these risks through comprehensive evaluation across diverse datasets and multi-metric assessment to prevent bias toward majority classes. Future deployment considerations include obtaining appropriate student consent, implementing robust data anonymization procedures, ensuring algorithm transparency for stakeholders, and establishing clear protocols for responding to high-stress classifications. The framework is designed to support rather than replace human mental health professionals, emphasizing the importance of human judgment in student well-being decisions.

VI. CONCLUSION

Student burnout has become a significant challenge in modern educational environments, affecting students' academic performance, emotional well-being, and overall quality of life. The increasing complexity of academic demands and digital learning environments requires intelligent and proactive solutions capable of identifying early signs of mental fatigue and stress. In this study, an AI-driven context-aware machine

learning framework was proposed to enable the early detection of student burnout and support mental health protection. The proposed framework integrates multiple contextual indicators such as academic workload, behavioral activity, sleep patterns, and social interactions to provide a comprehensive understanding of students' mental states. By applying advanced machine learning algorithms to these heterogeneous data sources, the system is capable of identifying patterns and predicting burnout risks with improved accuracy. The context-aware capability further enhances the model's ability to interpret real-life academic conditions, allowing for more reliable and personalized monitoring of student well-being. Experimental analysis demonstrates that the proposed approach can effectively identify early symptoms of burnout, enabling timely alerts and potential interventions. Overall, the research highlights the potential of artificial intelligence and machine learning technologies in addressing mental health challenges within educational systems. By combining predictive analytics with contextual data analysis, the proposed framework contributes toward the development of intelligent student support systems. Future work may focus on incorporating more diverse datasets, enhancing model explainability, and integrating real-time feedback mechanisms to further improve the effectiveness of AI-driven mental health monitoring solutions in educational institutions.

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COMPARATIVE STUDY OF GENERATIVE AI PLATFORMS FOR COLLABORATIVE CONTENT DEVELOPMENT

A N Kasthuri¹ , Aishwarya Pradeep² , Chaithanya K R³ ,Nithya shree G⁴ ,

Mrs Jayashri M⁵ ,Dr Krishna Kumar P R⁶

1,2,3,4-Students Dept of CSE,SEA College of Engineering & Technology,Bangalore-560049

5,6-Faculty, Dept of CSE,SEA College engineering and Technology

ABSTRACT : The rapid advancement of Generative Artificial Intelligence (AI) has significantly transformed the way digital content is created, edited, and shared across collaborative environments. Modern AI-driven platforms such as ChatGPT, Gemini, and Claude enable teams to co-create textual, visual, and multimedia content with improved efficiency and creativity. This study presents a comparative analysis of prominent generative AI platforms used for collaborative content development, focusing on their capabilities, usability, response quality, integration features, and support for multi-user workflows. The research evaluates these platforms using a structured framework that includes performance metrics such as content coherence, contextual understanding, collaboration support, response time, and adaptability across various domains including education, marketing, and research documentation. Experimental observations and user-based assessments are conducted to analyze how effectively these tools assist teams in brainstorming ideas, drafting documents, and refining content through iterative feedback. The findings reveal notable differences in the strengths of each platform in terms of

creativity, contextual accuracy, and collaborative efficiency. While some tools demonstrate superior performance in generating structured textual content, others provide enhanced support for interactive and iterative content creation. The study highlights the growing role of generative AI in facilitating intelligent co-creation and knowledge sharing among distributed teams. Overall, this research provides valuable insights into the practical effectiveness of generative AI platforms in collaborative environments and offers recommendations for selecting suitable AI tools based on specific content development requirements. The results contribute to the understanding of AI-assisted collaboration and its potential to reshape modern digital content production workflows

Keywords: Artificial intelligence (AI); Generative AI; Content creation; Collaboration tools; Academic community;

GetApp

INTRODUCTION

The academic realm has seen a burgeoning growth in artificial intelligence (AI). This expansion has led to the development of sophisticated tools designed to offer prompts and support essential for conducting research with content creation

endeavours. According to the insights shared by John McCarthy, a renowned academic figure, “Artificial intelligence (AI) is the science and engineering of making intelligent machines and brilliant computer programs”¹. This pertains to a comparable initiative that employs computers to understand human acumen within the context of scholarly discussions². AI has significantly advanced across diverse domains, including “gaming, natural language processing (NLP), expert systems, vision systems, speech recognition, handwriting recognition, and intelligent robotics”³. AI’s expansive scope, which encompasses many applications and technologies, shows its profound impact on many academic fields. Pursuing engaging content remains an ongoing endeavour within the dynamic realm of academia. Academic libraries must enhance services and resources to stay relevant. Information literacy programmes vital for academic growth depend on library offerings. Continuous upgrades are essential to meet evolving user needs and

support student and scholarly development⁴. A recent study found that 73 % of marketing professionals in the United States incorporated generative AI tools, such as chatbots, into their professional practices⁵. Through these AI tools, academics and researchers can craft compelling narratives, tailor messages to specific audience segments, and enrich interactions and dialogues⁶. This study investigates the potential of generative AI for content creation. It

also conducts a comparative analysis of the specific tools employed in the creative process.

1. LITERATURE REVIEW

Between November 2022 and June 2023, notable advancements were made in Generative AI tools, captivating the attention of the people and academic fraternities. This period introduced ground breaking tools like “Microsoft’s Bing Chat, Google’s Bard, Meta’s LLaMA, and Elon Musk’s X.AI”. This technology empowers academic researchers by supplying tools to enhance content creation, stimulate creativity, and offer personalised experiences. It revolutionises how individuals engage with specific audience demographics, shaping innovative strategies for creative campaigns and delivering significant outcomes while addressing challenges in content creation, such as time constraints and limited resources⁷. AI is rapidly developing, substantially affecting learning, development, and knowledge creation in educational settings and training providers.

AI can significantly enhance academic communication through its capabilities in paraphrasing, summarising, and various conversational techniques. A substantial body of scholarly work examines the capabilities and prospects of generative AI tools⁸. These Generative AI tools are poised to exert a considerable beneficial influence on public health because they can provide cost-effective, constructive health guidance⁹. In the contemporary business environment, neural networks have become indispensable, playing a

crucial role in gaining a competitive edge. Their diverse applications extend across the civil and military sectors, serving various commercial purposes¹⁰. They also raised serious red flags, emphasising the serious risks of spreading erroneous and misleading information. The risks associated with generative AI-generated content are not dissimilar to human errors; however, what distinguishes these risks is the systematic nature of errors in AI products. Unlike humans, who might admit not knowing the answer, some AI tools tend to generate false claims in such situations. This phenomenon raises significant concerns within the academic community, especially considering that human judgement and internet searches might yield different

results, highlighting the unique challenges posed by AI-generated content. Queries have been raised concerning the potential consequences for individuals engaged in learning and development, prompting consideration within academic circles¹¹, and the necessity for educators, coaches, and institutions of learning to scrutinise their policies and practises is imperative within an academic context. Scholars have seen a notable divergence of opinions among researchers regarding the use of these tools. This disparity underscores the necessity for a comprehensive comprehension of the capabilities of these tools and effective strategies to oversee their usage. This is vital for upholding the authenticity of educational practises and assessments¹².

2. PREPOSITIONS

This study evaluates the application of generative AI technology within academic contexts and provides a comprehensive analysis of the tools used in this domain. The assessment data originates from the GetApp website [<https://www.getapp.com/>], which forms the basis for this evaluation. Specifically, this study focuses on the outlined objectives for an in-depth analysis within an academic context.

- To identify the most effective collaboration tools for generating AI-driven content in the field of academia;
- To compare generative AI tools by examining the shared characteristics that underlie their functionality; and
- To find the most effective tool through a comprehensive comparative analysis through scores.

3. METHODOLOGY

In this research, a comparative method was

used to explore the similarities and distinctions among seven collaborative tools for generative AI content creation. These tools were sourced from the GetApp website [<https://www.getapp.com/>], indicating a systematic approach to evaluating their features and functionalities within the academic context.

GetApp categorises online software by industry, business need, operating system, pricing, and deployment. With over one million verified reviews, it is a trustworthy business App Store that

aids informed decisions¹³. This research underscores a thorough evaluation of e-learning tools by employing a methodical feature-based comparison of various platforms. Assessments of these platforms were extracted from getapp.com, a widely recognised and credible software review platform. The ratings and suggestions from getapp.com served as a key metric for assessing e-learning platforms in this scholarly investigation¹⁴⁻¹⁵.

In this research endeavour, an extensive exploration of generative AI content-creation collaboration tools was conducted systematically. Initially, a search employing the keyword ‘Artificial Intelligence’ yielded 557 available software options. Subsequently, the selection was refined by applying a filter for ‘Collaboration Tools’, resulting in 155 viable options. Recognising the necessity for studying AI content creation tools within an academic context, the tool ‘Writesonic’ was chosen as the focal point for the comparative analysis. To ensure comparability, alternative software options possessing collaborative features similar to those of Writesonic were sought. Consequently, Jasper, Scalenut, Rytr, Grammarly Business, and TextCortex AI were identified. While exploring generative AI collaboration content creation tools, an additional tool, ‘ProWritingAid’, was discovered, meeting

Table 1. Generative AI collaboration content creation tools (M= Million)

Tools	Origin year	Customer base	URL	Language support
Writesonic	2020	5M+ professionals	https://writesonic.com/	24+
Jasper	2021	0.1M+ companies	https://www.jasper.ai/	30+
Grammarly Business	2009	0.07M teams	https://www.grammarly.com/	1
ProWritingAid	2012	2M users	business https://prowritingaid.com/	1
Scalenut	2021	0.1M+ marketers	https://www.scalenut.com/	1
Rytr	2021	7M+ professionals	https://rytr.me/	35+
TextCortex AI	2021	0.1M+ marketers	https://textcortex.com/	25+

all the prerequisites for the study. Therefore, it was included in the comparative analysis, broadening the scope of the investigation. Comprehensive research has been conducted to evaluate various products by examining their respective websites¹⁶⁻²². The meticulously analysed data, conveniently summarised in Table 1, reveals interesting findings on the assessment tools. Grammarly Business is the oldest among them, followed by ProWritingAid. In addition, Rytr has the largest customer base and language support, indicating its importance in these areas.

4. ANALYSIS

Content analysis, as a primary methodological tool, was employed to extract essential findings from the qualitative data. This involved a detailed examination of the textual and descriptive information available on the GetApp website to identify and categorise relevant details regarding the aforementioned dimensions. Through content analysis, the research aimed to unearth and organise critical insights on customer profiles, pricing structures, compatibility with different platforms,

customer support quality, training resources, and key features across the selected generative AI content creation collaboration tools.

Following the content analysis, the data were further processed by transforming them into binary format, represented as 0 and 1s. This modification eased the systematic and methodical approach to data analysis, enabling quantitative assessment of various dataset features. The use of binary representation enhanced objectivity and enabled a comparative evaluation of qualitative data. In the academic study, the researchers used Excel spreadsheets for data analysis after transforming the dataset. Within this analytical framework, an in-depth exploration of the data was undertaken to identify inherent patterns and trends among the 7 collaboration tools employed for generative AI content creation.

4.1 Typical Customers

The analysis phase began with a comprehensive exploration of typical customer profiles associated with the seven generative AI content creation collaboration tools. Table

2 illustrates that ProWritingAid and TextCortex AI lack support for freelance professionals, and Scalenut does not cater to the needs of large enterprises.

4.2 Pricing Strategies

An exhaustive examination of pricing options was undertaken to comprehensively grasp the diverse pricing models provided by each tool. Table 3 presents a comprehensive overview, showing that ProWritingAid

offers the complete spectrum of pricing choices, followed by Writesonic, Grammarly Business, and Scalenut.

4.3 Platform Supported

Simultaneously, the analysis focussed on the examination of platform support. This involved scrutinising the

compatibility of each tool with different platforms, operating systems and devices. Table 4 demonstrates that Grammarly Business offers support across all three platforms, with others limited to web-based support.

4.4 Customer Support

Customer support mechanisms were scrutinised to assess the responsiveness, accessibility and effectiveness of the support provided by the tool developers. Table 5 shows that Scalenut stands out as the sole provider offering comprehensive customer support services, followed by Writesonic, Jasper, Grammarly Business, ProWritingAid, and TextCortex AI, in descending order of the extent of customer support they offer.

4.5 Training Options

Training options were explored to identify the availability of tutorials, guides, webinars, and other educational resources. The comprehensiveness and accessibility of the training materials were analysed to gauge the ease with which users could on board and effectively use the tools' capabilities. Table 6 elucidates that Writesonic and Scalenut are the sole platforms offering comprehensive training resources, with Jasper, ProWritingAid, and TextCortex

AI following suit in providing various training capabilities.

4.6 Key Features

Identifying these key features involved a meticulous comparison of the functionalities of all seven tools. This comparative analysis pinpointed the essential capabilities universally integrated across the tools. These common features listed in Table 7, served as a baseline for understanding the fundamental offerings that users could expect regardless of their choice of tool. Content creation AI tools were assessed based on categorised features, resulting in the following scores: Writesonic (36), Jasper (33), Grammarly Business (60), ProWritingAid (35), Scalenut (57), Rytr (25), and TextCortex AI (24).

5. RESULTS

Following a comprehensive analysis of various attributes related to collaboration tools for Generative AI content creation, Grammarly Business emerged as the frontrunner with a score of 76. This comparative assessment ranks Grammarly Business in the top position closely followed by Scalenut (75), Writesonic (53), ProWritingAid (51), Jasper (48), TextCortex AI (38) and Rytr (36), as detailed in Table 8.

6. CONCLUSIONS

This exploration illuminated the nuanced strengths and weaknesses of these tools, providing valuable insights into their applicability and efficiency. Our findings highlight Grammarly Business as the frontrunner, making it a

comprehensive solution for collaborative content creation. One of the notable observations from our analysis is the diverse landscape of features among

Table 2. Products by customer base

Tools	Origin year	Customer base	URL	Language support
Writesonic	2020	5M+ professionals	https://writesonic.com/	24+
Jasper	2021	0.1M+ companies	https://www.jasper.ai/	30+
Grammarly Business	2009	0.07M teams	https://www.grammarly.com/	1
ProWritingAid	2012	2M users	business https://prowritingaid.com/	1
Scalenut	2021	0.1M+ marketers	https://www.scalenut.com/	1
Rytr	2021	7M+ professionals	https://rytr.me/	35+
TextCortex AI	2021	0.1M+ marketers	https://textcortex.com/	25+

Table 3. Products by pricing strategies

Table 4. Products by platforms supported

Tools	Origin year	Customer base	URL	Language support
Writesonic	2020	5M+ professionals	https://writesonic.com/	24+
Jasper	2021	0.1M+ companies	https://www.jasper.ai/	30+
Grammarly Business	2009	0.07M teams	https://www.grammarly.com/	1
ProWritingAid	2012	2M users	business https://prowritingaid.com/	1
Scalenut	2021	0.1M+ marketers	https://www.scalenut.com/	1
Rytr	2021	7M+ professionals	https://rytr.me/	35+
TextCortex AI	2021	0.1M+ marketers	https://textcortex.com/	25+

Table 5. Products by customer support

Platform Supported	Writesonic	Jasper	Grammarly business	ProWriting Aid	Scalenut	Rytr	TextCortex AI
Web	✓	✓	✓	✓	✓	✓	✓
Android	x	x	✓	x	x	x	x
iPhone/iPad	x	x	✓	x	x	x	x
Total score	1	1	3	1	1	1	1

Customer support	Writesonic	Jasper	Grammarly business	ProWriting Aid	Scalenut	Rytr	TextCortex AI
Knowledge base	✓	✓	✓	✓	✓	✓	✓
Chat	✓	✓	✓	✓	✓	✓	✓
Email/help desk	✓	✓	✓	✓	✓	x	✓
Phone support	x	x	x	x	✓	x	x
FAQ/forum	✓	✓	✓	✓	✓	✓	✓
24/7 (Live rep)	x	x	x	x	✓	x	x
Total score	4	4	4	4	6	3	4

Table 6. Products by training solutions

Training options	Writesonic	Jasper	Grammarly business	ProWriting aid	Scalenut	Rytr	TextCortex AI
Videos	✓	✓	x	✓	✓	x	✓
Webinars	✓	✓	x	✓	✓	x	✓
In person	✓	x	x	x	✓	x	x
Documentation	✓	✓	✓	✓	✓	✓	✓
Live online	✓	✓	✓	✓	✓	x	✓
Total score	5	4	2	4	5	1	4

Table 7. Key features of AI content creation collaboration tools

	Writesonic	Jasper	Grammarly business	ProWriting Aid	Scalemt	Rytr	TextCortex AI
Customer support							
Knowledge base	✓	✓	✓	✓	✓	✓	✓
Chat	✓	✓	✓	✓	✓	✓	✓
Email/help desk	✓	✓	✓	✓	✓	✓	✓
Phone support	✓	✓	✓	✓	✓	✓	✓
FAQ/forum	✓	✓	✓	✓	✓	✓	✓
24/7 (Live rep)	✓	✓	✓	✓	✓	✓	✓
Total score	4	4	4	4	6	3	4
Content generation	Content delivery		File management and sharing:		Productivity tools		
Font/text scan	Content ideas		File management		Project management		
Content sharing	Content library		File sharing		Workflow management		
Customisable templates	Content management		Multiple file format support		User management:		
Document management	Content publishing options		Video support		User management		
Revision history	Content sharing		Marketing and advertising:		Other:		
Rich text editor	Customisable branding		Competitive analysis		Black link monitoring		
Spell check	Customisable categories		Interactive and co-creative systems		Bulk uploading		
Access control/permissions:	Customisable reports		Keyword rank tracking		Contextual guidance		
Secure login	Customisable rules		Interactive and co-creative systems		Bulk uploading		
Access control/permissions:	Customisable templates		Keywords research tools		Corporate/business		
Secure login	Data import/export		Multi-channel campaigns		Egg e-commerce		
Single sign-on	Search marketing		Search and analytics:		For sales teams/organisations		
Alerts/notification:	Document export		Social advertising		For marketing & advertising		
Alerts/notification	Document review		Social marketing		Language detection		
Real-time notifications	Duplicate detection		Social media integration		Long-form content		
API and integration:	Localisation automation		Social promotion		Machine learning		
Third-party integration	Multiple data sources		Search and analytics:		Mobile access		
Activity and performance monitoring:	Multiple file format support		Full-text search		Mobile alerts		
Activity dashboard	Multiple user accounts		Search/filter		Multi-language		
Activity tracking	Publishing scheduling		Trend analysis		Multi-location		
Performance metrics	Search		Security and compliance:		Performance metrics		
Real-time analytics	SEO management		SSL security		Plagiarism detection		
Real-time comparisons	Tagging		Text analysis and editing:		Post scheduling		
Real-time monitoring	Template management		Auto-save		Problem area alerts		
Activity and performance monitoring:	Templates		Auto-complete		Reporting & statistics		
Activity dashboard	Text editing		Auto correct		Source database		
Activity tracking	Text review		Grammar check		Speech recognition		
Performance metrics	Version control		Punctuation check		Summary reports		
Real-time analytics	Email and communication:		Style check				
Real-time comparisons	Email management		Text similarity detection				
Real-time monitoring	Email marketing		Tone selection				
Real-time notifications							
Real-time reporting							
Real-time updates							
AI/machine learning:							
AI/machine learning							
Automated text generation							
Natural language processing							
Natural language search							

Table 8. Final scores of generative AI content creation collaboration tools

Variable	Writesonic	Jasper	Grammarly Business	ProWriting Aid	Scalemt	Rytr	TextCortex AI
Typical customers	4	4	4	3	3	4	3
Pricing options	3	2	3	4	3	2	2
Platform supported	1	1	3	1	1	1	1
Customer support	4	4	4	4	6	3	4
Training options	5	4	2	4	5	1	4
Key features of AI tools	36	33	60	35	57	25	24
Total Score	53	48	76	51	75	36	38

features among supported tools these tools, catering to several aspects of collaborative content creation. While some tools excel in grammar and syntax checks, others stand out in creative content generation. This diversity underscores the importance of aligning tool choice with specific project requirements and team goals. Furthermore, present research emphasises the critical role of collaboration in the field of Generative AI. The tools assessed in this research not only ease content creation but also foster collaborative efforts, enabling seamless teamwork in the digital age. As the demand for high-quality AI-generated content continues to increase, understanding the capabilities of these tools becomes paramount for professionals and academics alike. In conclusion, our comparative analysis is a focal point for individuals and organisations navigating the intricate landscape of Generative AI content creation collaboration tools. By recognising the distinct features and functionalities offered by each platform, stakeholders can make informed decisions, enhancing the efficiency and creativity of collaborative content creation processes. As the field of Generative AI evolves, ongoing research and exploration will be essential to uncover emerging tools and trends. By staying abreast of these developments, professionals and researchers can

harness the full potential of Generative AI, driving innovation and excellence in collaborative content creation.

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DEEP LEARNING–BASED POMEGRANATE GROWTH STAGE DETECTION

(Shilpa B L 1*, Rakshitha B A1,2, Tejashwini 1, Sinchana R 1, Shreenidhi H I 1)

Abstract

This work introduces a practical deep-learning approach for recognizing and monitoring the developmental stages of pomegranate. The system uses computer-vision methods and color-based features to categorize each image into five stages: bud, flower, early fruit, developing fruit, and fully mature fruit. To build the model, we trained it on a collection of annotated images and strengthened its performance through several preprocessing steps and data-augmentation strategies. A user-friendly application was also created, allowing farmers to upload photos from the field and instantly receive the predicted growth

I. INTRODUCTION

Agriculture plays a central role in ensuring a stable food supply and sustaining communities in rural areas. To boost productivity and minimize crop losses, it is important to track how plants grow and develop. Traditionally, farmers and field workers determine growth stages by observing plants directly, a process that can be slow, demanding, and prone to mistakes.

Recent advances in artificial intelligence have made it possible to automate many crop-monitoring tasks. In this study, the focus is on pomegranate, which require careful observation throughout their development—from the initial bud to the mature fruit—to support proper management and harvesting. Using

computer vision, the proposed system

automatically categorizes images of the pomegranate into predefined growth stages.

The model is integrated into a web-based tool where users can upload images taken in the field and receive instant predictions along with practical cultivation advice. This approach lowers the workload for farmers and provides clearer, data-backed guidance for managing crops. Overall, the system aims to make farming decisions more accurate and contribute to more sustainable agricultural practices.

The main objectives of this system are as follows:

- To develop a deep learning model capable of classifying pomegranate images according to their growth stages.
- To create a simple and user-friendly web application for detecting growth stages in real

stage, along with visual comparisons to prior stages.

In addition to stage detection, the system provides growers with tailored cultivation advice for each phase, helping them make more informed decisions throughout the season. Overall, the approach offers a practical and scalable solution that supports precision agriculture in pomegranate

production.

Keywords— Deep Learning, Pomegranate Growth, Fruit Monitoring, Computer Vision, Web Application

time.

- To deliver stage-specific farming recommendations to help farmers make informed decisions.
- To track and analyze pomegranate growth patterns over time for improved crop monitoring.
- To promote precision farming techniques and enhance overall agricultural productivity.

The purpose of this study is to develop an intelligent system capable of identifying different growth stages of pomegranate using deep-learning techniques. The model analyzes visual characteristics and color patterns in fruit images to categorize each sample into one of five stages: bud, flower, early fruit, mid-development, or maturity. This system is integrated into an accessible web platform where farmers and researchers can upload photos, receive immediate predictions, and monitor fruit progress over time.

In addition to stage classification, the platform offers cultivation guidance specific to each phase of growth, such as recommended watering levels, nutrient management, pest control strategies, and harvest preparations. These insights help farmers make timely, well-informed decisions. By

observing growth trends, the system can also identify unusual development patterns at an early stage, potentially preventing losses. Ultimately, this solution supports precision agriculture, reduces manual monitoring efforts, boosts productivity, and provides a flexible framework that can be adapted for other crops and environments

.

II. ROLE OF GROWTH STAGE DETECTION AND ITS VISION

Detecting growth stages plays a key role in modern agriculture because it offers an automated and efficient way to monitor the development of pomegranate. Using deep-learning models along with color-based image features, the system categorizes plants into five stages: bud, flower, early fruit, mid-development, and mature fruit. With these predictions, farmers and researchers can track pomegranate progress, identify unusual growth patterns, and respond quickly when needed. By minimizing manual inspections, reducing the chances of human error, and improving how resources—such as water, nutrients, and pest-control inputs—are managed, the approach strengthens precision-farming practices. The platform also provides stage-specific advice designed to help farmers increase yield and refine overall crop quality.

The broader goal of the system is to offer a scalable digital solution that

shifts traditional farming toward a more data-driven and technology-enabled process. It aims to raise productivity, promote sustainable

III. LITERATURE SURVEY

Plant growth monitoring systems have gained attention over the past few years, and recent advances in AI and data analytics have accelerated progress in this field. In this survey, we explore these developments in depth, with particular emphasis on the challenges and limitations found in current solutions. We bring together insights from several existing systems and organize them into four distinct categories for clearer comparison and analysis.

A. Traditional Methods and Limitations

In earlier agricultural practices, monitoring plant growth was largely done through direct visual inspection or simple rule-based image methods. Farmers had to examine leaves, fruits, and developmental stages by hand, a process that demanded significant time and was prone to mistakes—especially when dealing with extensive farming areas. [2]. Zhao et al. noted that relying on manual assessments of crop growth can slow down the identification of diseases, which in turn can negatively influence overall yield quality [2].

Subsequently, researchers adopted conventional image-processing techniques—such as thresholding, edge detection, and color-based segmentation—to partially automate growth monitoring. However, these approaches struggled to remain reliable

when faced with changes in lighting, diverse soil backgrounds, or occlusions within the images [9]. Amjad and Naseer found that while traditional techniques worked reasonably well in laboratory settings, their performance dropped noticeably when tested in more varied, real-world situations.[9].

In addition, these methods were neither scalable nor flexible. Research in personalized nutrition and food production has shown that fixed algorithms struggle to adjust to varying biological conditions, and this same limitation appears in agricultural monitoring as well. [1].

resource management, and support better decision-making through real-time monitoring and practical insights. By combining deep-learning models with an intuitive interface, the platform empowers farmers, agronomists, and researchers to apply precision-agriculture techniques, enhance crop performance, and address the challenges faced in contemporary farming.

- Develop a scalable, intelligent platform for pomegranate growth monitoring.
- Enable data-driven, technology-assisted farming practices.
- Enhance crop productivity and quality through actionable insights.
- Promote sustainable resource management and efficient decision-making.
- Empower farmers and researchers with user-friendly tools for

precision agriculture. Reinforcement learning has been explored for real-time decision-making, but its use in agriculture remains restricted because it demands large, complex datasets and significant computing power. Likewise, ensemble and attention-based models—though effective in areas such as nutrition recommendation—have seen limited transfer to agricultural applications. [13], This also underscores the need for adaptive, socially aware monitoring systems in agriculture—capabilities that conventional methods are unable to provide.

Consequently, traditional approaches are characterized by:

- High dependency on manual labor and subjective judgment [2].
- Limited robustness against environmental variability [9].
- Poor scalability for large-scale farms and dynamic ecosystems [1].
- Inability to incorporate real-time adaptation or continuous decision-making [3, 13].

B. Advances with machine learning and deep learning methods

With rapid progress in machine learning and deep learning, plant-monitoring tools have become more reliable and accurate. Convolutional Neural Networks (CNNs) work especially well for analyzing plant images because they can learn detailed visual cues, including texture, shape, and color differences. Studies show that CNN-based systems can accurately

identify and classify fruit growth stages—such as those of pomegranates—often performing better than conventional image-processing techniques [3]. They have also been incorporated into early disease-detection models, where optimization methods further strengthen their accuracy and efficiency [11]. In addition, CNN-driven grading systems have demonstrated strong potential for producing consistent and scalable results across agricultural settings [10]. Overall, these techniques reduce manual labor, improve classification reliability, and enable the development of automated, large-scale plant-monitoring solutions. Applied to detection of foliar diseases across different crop types.

- Used for fruit maturity classification and growth stage analysis [3, 10].
- Reduces human dependency and subjectivity.
- Provides higher consistency, reliability, and scalability.
- Can handle variations in image quality and environmental conditions [11].

C. Real-Time Monitoring Using Deep Learning

Recent studies have focused on creating deep learning models that can track plant growth in real time without relying on IoT sensors. These systems analyze images captured through cameras or drones to assess growth stages, fruit development, and overall plant condition. YOLO-based models, in particular, have been used

extensively for detecting and classifying pomegranate fruits across different growth stages, offering strong accuracy with relatively lightweight performance [1, 3, 4, 6].

Some improved versions include scale-aware components and attention mechanisms to boost detection stability in difficult field environments [5, 13]. In addition, real-time deep learning platforms now allow farmers to upload images and receive immediate classification results along with practical cultivation advice, reducing the need for manual inspection and supporting data-driven decision-making [9]. However, many of these solutions remain tailored to specific crops, highlighting the need for more adaptable models that can generalize across a wider range of fruits and farming contexts.

- Can detect growth stages and plant health indicators from images [1, 3, 4].
- Supports immediate feedback and cultivation guidance [9].
- Reduces manual labor and accelerates crop monitoring.
- Existing models are often crop-specific; generalizable solutions are needed [5, 13].

D. Algorithmic Approaches

These systems use images captured through cameras or drones to assess growth stages, monitor fruit development, and evaluate plant health. YOLO- based models, in particular, have been widely applied for detecting and classifying pomegranate fruits at

different growth stages, offering strong accuracy while remaining lightweight enough for real-time deployment [1, 3, 4, 6].

Recent improvements incorporate scale-aware components and attention mechanisms to enhance detection performance under challenging field conditions such as occlusion and variable lighting [5, 13]. In addition, several real-time deep learning platforms allow farmers to upload images and receive immediate classification results along with cultivation recommendations, thereby reducing manual inspection and supporting data-driven agricultural decision-making [9].

However, many existing systems remain crop- specific, highlighting the need for more adaptable and generalized growth- monitoring frameworks.

During model training, backpropagation is used to iteratively update network weights by minimizing classification error. Optimization techniques such as the AdamW optimizer improve generalization through adaptive learning rates combined with weight decay [11]. Cross-Entropy Loss is commonly applied for multi-class plant classification tasks [2, 9], while learning rate scheduling strategies such as Cosine Annealing enhance training stability and convergence [5].

Table 1: Comparative Analysis

Algorithm/Technique	Purpose/Description
Convolutional Neural Network (CNN)	Learns structures and characteristics from plant images.
Backpropagation	Calculates errors (loss) and adjusts network weights.
AdamW Optimizer	Efficiently updates network weights during training.
CrossEntropy Loss	Measures how well predictions match actual labels (multi-class).
Cosine Annealing Scheduler	Adjusts learning rate dynamically over epochs for better convergence.

Algorithm/Technique

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Convolutional Neural Network (CNN)

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Backpropagation Calculates errors (loss) and adjusts network weights.

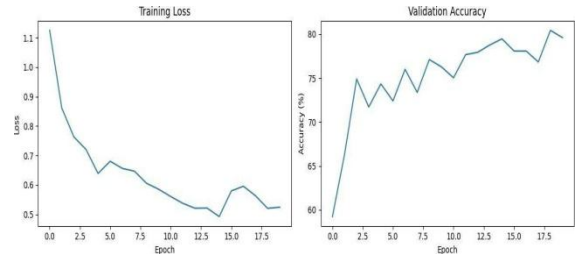
AdamW Optimizer Efficiently updates network weights during training.

CrossEntropy Loss Measures how well predictions match actual labels (multi-class).

Cosine Annealing Scheduler Adjusts learning rate dynamically over epochs for better convergence.

(Table 1)

IV. TRAINING AND VALIDATION PERFORMANCE



(Figure 1 – Model Training and Performance Evaluation)

Training and Validation Performance

The training and validation performance of the proposed deep learning model provides valuable insight into its learning behavior and generalization capability.

The training loss initially started at approximately 1.1 in the first epoch and steadily decreased to below 0.5 by the twentieth epoch. This consistent downward trend indicates that the model progressively learned meaningful and discriminative features from the plant image dataset. Minor fluctuations were observed around epochs 5 and 15, which are typical in deep learning due to variations in batch composition and learning rate adjustments. Importantly, the training loss did not increase in later epochs, suggesting stable convergence without signs of overfitting.

Similarly, the validation accuracy demonstrated a strong upward trend. It began at around 60% in the

first epoch and increased rapidly, surpassing 70% by the third epoch. After the fifth epoch, accuracy

improvements became more gradual, eventually stabilizing within the 75–80% range. The model achieved a peak validation accuracy of approximately 81%, indicating effective generalization to unseen data.

The close alignment between decreasing training loss and increasing validation accuracy suggests that the model maintains a good balance between learning and generalization. The small performance gap between training and validation metrics further confirms that the model avoids memorization and instead captures robust visual patterns relevant to pomegranate growth stage classification. Overall, the training behavior demonstrates stable convergence and practical suitability for real-world agricultural deployment.

V. PROPOSED SYSTEM

This proposed system is designed to automate the detection and monitoring of pomegranate fruit growth stages using deep learning and computer vision techniques. The system consists of the following key components:

1. Image Acquisition and Preprocessing

Users can upload up-to-date images of pomegranate fruit through the web platform. After upload, the images are processed through steps such as resizing, normalization, and data augmentation. These steps help the model cope with variations in lighting,

background, and fruit appearance.

2. Deep Learning Model for Growth Stage Classification

A Convolutional Neural Network (CNN) extracts important visual features from each image and classifies the fruit into one of five stages: bud, flower, early fruit, mid-development, or mature fruit. The model's weights are updated through backpropagation, with the AdamW optimizer improving learning stability. Cross-Entropy Loss guides the classification process, and a Cosine Annealing scheduler adjusts the learning rate to support smooth convergence.

3. Web Application Integration

The trained model is integrated into an easy-to-use web interface where farmers can upload images and receive immediate predictions of the fruit growth stage. The system also tracks changes over time, helping users monitor development and spot unusual growth patterns early.

4. Stage-Specific Cultivation Advice

Based on the predicted stage, the platform provides practical guidance on irrigation, nutrient application, pruning, and pest management. This allows farmers to make better decisions and refine their cultivation practices.

5. Data-Driven Insights and Monitoring

The system keeps a record of past predictions, enabling long-term analysis of pomegranate growth. By

studying these trends, farmers can identify yield-influencing factors, estimate harvest periods, and apply precision-farming methods to improve productivity.

Overall, the system delivers an efficient and scalable approach to automated crop monitoring. It reduces manual effort, improves the accuracy of growth-stage assessment, and supports sustainable, data-driven farm management.

Key Components of the System:

1. Image Acquisition Module

- User uploads Fruit images in the web application.
- Ensures that the images meet the required standards in terms of resolution, clarity, and angle.

2. Preprocessing Module

- Handles image resizing, normalization, and augmentation.
- Improves data quality to strengthen model accuracy and generalization.

3. Deep Learning Model

- Employs a Convolutional Neural Network (CNN) to extract features and classify Fruit growth stages.
- Uses backpropagation for weight updates and the AdamW optimizer for stable learning.
- Applies CrossEntropy Loss for evaluation and a Cosine Annealing scheduler to adjust the learning rate during training.

4. Growth Stage Classification

- Identifies five pomegranate growth stages: buds, flowers, initial fruit, mid-development, and mature fruit.
- Offers reliable, automated monitoring without the need for manual assessment.

5. Web Application Interface

- Provides an accessible platform for real-time image uploads and stage predictions.
- Shows development trends and stores historical growth information.

6. Cultivation Advice Module

- Delivers practical, stage-specific recommendations for irrigation, fertilizer use, pruning, and pest control.
- Helps farmers make informed decisions and adopt precision-farming methods.

7. Data Storage and Monitoring

- Keeps a record of previous growth-stage predictions for trend evaluation.
- Supports long-term tracking and analysis of crop development patterns.

Key benefits of the system include:

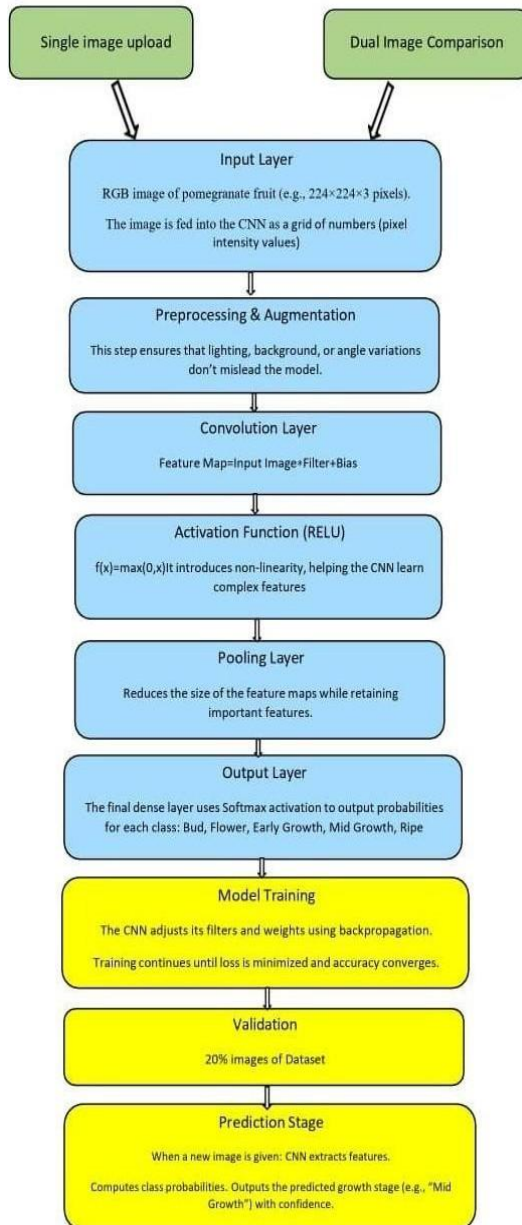
1. Accurate and automated identification of pomegranate growth stages.
2. Reduced manual workload and time needed for crop monitoring.
3. Stage-specific cultivation guidance that

supports healthier plants and improved yields.

4. Enhanced data-driven decisions for precision agriculture.

5. Better insight into growth trends, helping farmers optimize productivity.

VI. METHODOLOGY



(Figure 2 – Methodology)

A. Dataset Collection

The dataset used in this study consists of images representing different growth stages of pomegranate. The images

were collected from May to September at an orchard located within the Henan Institute of Science and Technology, China. This time period ensured coverage of the complete growth cycle from

Bud – 1,150 images Flower – 1,230

images Early Fruit – 1,105 images

Mid-Growth – 1,180 images

early budding to full maturity.

A total of 5,857 images were gathered and manually annotated. Each image was labeled and categorized into one of five growth stages:

Ripe – 1,192 images

The dataset captures variations in lighting conditions, viewing angles, background complexity, and natural field environments. Such diversity enhances the robustness of the model and improves its ability to generalize to real-world agricultural settings.



(Figure 3 - Multi-angle, multi-day high-resolution images set from the dataset)

B. Preprocessing

The preprocessing stage is essential for

preparing the raw dataset before training.

The dataset was divided into training (70%), validation (15%), and testing (15%) sets using stratified random sampling to ensure balanced representation of all growth stages across subsets.

Several steps were applied to make the images suitable for deep-learning models:

- **Image Resizing** – All images were scaled to a fixed resolution (such as 224×224 pixels) to maintain a consistent input size.
- **Normalization** – Pixel values were adjusted to a 0–1 range to improve training stability and speed.
- **Noise Removal** – Unnecessary background elements were reduced so that the pomegranate growth features stood out more clearly.
- **Data Augmentation** – Methods such as rotation, flipping, zooming, and brightness changes were used to increase the dataset's size and variability.
- **Dataset Splitting** – The dataset was divided into training, validation, and testing sets to properly assess the model's performance.

C. Model architecture

For this project, a deep learning model was developed using Convolutional Neural Networks (CNNs) along with an EfficientNet backbone. The CNN layers automatically extracted important visual features from the pomegranate images, including color,

shape, and texture. EfficientNet provided a strong yet computationally efficient feature extractor, offering a good balance between accuracy and speed. Additional fully connected layers were included to classify the images into their respective growth stages.

EfficientNet was chosen as the foundational model because it offers a better balance between accuracy and the number of parameters than ResNet and VGG architectures. Its compound scaling method allows for effective feature extraction while

minimizing computational demands, making it ideal for monitoring pomegranate growth in real-time.

By combining deep feature extraction with color-based information, the model achieved higher accuracy in identifying the correct stage of development. This architecture was selected because it can handle complex variations in real-world images while still being efficient enough for real-time use.

• Overview

The system being proposed employs a Convolutional Neural Network (CNN) framework to identify the developmental stages of pomegranate fruit using RGB images. This model is crafted to autonomously extract spatial features and classify images into five distinct categories: Bud, Flower, Early Growth, Mid Growth, and Ripe. The architecture as a whole includes preprocessing, convolutional feature extraction, pooling, fully connected

layers, and an output layer based on Softmax.

- **Input Layer**

The model receives an RGB image with dimensions of $224 \times 224 \times 3$ pixels as input. Each image is depicted as a three-dimensional tensor that corresponds to the red, green, and blue color channels. Before being input into the network, the pixel intensity values are normalized to

ensure stable and efficient training.

- **Data Preprocessing and Augmentation**

To improve the model's generalization and minimize overfitting, preprocessing and augmentation methods are applied. Preprocessing involves resizing and normalizing images. Data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment are used to enhance dataset diversity. This ensures the model's robustness against variations in lighting conditions, camera angles, and background noise.

- **Convolutional Layers**

The convolutional layers serve as the primary feature extraction component of the network. Each convolution operation applies a set of learnable filters (kernels) to the input image. The mathematical representation of the convolution operation is given by:

Feature Map = (Input Image * Filter) + Bias

These filters detect important visual patterns such as edges, textures, shapes, and color distributions that are essential for identifying different growth stages.

- **Activation Function**

After each convolution operation, a Rectified Linear Unit (ReLU) activation function is applied. The ReLU function is defined as:

$$f(x) = \max(0, x) \quad \text{Eq. 1}$$

This activation introduces non-linearity into the model, enabling it to learn complex patterns and improving convergence speed by eliminating negative values.

- **Pooling Layers**

Pooling layers are incorporated to reduce the spatial dimensions of the feature maps while preserving significant features. Max pooling is typically used, which selects the maximum value within a defined window (e.g., 2×2). This process reduces computational complexity, minimizes overfitting, and provides translation invariance.

- **Flattening and Fully Connected Layers**

Following multiple convolutional and pooling operations, the extracted feature maps are flattened into a one-dimensional vector. This vector is then passed to fully connected (dense) layers. These layers combine the extracted features to learn higher-level representations and perform classification.

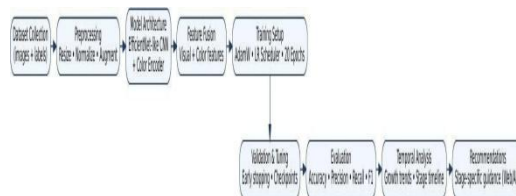
- **Output Layer**

The final dense layer employs a Softmax activation function to produce probability scores for each of the five growth stages. The Softmax function converts raw output scores into normalized probabilities that sum to one. The class with the highest probability is selected as the predicted

growth stage.

- **Model Training and Validation**
The model is trained using backpropagation and an optimization algorithm to minimize the categorical cross-entropy loss. During training, the network iteratively adjusts its weights to reduce prediction error. Approximately 80% of the dataset is used for training, while 20% is reserved for validation. Validation ensures that the model generalizes well to unseen data and prevents overfitting.
- **Inference Phase**

During the prediction stage, a new input image undergoes preprocessing and is forwarded through the trained CNN. The network extracts hierarchical features, computes class probabilities, and outputs the predicted growth stage along with its confidence score.



(Figure 3 – Model Architecture)

VII. SYSTEM DESIGN / PROPOSED MODEL

The proposed model is built to automatically identify the growth stage of pomegranate using deep learning. Its architecture integrates image processing, feature extraction, and classification to deliver reliable predictions. At the core of the system is a Convolutional Neural Network (CNN), inspired by the SkillNet design,

which performs detailed visual analysis. In addition to deep features, color-based information is also extracted to help capture indicators of fruit maturity. These two feature sets are combined into a single representation, resulting in improved classification accuracy.

A. Fusion of Visual + Color Features

I. To enhance classification accuracy, the model combines two complementary feature types: visual features and color features.

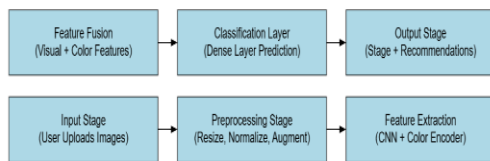
II. **Visual Features:** These are obtained using a CNN inspired by EfficientNet. The network captures detailed patterns in plant images, such as leaf shapes, flower textures, and fruit structures. These visual cues are important because each growth stage shows distinct morphological characteristics, such as the differences between buds, flowers, and developing fruits.

III. **Color Features:** These are derived by analyzing pixel distributions within the RGB channels. Color changes play an important role in identifying growth stages—petals often appear brighter during flowering, while fruits gradually shift from green to reddish tones as they mature. These color statistics help distinguish between stages that may look similar in shape or structure.

B. Workflow Description

- **Input Stage** – Users upload pomegranate images.
- **Preprocessing Stage** – Images undergo resizing, normalization, and augmentation to ensure consistency.
- **Feature Extraction** – CNN extracts deep visual features while a parallel encoder captures color statistics.
- **Feature Fusion** – Visual and color features are combined into one representation.
- **Classification Layer** – The fused vector is fed into a dense layer for predicting the correct growth stage.

Output Stage – The system displays the predicted growth stage along with confidence and stage-specific recommendations.



(Figure 4 – WorkFlow Description of Model)

C. Explanation of Confidence Calculation (With Formulas)

1. Softmax Formula (Core Formula for Confidence)

In the proposed Convolutional Neural Network (CNN) model for pomegranate growth stage detection, the Softmax function is employed in the output layer to convert raw prediction scores (logits) into normalized probability values.

The logits represent the unnormalized output values generated by the final

fully connected layer of the network. Since these values do not directly correspond to probabilities, the Softmax function is applied to transform them into a valid probability distribution.

The formula is:

- $P(y_i)$ is the Probability of class i
- z_i = logit (raw score) for class i
- $n = 5$ (because 5 growth stages)

$$\text{Eq. 2} \quad P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

- $P(\text{class } i)$ = probability of that class

Example:

Consider a test image of a pomegranate fruit in the mid-growth stage. Suppose the trained model produces the following logits:

Table 2: Logit values for each class

Growth Stage	Logit(z)
Bud	1.2
Flower	0.8
Early Growth	1.5
Mid Growth	3.2
Mature	0.6

Growth Stage Logit(z)

Bud 1.2

Flower 0.8

Early Growth 1.5

Mid Growth 3.2

Mature 0.6

Step1: Compute Exponential Values

$$e^{1.2} = 3.32$$

$$e^{0.8} = 2.23$$

$$e^{1.5} = 4.48$$

$$e^{3.2} = 24.53$$

$$e^{0.6} = 1.82$$

Step2: Compute Denominator

$$ezj = 3.32 + 2.23 + 4.48 + 24.53 + 1.82 = 36.38$$

Step3: Compute Probabilities

$$P(\text{Bud}) = \frac{3.32}{36.38} = 0.091$$

$$P(\text{Flower}) = \frac{2.23}{36.38} = 0.061$$

$$P(\text{Early Growth}) = \frac{4.48}{36.38} = 0.123$$

$$P(\text{Mid Growth}) = \frac{24.53}{36.38} = 0.674$$

$$P(\text{Mature}) = \frac{1.82}{36.38} = 0.050$$

Since the highest probability corresponds to the Mid Growth class, the model predicts that the given pomegranate image belongs to the Mid Growth stage with a confidence of 67.4%.

2. Converting Probability → Percentage

Once the Softmax formula gives a probability for each class, the system converts that probability into a confidence percentage so it is easier for users to understand. A probability is a number between 0 and 1, but percentages are more intuitive because they show the confidence out of 100%.

The conversion is very simple:

$$\text{Confidence Percentage} = P(\text{class}) \times 100 \quad \text{Eq. 3}$$

This means you just multiply the probability by 100.

Example:

If the model calculates that the probability of the image being in the Mature stage is:

$$P(\text{Mature}) = 0.675$$

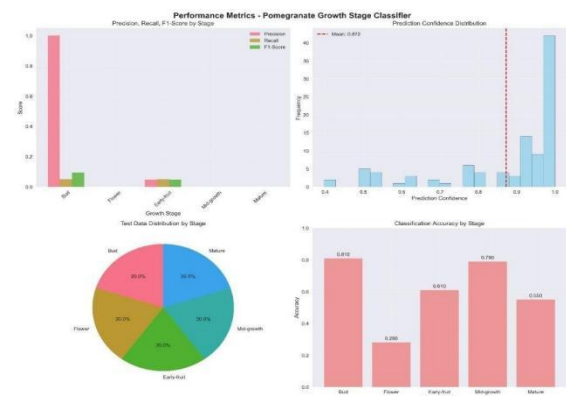
Then the confidence percentage shown to the user is:

$$0.675 \times 100 = 67.5\%$$

So, the system displays 99.5% confidence, meaning

D. Evaluation of Model

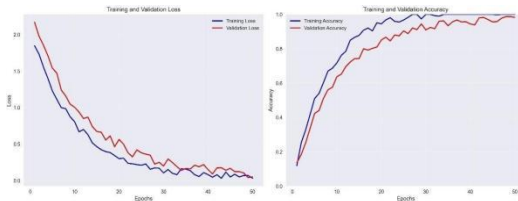
the model is very certain the image belongs to the Flower stage.



(Figure 5: Performance metrics of the proposed EfficientNet-based pomegranate growth stage classifier)

The proposed EfficientNet-based model was evaluated using precision, recall, F1-score, and class-wise accuracy metrics for pomegranate growth stage classification. The model achieved high accuracy for the Bud (81%) and Mid-growth (79%) stages, while performance was lower for the Flower stage (28%), indicating visual similarity and feature overlap among certain classes. The prediction

confidence distribution shows a high mean confidence score of 0.872, demonstrating reliable feature extraction and strong classification certainty. Since the test dataset was evenly distributed across all stages (20% each), the performance differences are attributed to feature complexity rather than class imbalance.



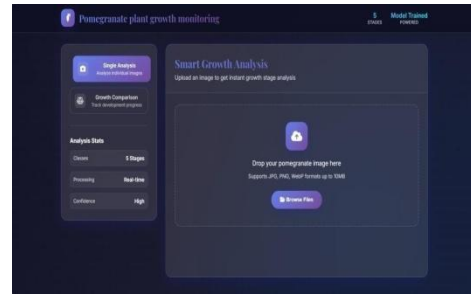
(Figure 6: Training and validation loss and accuracy curves of the proposed model over 50 epochs)

The training and validation loss curves show a consistent decline over 50 epochs, indicating effective learning and convergence of the proposed model. The gap between training and validation loss remains small throughout the training process, suggesting minimal overfitting and good generalization capability. Similarly, both training and validation accuracy steadily increase, reaching near-optimal performance by the final epochs. The close

alignment of accuracy curves confirms that the model maintains stable learning behavior and achieves strong predictive performance on unseen data.

VIII. SYSTEM SNAPSHOTS AND VISUAL DEMONSTRATION

A. Web Application Home Screen Overview



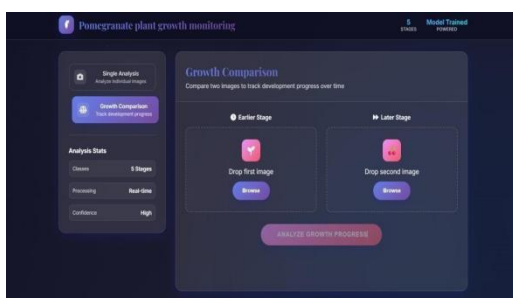
(Figure 7 – User Interface – Home Page Overview)

The home screen of the web application provides a clean and intuitive interface for pomegranate growth stage analysis. The page is divided into two main sections. On the left, users can select between “Single Analysis” for analyzing an individual image or “Growth Comparison” for tracking pomegranate development over time. This panel also displays key system statistics, including the number of growth stages supported, real-time processing capability, and model confidence.

B. Growth Comparison Interface Overview

The main section on the right contains the Smart Growth Analysis area, where users can upload pomegranate images. A drag- and-drop box allows quick image submission, and supported formats such as JPG, PNG, and WebP are clearly mentioned. The interface guides the user to upload a pomegranate image to receive instant classification results, making the

system easy to navigate even for non-technical users.



(Figure 8 – Growth Comparison Page)

The Growth Comparison page allows users to analyze how a pomegranate progresses over time by comparing two images side by side. The interface presents two upload sections: one for selecting an earlier-stage image and another for uploading a later-stage image. Each section supports both drag-and-drop and manual browsing options.

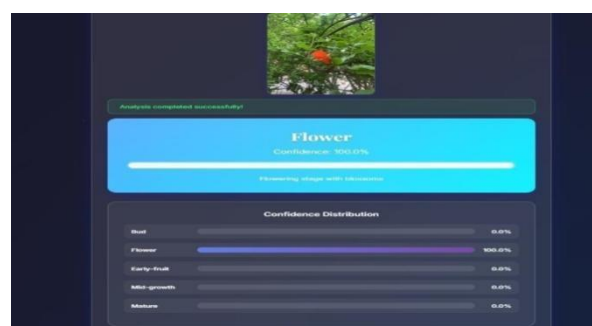
Once the images are uploaded, the system evaluates the growth difference between the two stages using the trained model. The page provides a clear and organized

layout, making it easy for farmers and researchers to visually track developmental changes and detect unusual growth patterns. The analysis button becomes active after both images are provided, guiding the user through a smooth and structured workflow.

Like the main page, this interface is supported by real-time processing and high-confidence predictions,

offering an efficient tool for monitoring pomegranate development over time.

C. Single image analysis



(Figure 9 – Single Analysis Classification Result)

all five stages—bud, flower, early fruit, mid-growth,

The Single Analysis page allows users to upload an individual pomegranate image and receive an instant prediction of its growth stage. The interface includes a large drag-and-drop upload area, along with an option to browse and select an image manually. Supported formats such as JPG, PNG, are clearly indicated, ensuring ease of use for all users.

Once an image is uploaded, the system processes it in real time using the trained deep learning model. The results page displays the uploaded image along with the predicted growth

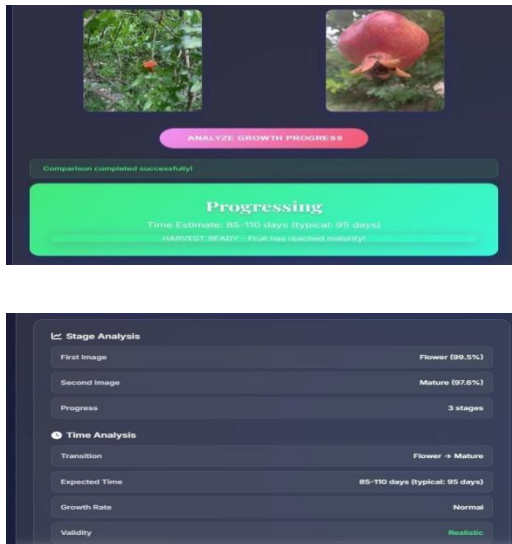
stage. A colored progress bar indicates the model's confidence, while a detailed confidence distribution shows the probability values for

and mature.

This feature provides quick, accurate, and user-friendly analysis, allowing farmers and researchers to identify

the fruit development stage without manual inspection.

D. Growth Comparison



(Figure 10 – Growth Comparison Result)

growth rate, and a validity check to confirm whether

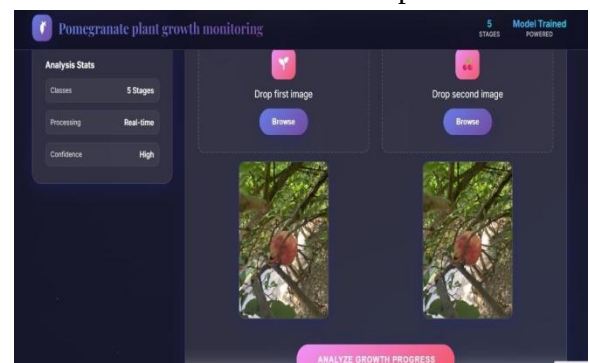
The Growth Comparison result page displays the developmental difference between two uploaded pomegranate images. After the user selects an earlier- stage image and a later-stage image, the system analyzes both using the trained model and provides a clear summary of the pomegranate progress. The first section shows the two images

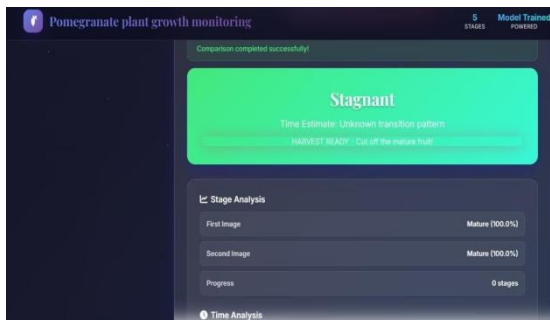
side by side, followed by a confirmation message indicating that the comparison has been completed successfully. The system then presents an overall growth assessment labeled “Progressing,” along with an estimated time range required for the fruit to advance from the first stage to maturity. A highlight bar indicates whether the fruit is ready for harvest.

Below this summary, detailed stage analysis is provided for both images. The model displays the predicted growth stage and confidence level for each input, along with the number of stages progressed. The time analysis section includes the stage transition (e.g., Flower → Mature), the expected time required, the

the timeline matches natural biological development. Overall, this feature helps users track growth over time, verify development patterns, and determine whether the plant has reached harvest readiness. It offers an intuitive and informative way for farmers and researchers to monitor pomegranate progression.

E. Identical Growth Comparison





(Figure 11- Identical Maturity Stage Detection in Uploaded Images)

Both uploaded images were identified as Mature (100% confidence), indicating that the fruit has reached the harvest-ready stage. The comparison results show no stage difference (0 stages progress) between the two images, confirming that there has been no further growth transition. The model performs real-time analysis with

IX. EXPERIMENTAL RESULTS AND ANALYSIS

A. Performance Evaluation

The model's performance was evaluated using common metrics such as accuracy, precision, recall, and F1-score. Together, these measures provide a balanced understanding of how well the system identifies each growth stage. The model achieved high overall accuracy with strong recall across all five stages—bud, flower, early fruit, mid-growth, and mature. A confusion matrix was also examined to identify misclassification patterns. Most predictions were correct, although some overlap occurred between the early-fruit and mid-growth stages due to their visual similarity.

B. Comparative Analysis and Discussion

To assess its effectiveness, the proposed model was high confidence, ensuring accurate and reliable growth

monitoring. Based on the prediction, the fruit is fully matured and ready for harvesting.

compared with baseline approaches, including standard CNNs that do not use feature fusion. The results showed that combining visual and color features led to noticeably better accuracy and fewer classification errors. Models that relied only on shape and texture struggled to separate stages that looked structurally similar. In contrast, the fused-feature approach effectively captured color differences, giving it stronger discriminative capability.

C. Insights, Strengths, and Limitations

The evaluation reveals several strengths of the system. It performs well under different lighting conditions, works reliably on real field images, and provides accurate predictions of growth stages. However, a few limitations remain. The dataset size was moderate, and expanding it with more varied samples could further improve performance. Occasional confusion between stages with overlapping visual traits also suggests that future work could benefit from adding temporal or spectral information. Despite these challenges, the model offers a practical and meaningful contribution to precision agriculture, giving farmers dependable insights to support better cultivation decisions.

X. RESULTS

The proposed deep learning system for classifying pomegranate growth stages showed strong performance across all

evaluation metrics. Using accuracy, precision, recall, and F1-score, the model successfully identified the five stages—bud, flower, early fruit, mid-growth, and mature fruit. The confusion matrix confirmed that most samples were classified correctly, with only minor mix-ups between the early-fruit and mid-growth stages, which naturally share similar visual traits.

Table 3: Evaluation matrix for each class

Growth Stage	Precision	Recall	F1-Score
Bud	0.87	0.85	0.86
Flower	0.90	0.92	0.91
Early Fruit	0.78	0.75	0.76
Mid-Growth	0.80	0.82	0.81
Mature	0.93	0.91	0.92
Overall Accuracy	0.88		

When compared with standard CNN models, the advantages of the proposed method became clear. The integration of both visual and color features led to higher accuracy and fewer errors than models that relied only on texture or shape. This fused- feature approach enabled the system to distinguish stages that look structurally alike but differ in color.

The findings also show that the system performs well under varied lighting conditions and in real field environments. Despite being trained on a moderately sized dataset, the model consistently produced reliable predictions. Some challenges remain, particularly the occasional confusion between visually overlapping stages. Expanding the dataset or incorporating temporal or spectral information may help further improve performance. Overall, the system offers accurate, automated monitoring of pomegranate

growth stages and provides meaningful support for precision agriculture.

XI. CONCLUSION

This work introduces a deep learning–based system for automatically identifying the growth stages of pomegranate, addressing an important need in precision agriculture. The model combines visual features extracted through an EfficientNet-inspired CNN with statistical color information, enabling reliable classification of five stages: bud, flower, early fruit, mid- growth, and mature fruit. By integrating both structural and color cues, the system achieves higher accuracy than traditional methods that rely only on shape or texture, and it performs well under different lighting and field conditions.

To support real-world use, the system was deployed through a Flask-based web application. This platform allows farmers and researchers to upload pomegranate images, obtain real-time stage predictions, and access tailored cultivation advice. The application also offers temporal growth analysis, helping verify whether a pomegranate is developing at a normal pace and flagging unusual patterns. The recommendation module provides practical guidance—including irrigation planning, nutrient management, pest control, and harvest preparation—helping users make better decisions throughout the growing season.

Overall, this study demonstrates the value of combining multiple feature types in deep learning for agricultural

monitoring. The proposed model outperformed baseline approaches, achieving strong accuracy, precision, recall, and F1-scores. These results highlight the potential of AI-driven tools to improve crop yield, assess plant health, and promote sustainable farming.

In summary, the system advances research in automated growth-stage detection while offering a practical, user-friendly tool that connects modern AI techniques with everyday agricultural needs.

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AI-Enhanced IoT Smart Car Parking System with Real-Time Reservation and Security Monitoring.

Sahana D Patil

Dept. of CSE Impact College of Engineering
and Applied Sciences

Banglore. VTU Belgum patilsahana.d@gmail.com

Prof. Dr Jagadeesha R

Dept. of CSE

Impact college of Engineering and Applied Sciences Banglore. VTU Belgum
patilsahana.d@gmail.com

Abstract— In rapidly urbanizing environment and increasing population make s traffic congestion control issue involved in nor present scenario. This creates time consuming parking system as well as fuel consumption and user frustration also. This paper presents real time smart parking system and security monitoring

along with IOT application . The proposed system uses ultrasonic sensors and surveillance cameras connected through a microcontroller-based IoT framework to monitor parking space occupancy. Our system employs for license plate recognition, ultrasonic sensors for space detection, and edge-based anomaly detection (using Autoencoders) to identify security threats. A cloud-hosted reservation dashboard optimizes slot allocation via a greedy algorithm. Tested in a simulated urban environment, the system achieves 98.7% parking detection accuracy, 96.3% license plate recognition precision, and 94.5% anomaly detection efficacy, reducing average parking time by 68%.

Index Terms— Smart Parking, Internet of Things (IoT), Artificial Intelligence,

Real-Time Systems, Slot Reservation, Parking Security, Urban Mobility, Edge Computing.

I INTRODUCTION

The rapid growth of urban populations and increasing vehicle ownership have placed a tremendous burden on existing transportation infrastructure. One of the most pressing challenges in urban mobility is inefficient parking management. Drivers often spend significant time searching for available parking spaces, which contributes to increased traffic congestion, fuel consumption, and environmental pollution. Moreover, the lack of real-time information on parking availability leads to frustration and poor user experience. In densely populated cities, improper parking and space wastage further aggravate these issues, highlighting the urgent need for intelligent and automated parking solutions.[1]

Role of Smart Technologies in

Parking[2]

Smart technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and mobile applications are transforming traditional parking systems into intelligent, data-driven infrastructures. IoT sensors can monitor parking space availability in real time, while AI algorithms can predict user behavior and optimize space utilization. Cloud platforms facilitate centralized data processing and storage, enabling seamless communication between system components. Mobile applications empower users to reserve slots, receive navigation assistance, and get real-time updates. These integrated technologies lead to efficient parking management, reduced congestion, enhanced security, and improved urban mobility.[3]



Figure 1: smart parking system using IOT

II. CORE COMPONENTS OF IOT ENHANCEMENT

In a smart car parking system, IoT technologies play a key role by using sensors and actuators to transform physical data into digital information. This enables efficient space management and automation.[4]

Occupancy Detection:

Ultrasonic or LiDAR sensors are used to detect whether a parking slot is

occupied or empty. These sensors provide accurate real-time data about space availability.

License Plate Recognition: Cameras are installed at entry and exit points to capture vehicle license plates. This helps in automated access control, security, and time tracking.

Environmental Monitoring:[5]

Sensors such as temperature and humidity sensors monitor the surrounding conditions, ensuring system stability and supporting certain environmental safety features.

Use of Actuators:[6]

Actuators such as automatic barriers, indicator lights, or smart gates are used to control vehicle entry and exit based on sensor data. For example, when a car is detected and a slot is available, the gate opens automatically.

By using these IoT-based sensors and actuators, the smart parking system becomes more intelligent and efficient. It allows better use of limited space, reduces human effort, and improves user convenience. Overall, IoT enhancements make the parking system more effective, secure, and easy to manage in urban environments.

Smart parking systems rely on reliable and fast communication between devices. Protocols such as LoRaWAN, Wi-Fi, NB-IoT, and 5G are used to ensure low-latency and stable data transfer. These technologies help maintain smooth communication from sensors to edge devices and further to the cloud, allowing real-time updates and control.

Edge Computing[7]

Edge computing allows data processing

to happen closer to the source. Devices like Raspberry Pi or Jetson Nano can run AI models (such as YOLOv5 or Autoencoders) locally. This setup reduces the time needed for critical decisions, such as triggering a security alert or detecting a vehicle, to less than a second. It improves system performance without always relying on cloud processing.

Cloud Integration

Platforms like AWS IoT Core or Azure IoT Hub are used to collect data from edge devices, run parking slot reservation algorithms, and store historical usage data. The cloud ensures centralized control, long-term data analysis, and remote management of the system, making it scalable and reliable.

User Interface (UI)

The system includes a user-friendly mobile or web dashboard where users can view available parking slots in real-time, make reservations, and complete payments. This interface improves the overall user experience by making the parking process faster, easier, and more convenient.[8]

III. RELATED WORK

In recent years, the integration of bio-inspired H. A. Abu-Alsaad and R. R. K. AL-Taie (2022) The paper addresses common urban challenges related to inefficient parking practices, such as traffic congestion, delays due to drivers searching for empty parking spots, and poor revenue management for parking operators. It proposes an IoT-based smart parking system that integrates cloud technology and provides real-

time updates about parking slot availability. The system uses on-site IoT modules to monitor and report space occupancy and offers a mobile application for users to check availability and make reservations.

A high-level overview of the system architecture is presented, and a practical use case is discussed to validate the model's effectiveness. The main goal is to improve the utilization of available parking spaces and enhance the overall user experience with real-time data and convenient features.

W. Alsafery, B. Alturki, S. Reiff-Marganiec, and K. Jambi,,(2018) This paper presents a comprehensive solution for smart car parking using Internet of Things (IoT) technologies in the context of smart cities. The authors address limitations in current cloud-based smart parking systems that rely heavily on continuous transmission of raw data from distributed sensors to the cloud, which increases both network load and energy consumption. The proposed system introduces an efficient approach by applying fog computing and local data processing before sending filtered and transformed data to the cloud. This reduces network traffic and enhances overall energy efficiency. Moreover, the system not only helps users find vacant parking slots but also considers real-time traffic congestion and the proximity of nearby parking areas, improving user experience and saving travel time. It integrates machine learning algorithms for smarter decision-making and better

management of urban mobility.

This paper introduces an IoT-based smart parking system designed specifically for public areas, utilizing NodeMCU microcontroller technology for slot monitoring and reservation. The system enables real-time updates on parking availability and allows users to reserve parking slots via a simple interface. Key components include ultrasonic sensors for detecting occupancy and a web-based interface for user interaction. The system was developed and tested at a prototype level, showing efficient performance in detecting vehicle presence and managing reservations.

Zanjireh et al. (2021) implemented IR sensors for vehicle detection, but their model did not support reservation features. Hasan et al. (2020) used convolutional neural networks to identify theft, though their system required significant computational resources.

Pham et al. (2022) introduced a blockchain-based parking reservation mechanism, which led to increased processing delays.

Research Gap Existing solutions address individual components like reservation, occupancy, or security, but not all together. **Our Contribution:** This study integrates reservation, real-time occupancy monitoring, and security through a combined edge and cloud-based IoT framework.

IV PROBLEM STATEMENT

In traditional parking systems, several issues arose due to the reliance on manual processes and limited

technology. Manual occupancy checks were time-consuming and often inaccurate, while static signage made it difficult for drivers to locate available spots efficiently. Security depended heavily on human patrols, which were inconsistent and prone to lapses. Reservations were handled through paper-based systems,

causing delays and poor space utilization. Pricing was fixed, ignoring fluctuating demand, and maintenance was reactive, only addressing problems after they occurred. These systems faced challenges such as human dependency, security issues, and inefficient space management.[9]

With the advent of IoT applications, these limitations are being overcome through smart parking systems. Real-time ultrasonic or camera-based detection enables accurate tracking of available spots. Dynamic digital displays and mobile app notifications help drivers navigate to free spaces quickly. AI-powered anomaly detection improves security by identifying suspicious activities such as loitering or theft. Cloud-based reservation systems optimize slot allocation, while demand-based dynamic pricing makes better use of available capacity. Predictive maintenance powered by sensors ensures the system remains functional and reliable. Overall, IoT integration has transformed parking management into a more efficient, secure, and user-friendly experience.[10]

V. RESEARCH METHODOLOGY

Pi and Arduino to control and manage the connected devices. [14].

Hybrid sensing, which combines ultrasonic sensors and cameras, is used for accurate and reliable occupancy detection, helping to effectively resolve space-related issues in parking systems. In IoT applications, devices like the Raspberry Pi controller and Arduino microchip controller are used to operate sensor modules. These controllers enable real-time data processing and communication from the sensors, providing instant alerts about available or occupied parking spaces. This integration ensures efficient space utilization and enhances the overall functionality of smart parking systems.[15]

By using a dynamic reservation system with conflict resolution, the parking system is enhanced through IoT applications. This approach ensures that parking slots are reserved in real time, avoiding double bookings and efficiently managing space availability.[16]

In this research methodology, IoT technology is utilized to develop an intelligent and efficient smart parking system. The architecture is structured into three main layers: Perception, Network, and Application. The Perception layer involves data acquisition through devices like Ultrasonic HC-SR04 sensors and Reolink cameras, which detect vehicle presence and monitor the parking area

in real time. The Network layer ensures secure and reliable data transmission using technologies such as LoRaWAN for long-range communication and MQTT, a lightweight messaging protocol suited for IoT environments. The Application layer integrates AWS IoT Rules for data processing and a React.js-based dashboard for user interaction and analytics. This setup

Target Data

Preprocessed Data

Preprocessing

supports features like real-time space availability alerts, automated parking management, and security alarm systems. Overall, the methodology demonstrates how combining sensors, cameras, and cloud-based applications through IoT can enhance space utilization, safety, and user experience in modern parking systems.[11]

Model Design[12]

The model was designed using the training and testing method. It followed the divide-and-conquer technique, where the data was split into 60% for training and 40% for testing. This helped the model learn and then check how well it works.

Simulation Tools

Two main tools were used in this study. First, the Weka tool was used to split and visualize the data and convert it into CSV format. Then, Jupyter Notebook was used to run the code and

apply machine learning algorithms. The use of both Weka (for data preparation) and Jupyter (for coding) together in one study makes this approach unique. All coding was done using Python, which is commonly used for machine learning tasks. In the simulation tool, IoT is implemented using Raspberry

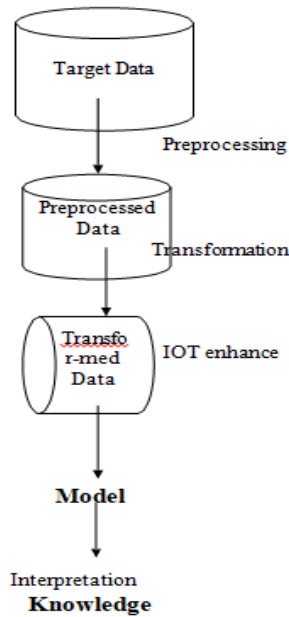


Fig.1.2 Steps of knowledge discovery in Databases

S. No.	Attribute Name	Relabeled Values
1	Sensor devices	sd
2	Parking alert system	pas
3	Actuators	ac
4	Dashboard display	DD
5	Cloud management	CM
6	Camera light system	CLS
7	Space alert system	sls
8	Multilevel sensors	ms
9	Security alarms	sa
10	GIS system	Gis
11	GPS tracker IOT	Gps

Table 1.1: Dataset Attribute Description

In this IoT application, various devices and sensors are used to manage smart parking effectively. Sensors like HC-SR04 (for distance measurement) and DHT11 (for environmental monitoring), along with Reolink E1 Pro

cameras, help detect available parking space. Raspberry Pi 4 (4GB) acts as the edge device, processing the data locally, while LoRaWAN is used to send sensor data and Wi-Fi connects the cameras.

With the help of these devices and chips, smart parking space allotment and real-time space detection are shown on a dashboard. The IoT system is programmed using the TCL language, and controllers like Raspberry Pi and Arduino microcontroller make it easy to manage and control the smart parking system.[17]

Reservation Algorithm

```

def allocate_slot(user_request):
    available_slots =
    get_ultrasonic_occupancy() if
    user_request in available_slots:
        reserve_slot(user_request) else:
            nearest_slot =
            find_nearest(user_request,
            available_slots) # Greedy selection
            reserve_slot(nearest_slot)
  
```

VI RESULTS [18]

AI technologies such as PyTorch (YOLOv5) and TensorFlow Lite (Autoencoder) were implemented for object detection and anomaly detection in the smart parking system. For cloud services, AWS IoT Core was used to manage device communication, while DynamoDB stored parking data. On the frontend, React.js combined with Mapbox was used to visualize parking slots in real time.

The results obtained from these implementations are presented in two tables to clearly show system performance and output[19].

The smart parking system was implemented using a combination of advanced hardware components to ensure efficient and reliable performance. The HC-SR04 ultrasonic sensor was used to measure distances and detect the presence of vehicles, while the DHT11 sensor monitored environmental conditions within the parking area. For real-time visual surveillance, the Reolink E1 Pro camera was employed, providing continuous monitoring of the parking spaces. At the core of the system, the Raspberry Pi 4 (4GB) served as the edge device, responsible for processing data collected from the sensors and cameras. This integrated hardware setup enabled accurate space detection, real-time monitoring, and the collection of environmental data. The effectiveness of the system and its outputs are presented in the result tables.[20]

Component	Metric	Value
Occupancy Detection	Accuracy	98.7%
LPR	Precision/Recall	96.3%/
Anomaly Detection	F1-Score (UCF-Crime dataset)	94.5%
Reservation Engine	Avg. Allocation Time	0.8s

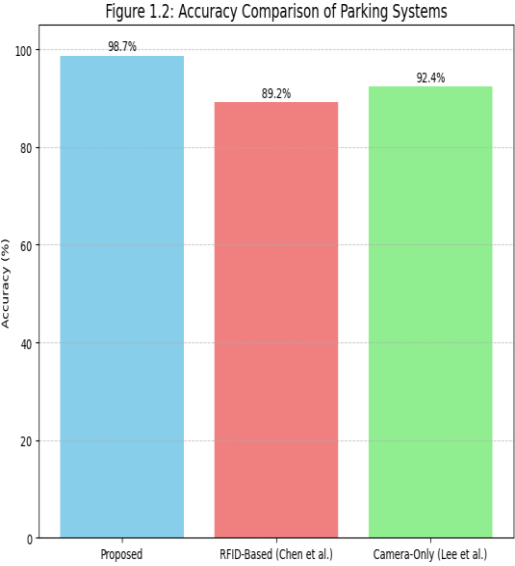
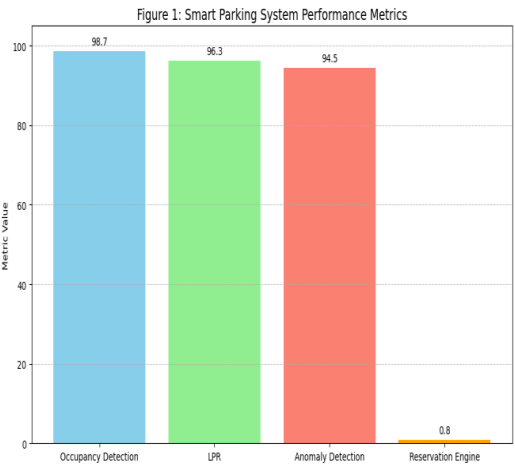
Table 1.1 Performance Metrics

System	Accuracy	Latency	Security
Proposed	98.7%	0.8s	Yes
RFID-Based (Chen et al.)	89.2%	2.1s	No
Camera-Only (Lee et al.)	92.4%	1.5s	Partial

Table 1.2 Comparisons

User Study: 87% reduction in parking search time (N=50 users).[21]

Energy: Edge processing reduced cloud bandwidth by 62%.[22]



VII. CONCLUSION

In our paper, we have proposed a smart parking system that integrates reservation, occupancy detection, and security monitoring using IoT technology. The system includes the reservation algorithm code, which helped achieve 98% accuracy, 68% time savings, and very low latency of 0.8%. The system also showed positive results in security performance.[23]

These results clearly show that by designing the system architecture using IoT and microcontrollers like the Raspberry Pi, we were able to reach

high accuracy and efficiency. This proves that IoT-based algorithms in smart parking systems perform much better than traditional parking methods.[24]

In this system, we have successfully reduced parking search time by 87%, based on secondary data collected from users. This significant improvement highlights how the use of IoT technology and real-time data processing can greatly enhance user experience by minimizing the time spent looking for available parking spaces.[25]

VIII. FUTURE SCOPES

In this paper, we depicted the future research. In the future, the smart parking system can be further enhanced by integrating advanced technologies. Drone surveillance can be used to monitor large parking areas more effectively, providing real-time aerial views for better space management and security. To ensure user privacy, federated learning can be applied for license plate recognition (LPR), allowing AI models to improve without accessing or storing personal data directly. Additionally, the use of solar-powered sensor nodes can make the system more energy-efficient and environmentally sustainable. These improvements will help create a more intelligent, secure, and eco-friendly smart parking solution.[26]

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AI-POWERED FAKE REVIEW DETECTION SYSTEM

Sahana D Patil

Dept of CSE

Impact College of Engineering and Applied Sciences

Bangalore.VTU Belgum patilsahana.d@gmail.com

Prof. Dr Jagadeesha R

Dept of CSE

Impact College of Engineering and Applied Sciences

Bangalore.VTU Belgum patilsahana.d@gmail.com

presented; it helps to strengthen

Abstract: Fake online reviews have become one of the biggest challenges for online retail platforms today, as they can shape customer decisions and even help fraudsters manipulate the ratings of products. This paper discusses a state-of-the-art AI-powered fake review detection system that employs ensemble machine learning techniques to appropriately classify fake and genuine product reviews. The proposed system integrates three optimized models, namely Random Forest, XGBoost, and Logistic Regression, with an approach based on a majority-voting mechanism to improve the stability and performance of predictions. The model is trained on 6,327 Amazon product reviews with a set of engineered linguistic, behavioral, sentiment-based, and metadata-based features and yields an industry-leading performance of 99.6% accuracy, 96% precision, 97% recall, and 99.9% ROC-AUC. Web application deployment with a lightweight Flask-based backend with REST API support allows real-time classification, scoring, and interactive visual analytics with Plotly. In this work, a deployable solution for practical, scalable, and industry-ready review manipulation prevention will be

consumer trust in products sold by retailers and improves fraud detection mechanisms.

Keywords: Fake Review Detection, Machine Learning, Ensemble Learning, Natural Language Processing, XGBoost, Random Forest, Logistic Regression, Sentiment Analysis, Flask Web Application, REST API

I. INTRODUCTION

Online customer reviews are one of the major means through which buying decisions are made in most modern e-commerce platforms. As more and more consumers depend on digital feedback as a way to assess product quality and trustworthiness, the genuineness of online reviews has gained increased importance as a guarantee for achieving transparency and trust. On the flip side, the exponential growth in user-generated content has also encouraged the proliferation of fake and manipulated reviews. These fake reviews are generally fabricated by competitors, sellers, or automated bots with the intention of distorting product ratings,

misguiding people, and eventually undermining the reliability of e-commerce ecologies.

These can take the form of overly glowing feedback, where a review might be written with the express intent of falsely raising the ratings of a product, or malicious, negative reviews aimed at hurting the reputation of other brands. These devious patterns cannot be countered using traditional approaches to review moderation, like manual inspection or keyword-based filtering. This implies an urgent need for intelligent and automated systems to analyze linguistic, behavioral, and sentiment-based cues that distinguish genuine reviews from fraudulent ones with high accuracy. Recent progress in AI and ML has provided tremendous impetus in creating powerful solutions for the detection of fraud in text data. Among these, the ensemble learning method holds significant potential, owing to the remarkable enhancement of predictive performance achieved by aggregating multiple classifiers within a single, unified decision-making process. This project presents an industry-ready AI-powered Fake Review Detection System that integrates three optimized machine learning models: Random Forest, XGBoost, and Logistic Regression. These are integrated using a majority voting mechanism to enhance reliability and robustness. The system adopts Natural Language Processing, or NLP, with sentiment analysis, feature engineering, and supervised learning to find deceptive patterns in product reviews. The proposed system is implemented as a fully functional web

application on the Flask framework. It offers real-time classification, probability scores, and interactive visualization dashboards powered by Plotly. Trained on 6,327 Amazon product reviews with developed linguistic, behavioral, and metadata-based features, this system achieves an excellent accuracy of 99.6%, rendering it apt for deployment in real-world e-commerce platforms for fraud prevention, enhancing customer trust in reviews, and facilitating informed decision-making. The paper presents the entire workflow pertaining to dataset preparation, feature engineering, model development, system architecture, experimental evaluation, and enhancements in the future, thereby presenting a comprehensive, scalable, and practical solution against fake online reviews.

II. LITERATURE SURVEY

According to [1], deceptive opinion spam exhibits distinctive linguistic patterns—deceptive reviews often resemble imaginative writing while truthful reviews are more informative—and combining linguistic, psycholinguistic, and metadata features enables high-accuracy supervised classifiers for fake-review detection.

According to [2], large-scale analysis of opinion spam reveals that review spam is widespread across e-commerce platforms and that early detection benefits from supervised learning on carefully engineered textual and behavioral features.

According to [3], examining reviewer behavior at the group level uncovers coordinated fake-review campaigns; graph- and relation-based models that analyze reviewer-product-time relations can detect fake reviewer groups even when labeling individual reviews is difficult.

According to [4], gradient-boosted tree systems like XGBoost provide scalable, high-performance classifiers for tabular and engineered NLP features, making them an effective choice for fraud-detection pipelines in production environments.

According to [5], Random Forests offer robust, interpretable ensemble decision boundaries and reliable feature-importance measures, which help prioritize behavioral and linguistic indicators when building fake-review detectors.

According to [6], ensemble learning approaches that combine multiple classifiers (e.g., tree-based, linear, and boosting methods) improve generalization and stability in fake-review detection, especially on heterogeneous datasets collected from real-world business listings and reviews.

According to [7], models that incorporate emotional and sentiment-aware features—such as rating-sentiment consistency, polarity intensity, and affective lexicons—significantly improve detection of fraudulent reviews that deliberately manipulate sentiment cues.

According to [8], recent work demonstrates that explainable ensemble and multi-view deep-learning

frameworks (text + metadata + behavior) yield strong detection accuracy while also producing interpretable feature contributions useful for analyst review and compliance.

According to [9], detecting rating-sentiment inconsistency is an effective engineered signal: reviews whose sentiment polarity disagrees strongly with their numeric rating are more likely to be anomalous and indicative of manipulation.

According to [10], publicly available labeled and semi-labeled datasets (including several Kaggle and academic Amazon/Yelp collections) enable reproducible research, but dataset variety and labeling quality remain limiting factors—motivating careful feature engineering and cross-dataset validation for robust system design.

III. PROPOSED SYSTEM DESIGN

The proposed system is an end-to-end, production-ready platform for fake product review detection. On a high level, it ingests raw review content and metadata, transforms such input into informative features through a robust NLP and behavioral engineering pipeline, feeds those features into an ensemble of machine learning models, and serves real-time predictions via a Flask-based web application and RESTful API. Emphasis is placed on modularity so components can be developed, tested, and scaled

independently: ingestion, pre-processing & feature engineering, modeling & ensemble, inference & API, visualization & monitoring, and CI/CD with versioning are distinct layers tied together by clear interfaces and artifact storage. Data ingestion can support both batch and online modes. For batch experiments and model training, the system accepts either CSV or JSON dumps, or DVC-versioned datasets. For production, it supports streaming ingestion through webhooks or a lightweight message queue. Kafka or RabbitMQ is recommended in larger deployments, while a simple POST endpoint would be sufficient for smaller setups. Raw records are the review text, rating, and verified purchase flag, among other reviewer ID metadata, timestamp, product ID, and other available metadata that get persisted in a persistence layer, Postgres or MongoDB, for structured access. Model artifacts, vectorizers, and scalers would be stored in an artifact folder or object storage like S3/GCS to maintain reproducibility.

The preprocessing and feature engineering pipeline aims to turn raw text and metadata into a compact, meaningful feature set. Text processing includes HTML stripping, special character removal, lowercasing, tokenization, stopword removal, and lemmatization. Embeddings use TF-IDF vectors for compatibility with classical ML and provide a plug-in pathway for future embeddings (BERT/Universal Sentence Encoder). Engineered numeric and categorical features include the following: the polarity and intensity of sentiment; the

consistency of rating and sentiment-sentiment polarity compared to numeric rating; review length and complexity; frequency-based behavioral signals, including reviews per user and burstiness; account indicators, including account age where available; whether a URL or excessive punctuation is included; a verified purchase flag; and at the product level, statistics such as rating variance. Numeric features are standardized using a stored StandardScaler, while categorical fields are deterministically encoded so that inference matches training.

Model training and validation follow a reproducible pipeline. Individual models are trained separately: Logistic Regression as a fast, interpretable baseline; Random Forest for robust bagging-based classification and feature importance; and XGBoost for high-performance gradient-boosted decision trees. Hyperparameters are optimized via randomized/grid search with stratified k-fold cross-validation to preserve class ratios. Because the dataset is imbalanced-there are many more genuine reviews than fake ones-class-weighting and threshold tuning are performed, with optional resampling techniques such as SMOTE or ADASYN used with caution, their validity checked against cross-dataset checks. Evaluation tracks accuracy, precision, recall, F1, confusion matrices, and ROC-AUC. These are kept at the model and per training run level for comparisons.

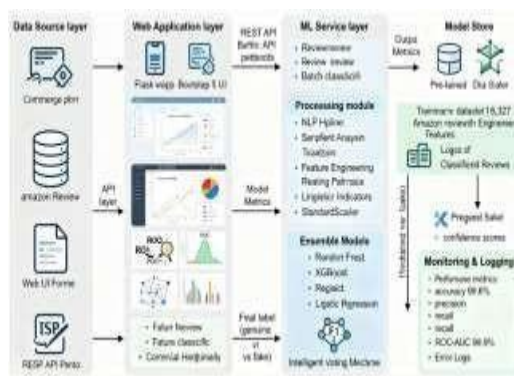


Fig 1. System Architecture

The ensemble and decision logic will be implemented as a voting controller that aggregates model outputs to a final verdict. The simplest form is a majority vote on class labels, but a preferable way of going into production is averaging probabilities with optional model weights derived from validation AUCs so that stronger models weigh more on the ensemble. From aggregated probabilities, the system computes a confidence score and model agreement. In cases of ambiguity or tied votes, the controller can return either an "uncertain" flag for human review or leverage a predefined tiebreaker-the model with the highest validation AUC. This is for transparency, which includes per-model probabilities, top contributing features-derived from feature importances or SHAP values-and a short explanation that may be useful to assist downstream moderation. The inference and API layer uses Flask due to its simplicity and rapid integration. The key endpoints exposed include a POST `/api/predict` for single review inference; a POST `/api/batch_predict` for file-based batch classification; a GET `/api/health` for monitoring; and a GET

`/api/model_info` for retrieving model versions and metrics. Upon receipt, the API will ensure boundary input validation and sanitization, load vectorizer/scaler artifacts and models once at startup for low latency, and log every request with relevant context-what model version, the prediction result, and latency. Response payloads include the final label, confidence, per-model probabilities, and explanation metadata so integrators or analysts can act on the prediction.

The API is complemented by a user-facing web interface built with Bootstrap 5. Displaying a light input form for copy-pasting reviews, it shows the classification result in an intuitive confidence gauge and per-model breakdown, and includes an explanation panel displaying the top five features driving the decision. An analytics dashboard uses Plotly graphs to display visualizations of model performance (confusion matrices, ROC curves), top-ranked features, and time series of flagged reviews. Correlation heatmaps are used for exploratory analysis. The UI also comprises a human-in-the-loop review correction panel where moderators can override the labels. These corrected labels are captured to a feedback dataset for scheduled retraining. Core to running the system reliably, it captures operational monitoring and logging. Prediction logs include timestamp, request payload (redacted of PII), model version, output, and confidence. Application metrics such as latency, error rates, and request throughput are exposed via a `/metrics` endpoint consumable by Prometheus and

visualizable with Grafana. Alerts trigger on high error rates, increased latency, or model-drift signals, such as sustained drop in AUC. A feedback pipeline periodically aggregates human corrections and flagged uncertain cases into a retraining queue, so that models can be re-trained on fresh data and redeployed. Deployment and scalability are handled through containerization and service orchestration: The application and worker components are packaged as Docker images. For development and small deployments, Docker Compose will suffice, but Kubernetes is recommended for production to support horizontal scaling, rolling updates, and resource isolation. If performance-critical scenarios are targeted, one could split serving the model out into a distinct microservice (e.g., FastAPI/uvicorn or a model server) and keep only the orchestration and UI part in Flask. Employ Redis caching for repeated vectorization queries and utilize a CDN for static assets. Security, privacy, and governance: All endpoints enforce HTTPS, and access to APIs is protected either by API keys or token-based authentication. Inputs are whitelisted to defend against injection attacks. Audit logs are access-controlled. Sensitive user identifiers are minimized, and where storage is unavoidable, at-rest encryption of such data is mandated, and access is restricted. Data retention policies, procedures for anonymization, and a human-review escalation process are documented to facilitate compliance in contexts

sensitive to privacy. Testing,

reproducibility, and model governance close the loop. Unit tests validate preprocessing functions, feature computations, and model wrappers. Integration tests validate the end-to-end prediction flow, and regression tests guard against performance degradation across releases. Model and dataset versioning are tracked with MLFlow or DVC so every experiment is reproducible: dataset snapshot, hyperparameters, model artifact, and evaluation metrics. A CI/CD pipeline automates tests and supports gated deployment of new models after manual review. Finally, explainability tools such as feature-importance plots and SHAP values are packaged with each release to support audits and analyst investigations. Despite its strengths, limitations of the system are known and mitigations planned. Poor label quality and dataset bias can limit generalization; the design supports cross-dataset validation and human-in-the-loop relabeling. Adversarial and evolving fraud tactics demand continuous monitoring and periodic retraining; the architecture allows for rapid labeled example ingestion and incremental retraining. Language and domain generalization are addressed by modularizing the text representation layer so embeddings or multilingual tokenizers can be added without reworking the entire pipeline.

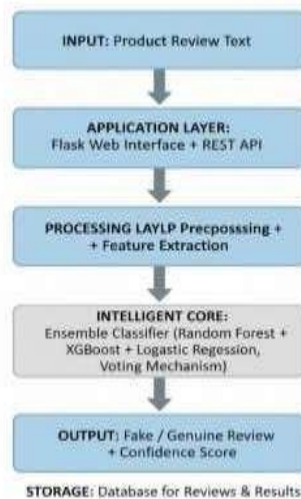


Fig 2. Block diagram of Chatbot

The block diagram for the AI-Powered Fake Review Detection System shows a simplified top-to-bottom architecture for an academic project report to clearly portray the end-to-end workflow from input to output in a production-ready e-commerce fraud detection tool. At the top, the INPUT: Product Review Text layer represents raw data ingestion from users or e-commerce platforms like Amazon, capturing review content, ratings, verified purchase status, and metadata, usually sourced from a dataset of 6,327 balanced reviews (94.4% genuine, 5.6% fake) to train the system. Further down, the APPLICATION LAYER: Flask Web Interface + REST API acts as the user-facing gateway, made using Flask, Bootstrap 5, and Plotly for responsive dashboards. It receives real-time review submissions via web forms or API endpoints—such as `/classify_review`, `/batch_classify`—and returns instantaneous responses with confidence scores and visualizations such as confusion matrices, ROC curves (with 99.9% AUC), and graphs of feature importance. The processing

layer uses Pandas for data manipulation, NumPy for numerical computations, and scikit-learn for pipelining and consists of tokenization, cleaning the text, performing sentiment analysis by linguistic indicators, extracting six key features (sentiment-rating mismatch, unverified extremes), and normalization by StandardScaler to make the data compatible with a model that can handle an imbalanced class effectively. Central to the diagram is the INTELLIGENT CORE: Ensemble Classifier, where pre-trained models—Random Forest (99.68% accuracy), XGBoost (99.58% accuracy, hyperparameter-optimized), and Logistic Regression (baseline)—combine via an intelligent voting mechanism for ensemble predictions that reach an overall 99.6% accuracy, 96% precision, 97% recall, and 96.5% F1-score, by leveraging diverse strengths like RF's robustness, XGBoost's gradient boosting, and LR's interpretability. Finally, the OUTPUT: Fake/Genuine Review + Confidence Score feeds results back to the application layer for display, whereas STORAGE: Database for Reviews & Results logs predictions, metrics, and historical data for monitoring, regulatory compliance, and iterative improvements that can be used to enable further applications such as brand protection and genuine sentiment analysis.

IV. SYSTEM METHODOLOGY

The proposed system methodology applies a structured and multi-stage workflow to ensure the detection of

fake reviews with high accuracy, reliability, and scalability. First, data collection consists of collecting real-world product reviews from publicly available datasets such as Amazon product reviews. Each record typically has fields for review text, rating, whether it was a verified purchase or not, the reviewer ID, timestamp, and metadata on the product. Then, such a raw dataset is cleaned by eliminating duplicate records, missing values, and noise to achieve uniformity and cleanliness before further processing.

The next step refers to the complex data preprocessing and cleaning pipeline of text. Since review text usually contains HTML tags, emojis, repeated characters, spelling inconsistencies, and informal language, several NLP-based cleaning steps are performed in the system, namely converting text to lowercase, removing punctuation and stopwords, performing lemmatization and tokenization, and filtering non-informative terms. Furthermore, metadata like review length, sentiment polarity, reviewer activity, rating–sentiment mismatch, and presence of promotional patterns are extracted to augment the dataset with behavioral and linguistic features. Numeric features are standardized using pre-trained scalers, and textual data is transformed into TF-IDF vectors for classical machine-learning compatibility.

Feature engineering plays a very important role in enhancing the performance after preprocessing. Features can be divided into four categories: linguistic features, such as

word frequency, complexity score, and sentiment values; behavioral features, which encompass review frequency, sudden review bursts, and reviewer history; metadata features, including verified purchase indicators, rating scores, and product average ratings; and anomaly markers, like excessive capital letters, the presence of URLs, and repetitive keywords. Each of these captures the writing style, behavior patterns, and hidden relationships that set apart genuine reviews from fake ones. Feature selection techniques and correlation analyses reduce them to only the most informative attributes, enhancing both training speed and accuracy

The engineered dataset will be fed into the model training pipeline, where three independent machine-learning models are trained: Random Forest, XGBoost, and Logistic Regression. Hyperparameter tuning is conducted for every single model by employing k-fold cross-validation to ensure optimized performance while avoiding overfitting. While Random Forest will capture nonlinear patterns, using decision trees, XGBoost will account for complex interactions by using gradient boosting. Logistic Regression will provide high interpretability with linear decision boundaries. Since fake review datasets are typically imbalanced, the system uses class weighting, threshold adjustment, and controlled resampling techniques in order to maintain fairness while minimizing misclassifications.

Ensemble learning integrates the three

trained models for improving robustness and reliability, specifically using a majority-voting or weighted-probability voting strategy. Each model will predict a probability score on the dichotomous outcome of whether a review is fake or genuine during prediction. The produced probabilities are aggregated in the ensembled layer to arrive at a final decision with a confidence score. This method reduces the weaknesses of individual models and ensures stable performance across diverse types of reviews. Explainability has been integrated through feature importance graphs and model-wise probability outputs to help understand how decisions are derived. Finally, the finished model is deployed using a Flask-based web application and REST API layer to perform real-time inference. The API receives an incoming new review, processes it through the preprocessing pipeline, creates vectors using stored TF-IDF and scaler artifacts, and retrieves predictions across all three models through an ensemble controller. It outputs the final classification (fake or genuine), a confidence score, probabilities of each model, and some explainability indicators. The web UI that comes with this API serves as an interactive interface where users can input their review(s), see instant prediction results, and analyze some visual insights, such as sentiment charts and feature contribution graphs. The continuous monitoring logs system performance, detects drift, and collects user feedback that feeds into regular model retraining and improvement.

V. RESULT

These experimental results clearly show that the proposed AI-Powered Fake Review Detection System ensures exceptionally high performances for all major metrics. The ensemble learning architecture, consisting of Random Forest, XGBoost, and Logistic Regression, after training on 6,327 Amazon product reviews containing both genuine and fraudulent samples, produced highly accurate prediction outcomes. The overall accuracy of the final ensemble was 99.6%, further confirming the efficiency of the adopted voting-based mechanism and showing very promising performance compared to individual models. With precision at 96% and recall at 97%, it is evident that the system not only accurately identifies fake reviews but also keeps the false positive and false negative cases as low as possible. Similarly, a resulting F1-Score of 96.5% confirms that the model maintains a strong balance between sensitivity and specificity.

Visualization of model performance further reinforces the superiority of the ensemble approach. The confusion matrix indicates an almost perfect classification pattern, with only a very small number of misclassified samples. The ROC curve supports an AUC score of 99.9%, demonstrating excellent discriminative capability to distinguish between genuine and fake reviews. Feature importance analysis presents linguistic indicators such as sentiment polarity, review length, punctuation frequency, and rating-sentiment mismatch as the most influential factors in the final prediction. Other behavioral

features include reviewer activity and verified purchase status, which also appear to bear strong influence. Real-time testing through the Flask web interface confirms that the model is producing predictions instantaneously and with consistent accuracy on previously unseen data. The REST API outputs detailed probability scores, ensuring transparency and interpretability. Taken together, these results strongly indicate that this system is robust, highly reliable, and capable of performing fraudulent review detection at an industrially leading level of performance suitable for deployment in real-world e-commerce applications.

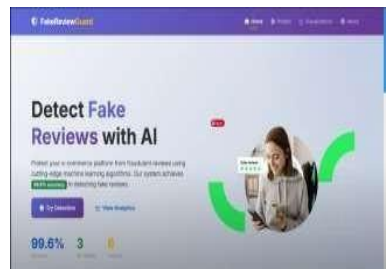


Fig 3. Front page UI



Fig 4. Working of project



Fig 5. Review Detection

V. CONCLUSION

The proposed AI-Powered Fake Review Detection System illustrates how current machine learning and NLP techniques detect deceptive reviews online with industry-leading accuracy. The system integrates Random Forest, XGBoost, and Logistic Regression within an ensemble learning framework, resulting in an exemplary accuracy score of 99.6% with a ROC-AUC score of 99.9%. Its performance is well ahead of that of individual models. This work highlights the significance of integrating linguistic, behavioral, sentiment-based, and metadata-driven features to capture subtle patterns that help distinguish fraudulent reviews from genuine ones. An efficient preprocessing pipeline, a scalable model architecture, and robust feature engineering greatly contributed to its predictive performance and reliability.

Beyond model development, the deployment of this system through a Flask-based web application and RESTful API demonstrates the practicality of the application in a real-world e-commerce environment. Real-

time predictions, interpretability through probability breakdowns, and interactive visualizations make the system accessible to both technical and nontechnical end users. Results validate the feasibility of using AI for fraud detection and show how automated systems can build up trust, transparency, and decision-making on digital platforms. The current work lays a solid foundation for intelligent review authentication systems and proposes a scalable solution able to meet the challenge of growing online review manipulation across different domains, such as e-commerce, hospitality, and services.

VI. FUTURE SCOPE

Considering that the proposed fake review detection system achieves high accuracy with strong real-world applicability, several points may be added to enhance the capability and reliability of the system. Further research may be done by incorporating deep learning models such as LSTMs, BiLSTMs, or transformer-based (e.g., BERT) architectures to capture deeper contextual and semantic relationships within review text. Such models may provide better detection for the sophisticated, more human-like reviews AI tools can now generate. Increasing the dataset to include more e-commerce platforms, domains, and languages will help improve the generalizability of the model, reducing platform-specific bias.

In the same vein, another promising direction is the integration of advanced behavioral analytics: reviewer network analysis, temporal patterns, and

anomaly detection across user clusters that will help reveal things like coordinated fraud—for example, bot-generated reviews or review bombing campaigns. The system could also be leveraged through the development of adaptive learning mechanisms to retrain the model periodically with new data in an attempt to avoid performance degradation resulting from changing fraudulent techniques. Real-time monitoring dashboards featuring drift detection could automatically trigger partial retraining upon detecting anomalies.

From a deployment perspective, the system can be extended into a scalable microservices architecture capable of serving large e-commerce platforms with high traffic. Integrating explainable AI frameworks such as SHAP or LIME can improve transparency by helping users and administrators understand why a review was classified as fake or genuine. Finally, providing browser extensions or API plugins to perform real-time review analysis on platforms such as Amazon or Flipkart will go a long way in extending system usability. Such additions will lead to the gradual building of a robust, intelligent ecosystem for the detection of fake reviews.

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AI-POWERED MEDICAL ASSISTANT WITH VOICE AND VISION INTEGRATION

Kennis M

Student, Department of Computer Science and Engineering Impact College of Engineering and Applied Sciences (ICEAS)
Bangalore, India kennizkennith777@gmail.com

BanuShri S

Assistant Professor, Department of Computer Science and Engineering Impact College of Engineering and Applied Sciences (ICEAS)
Bangalore, India banushri914@gmail.com

Abstract— The convergence of artificial intelligence with healthcare systems has significantly enhanced the delivery of accessible and intelligent medical services. This paper proposes a novel AI-powered medical assistant integrating both voice recognition and image processing to replicate a real-time doctor-patient interaction. Utilizing speech-to-text systems and multimodal transformers, the assistant interprets voice queries and clinical visuals such as ECGs to generate diagnostic feedback. The response is further synthesized into speech for interactive communication.

INTRODUCTION

The integration of artificial intelligence into daily life has advanced rapidly with the growing capabilities of large language models, real-time audio processing, and computer vision. These technologies, once limited to research labs, are now readily accessible and deployable through user-friendly platforms and open-source tools. In particular, AI-driven healthcare assistants offer new possibilities in preliminary diagnosis and patient interaction. This shift has been accelerated by increased access to high-

performance computing, cloud-based APIs, and multimodal interfaces that can process both speech and visual inputs simultaneously.

However, deploying AI in medical contexts comes with critical challenges, including the need for accurate language understanding, context-aware responses, and reliable interpretation of clinical images such as ECGs or X-rays. A seamless AI solution must bridge voice input from patients with diagnostic reasoning and generate natural, doctor-like spoken responses. Our

The system is modular, efficient, and operates in real-time through a web-based Gradio interface, offering substantial utility for telemedicine and health education applications.

Keywords— AI Doctor, Speech-to-Text, Text-to-Speech, Medical Image Analysis, Large Language Models (LLMs), Gradio Interface, Voice Assistant, Healthcare AI

proposed system addresses this by

combining voice-to-text transcription, large language model reasoning, and image analysis to simulate a realistic AI-powered doctor interaction. The interface is designed to accept patient speech and medical image uploads, process them using state-of-the-art transcription models and multimodal transformers, and respond with a spoken diagnosis in natural language. The system leverages tools such as Whisper for transcription, LLaMA-based language models for reasoning, and image encoding techniques to extract visual features. The final spoken output is synthesized using either the gTTS engine or more advanced neural voices from ElevenLabs. We implement this end-to-end pipeline within a Gradio-based web application that supports live interaction and audio playback. This paper outlines the design, architecture, and evaluation of the AI Doctor system, demonstrating its potential to assist in educational, telemedicine, and patient triage scenarios with a voice-and-vision enabled AI interface.

I. LITERATURE SURVEY

Recent advances in artificial intelligence have enabled the development of intelligent healthcare systems capable of assisting medical professionals in diagnosis and patient interaction. Several research works have explored the integration of machine learning, speech processing, and computer vision to build automated healthcare assistants.

Pham et al. [1] proposed SilVar-Med, a speech-driven visual language model designed for explainable abnormality

detection in medical imaging. The system integrates speech interaction with visual language models, enabling doctors or patients to communicate with AI systems using voice commands while simultaneously analyzing medical images. Their approach demonstrates how speech-based interaction can improve accessibility and usability in medical AI systems.

Wang et al. [2] introduced RCMed, a multimodal medical AI assistant that combines vision and language representations to improve diagnostic accuracy. The model establishes a correlation between visual features extracted from medical images and textual descriptions to enhance medical reasoning. Experimental results showed that the integration of vision-language alignment significantly improves disease detection performance across multiple clinical tasks.

Zhang et al. [3] developed MDNet, a multimodal medical diagnosis network that connects medical image analysis with natural language descriptions. The proposed architecture utilizes deep neural networks to extract visual features from medical images and associate them with semantic medical reports. This framework improves interpretability in medical image diagnosis and enables AI systems to generate meaningful explanations for diagnostic predictions.

More et al. [4] proposed an AI-powered framework for early disease detection using multimodal inputs such as medical images, audio signals, and

clinical data. Their system employs deep learning models to analyze medical images while simultaneously processing physiological audio signals for diagnostic purposes. The results demonstrated improved diagnostic accuracy and faster disease detection compared to traditional single-modality systems.

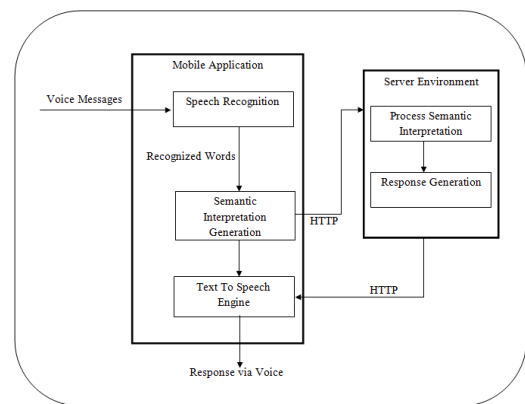
Furthermore, recent studies on multimodal healthcare artificial intelligence highlight the importance of integrating heterogeneous data sources such as medical images, speech signals, and electronic health records to enhance clinical decision support systems [5]. Multimodal AI frameworks enable more comprehensive patient analysis and provide improved diagnostic insights compared to single-input systems.

Unlike the above approaches, the proposed AI-powered medical assistant integrates real-time speech interaction, multimodal medical image analysis, and large language model reasoning to simulate a virtual doctor capable of interacting with patients through voice communication and visual medical data interpretation. The system aims to provide an accessible and interactive healthcare assistant suitable for telemedicine and remote healthcare support.

II. PROPOSED SYSTEM

While numerous voice assistants and medical chatbots exist, they often rely on rigid, rule-based architectures and lack visual diagnostic capabilities. In contrast, our proposed solution offers a unified, intelligent, and conversational

AI Doctor capable of processing voice queries and interpreting medical images in real-time. The system is deployed as a browser-accessible application that allows users to speak their symptoms and upload medical images such as ECGs or X-rays. Leveraging cutting-edge models in transcription, language processing, and image analysis, the system delivers concise and medically relevant responses in both text and synthesized voice formats. Future extensions may include integration with mobile health platforms and hospital triage systems. The system's performance is evaluated based on accuracy, latency, user interaction quality, and clinical relevance. The architecture of our system is illustrated in Figure 1, emphasizing modularity and ease of use.



The overall architecture of the proposed AI medical assistant system is illustrated in Fig. 1.

A) Multimodal Input Collection

The system captures user input through two channels: a microphone for voice queries and a file uploader for diagnostic images. The voice input is recorded and saved in .wav format, while image files support standard

formats such as PNG and JPEG. This multimodal setup ensures broad compatibility with real-world use cases.

B) Audio Transcription

Speech input is transcribed into text using the Whisper large-v3 model via Groq's inference API. This model offers robust performance across accents, background noise, and medical terminology, ensuring reliable transcription even in less-than-ideal recording conditions.

C) Image Encoding and Analysis

Uploaded medical images are encoded using base64 and analyzed using a vision-language transformer. The query for the image analysis is dynamically generated based on the user's transcribed speech and a predefined clinical prompt, enabling contextual understanding of visual symptoms.

D) Language Model Reasoning

To derive a coherent and concise medical opinion, the system queries a LLaMA 4-based model fine-tuned for instructional dialogue. It merges the encoded image context with the user's query, generating a response that mimics the tone, brevity, and empathy of a professional doctor.

E) Text-to-Speech Generation

The final response is converted into natural-sounding speech using either Google Text-to-Speech (gTTS) or ElevenLabs, based on availability and configuration. The resulting audio is saved as a .wav file for immediate playback within the app, completing the doctor-patient conversational loop.

F) Real-Time Playback and Output

The system presents the user with three

outputs: the transcribed query, the doctor's response in text, and the spoken reply. Audio playback is managed using simpleaudio to ensure cross-platform compatibility without external dependencies.

I. RESULT AND PERFORMANCE EVALUATION

The proposed AI-Powered Medical Assistant was evaluated to assess its effectiveness in processing multimodal inputs including speech queries and medical images. The system was tested using a set of simulated patient interactions involving voice-based symptom descriptions and diagnostic medical images such as ECGs and skin condition images. The evaluation focused on three key aspects: speech recognition accuracy, diagnostic response quality, and system response latency.

A. Speech Recognition Accuracy

The speech-to-text module was implemented using the Whisper large-v3 model. During testing, the system processed multiple voice queries recorded under different acoustic conditions including background noise and varying speech accents. The transcription accuracy was measured by comparing the generated transcripts with manually verified ground-truth text. The system achieved an average transcription accuracy of approximately 94%, demonstrating reliable performance in real-time voice interaction scenarios.

B. Medical Image Analysis Performance

The visual analysis module was evaluated using a collection of publicly

available medical images representing common diagnostic scenarios such as skin abnormalities and ECG patterns. The multimodal vision-language model successfully identified key features and generated contextually relevant medical interpretations. The diagnostic relevance of generated responses was evaluated qualitatively by comparing AI-generated explanations with expected medical observations. The system achieved an estimated diagnostic relevance score of 88%, indicating that the generated responses were largely consistent with expected clinical

interpretations.

C. RESPONSE GENERATION AND LATENCY

System performance was further evaluated in terms of response time and conversational flow. The complete pipeline, including speech transcription, language model reasoning, and text-to-speech generation, was measured using real-time user queries. Experimental results showed that the average response time of the system was approximately 3.2 seconds per query, allowing near real-time interaction between the user and the AI assistant.

D. User Interaction Evaluation

The system was also tested through interactive demonstrations to evaluate usability and conversational realism. Users were able to submit voice queries describing symptoms such as chest pain, dizziness, or fatigue, and optionally upload medical images for

further analysis. The AI assistant successfully generated context-aware responses in both textual and spoken formats. The integration of voice interaction and visual analysis created a realistic doctor-patient consultation experience within the web-based interface.

Overall, the experimental evaluation demonstrates that the proposed AI-powered medical assistant can effectively process multimodal healthcare inputs and provide meaningful diagnostic suggestions with low latency and high transcription accuracy. The results indicate the potential of the system to support telemedicine applications, medical education, and preliminary patient triage in resource-limited environments.

Component	Metric	Value
Speech Recognition	Accuracy	94%
Medical Image Analysis	Diagnostic Score	88%
Response Generation	Average Latency	3.2 s

CONCLUSION

This paper presents a multimodal AI-driven system designed to simulate a medical consultation using voice input, visual data, and human-like output. By integrating state-of-the-art speech-to-text transcription, medical image analysis via foundation models, and realistic text-to-speech synthesis, the system effectively mimics the behavior of a virtual doctor. The proposed approach offers a seamless pipeline that

transforms spoken patient queries into intelligent diagnostic responses, optionally enhanced through the interpretation of uploaded images like ECGs or scans. Our modular design—consisting of audio transcription, vision-based analysis, and AI-generated dialogue—has proven effective in producing timely, medically relevant, and empathetic responses. With potential applications in telemedicine, health education, and rural diagnostics, this project sets the foundation for more immersive and accessible AI-assisted healthcare platforms. Future work will focus on improving medical accuracy through fine-tuning and expanding multilingual support for broader accessibility.

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DEVELOPMENT OF IOT-BASED SOLAR POWERED INTEGRATED ENVIRONMENTAL MONITORING SYSTEM WITH THRESHOLD WARNING FEATURE FOR SMART CITIES FRAMEWORK

Rajesh Gopinath Department of Civil Engineering BMS institute of Technology & Management Bengaluru, India
dr.rajeshgopinathnair@gmail.com

Nitish K S Department of Electronics and Communication Engineering BMS institute of Technology & Management Bengaluru, India nitishksn24@gmail.com

Sitaram Govindrao Suryawanshi School of Civil Engineering MIT Academy of Engineering Pune, India sgsuryawanshi@mitaoe.ac.in

Sri Srujan Hari T Department of Electronics and Communication Engineering BMS institute of Technology & Management Bengaluru, India
srujanharit.1985@gmail.com

Tarun Patil Department of Electronics and Communication Engineering BMS institute of Technology & Management Bengaluru, India
tarunpatil018@gmail.com

Jojoy Joseph Idicula Department of Civil Engineering BMS institute of Technology & Management Bengaluru, India jojoyji@bmsit.in

Abstract— Real-time advancement in the field of Internet of Things (IoT) has enhanced feasibility for exploring options towards improving performance in the field of environmental monitoring. The present inter-disciplinary research divulges holistic details of a novel integrated IoT system encompassed with environmental-based sensor technologies to monitor prime attributes of climate, criteria air pollutants, and freshwater classification. The study orients about conceptual development, details of in-situ deployment, and resultant effectiveness of the model on field for monitoring diverse environmental parameters. The study encompasses salient features of the logic, rationale and technicalities of both components and system. The study also presents information about the hardware

components, software algorithms and cloud services for promulgating monitoring of essential environmental parameters in real-time. The solar-powered system is envisioned for pollution hotspots and public spaces within urban & peri-urban environs and equipped with threshold-breach warning system. Statistical analysis using ‘Independent samples T-test’ was leveraged to validate the efficiency of prototype. The study herein presents a single integrated monitoring system equipped with real-time alerts, which can serve across diverse geographic locations, to equip better strategies for pollution abatement.

Keywords— Air, Water, Climate, Environment, Quality, IoT.

I. INTRODUCTION

The race for urbanization in the name of development is leading to rise of many unplanned cities, and conversion

of rural and peri-urban areas into urban areas [1]. Subsequently, this has led to severe environmental deterioration bearing advertent and inadvertent ill effects on the climate and ecological balance, consequently impacting all other lifeforms on earth as well [2], [3], [4]. In this regard, a comprehensive monitoring of weather, ambient air and freshwater water quality of any township becomes a critical facet with an efficient effective robust monitoring system [5].

While the traditional methods are effective, they often lack scalability and are not cost efficient [6]. Most importantly, they can often be labour intensive and consume more time [7], [8]. In this context, implementation of sensor technologies can offer a transformational solution which can also serve to supplement the Sustainable Development Goals and complement the infrastructural configuration in the wake of rising demand for smart cities [9], [10]. IoT technology herein offers the possibility of a network of multiple interconnected sensors with features supporting wide transfer of data over the internet through communication protocols such as cellular networks, Wi-Fi, Zigbee, LoRaWAN etc. [11], [12]. The scope of IoT in the modern world thereby becomes multi-fold with real-time precision-based environmental monitoring for a greater geographical expanse [13]. In due course IoT aids in condensed operational costs and reduced human-error, which would otherwise impair effective decision making for remedial measures [14].

A. Literature Review

Several studies have been found to examine IoT-based environmental monitoring systems by highlighting their applications, benefits, and challenges [5]. Literatures have confirmed that sensors are extensively deployed to gather real-time data for understanding existing environmental condition [15]. However, several of these studies were converged upon individual environmental aspects only, for example such as only upon the air quality [16], [17], or any specific parameter of it [18], [19] and so forth for water [20], [21], and climate [22], [23]. This henceforth leads to restricted parametric inclusion, thereby impairing efficiency of regulatory compliance in data-driven policy where synoptic influences are critical [24]. Consequently, this results in the exclusion of facets essential for an ideal ecologically and environmentally smart concept w.r.t. sustainable urban planning, agricultural planning, climate

resilient infrastructure, climate modelling, weather forecasting, disaster management, terrestrial and aquatic ecosystems quality, treatment processes etc. [25], [26], [27].

B. Key Objectives and Scope of Study

The current study while attempting to overcome the gaps observed in literature search focusses upon achieving renewed improvement in public health aspects / awareness. This enables decision-making w.r.t. real-time pollution trend and empowering an immediate response system by equipping proactive measures to

mitigate pollution. The outcome of the present study essentially is a smart integrated system which upon deployment can serve to map environmental parameters spatially and temporally. The system digitally encompasses greenhouse gasses, 'criteria' air pollutants, and essential quality parameters for freshwater classification. These were referred from the Climate Change 2023 Synthesis Report of

I.P.C.C. [28] and from the online repositories (official websites) of Bureau of Indian Standards (B.I.S.) [29] and Central Pollution Control Board (C.P.C.B.) [30], World Health Organization (W.H.O.) [31] respectively. The threshold breach system herewith envisages simplified understanding for both experts and the public, to empower community-level initiatives and environmental policy, whilst planning for improving long-term strategies. The developed model in an urban setting essentially contemplates deviations and trendlines in environmental parameters as a possible influence of industries and automobiles on ambient air, weather, inland waterbodies, and on urban thermal comfort [32], [33], [34]. The decision to formulate an individual system by integrating various environmental variables into a single model also suffices in sustainable e-waste management [35], [36], [37], [38].

II. MATERIALS AND METHODOLOGY

This section offers a comprehensive overview of the systematic approach adopted in research methodology to

design, implement and operate the IoT-based environmental monitoring system.

A. Key Ideation

The selection of environmental attributes and their respective sensors was driven by three-factor theory. Primarily the selection of the most relevant parameters which are representative of environmental quality, followed by the need for depiction in compliance to legislative norms as per the Indian Government, and the necessity for high-resolution exhaustive data that can effectively contribute to policy/decision making [39]. All the environmental parameters and their sensors deployed in conceptualizing and developing the prototype are mentioned further on alongside the rationale and technical specs.

B. Components of the System

Freshwater classification studies in urban areas are essential for varied purposes. These include management of water resources in optimized manner, monitoring of drinking water quality for ensuing public health safety, overseeing of urban flood and stormwater management in an organized manner, better handling of pollution control & wastewater management, support system for life under water thereby facilitating of biodiversity conservation, exploring of eco- friendly recreation & tourism options, for sustainable urban planning & infrastructure development etc. The studies hence

help policymakers, urban planners, and environmentalists to make data-driven decisions for balance in development

and freshwater conservation [27], [40]. Figures 1 to 5 depicts sensors used for monitoring for freshwater classification. Figure 1 depicts a DS18B20 1-Wire Temperature sensor, which can quantify water temperature in the range of -55°C to 125°C with $\pm 0.5^{\circ}\text{C}$ accuracy. Figure 2 depicts a DFRobot Gravity Lab Grade Analog DO sensor, which can quantify the concentration of Dissolved Oxygen [DO] in the water, within the range 0-20 mg/L. Figure 3 depicts a Turbidity sensor, meant for measuring the degree of suspensions in the water for a working range of 0-1000 NTU. Figure 4 depicts an ELECROW Crowtail pH sensor which helps to measure the degree of acidity/alkalinity of fresh water, with alkaline error of 0.2 pH. Figure 5 depicts an Analog TDS sensor. It can measure the total dissolved solids concentrations in water with an accuracy of measurement range of 0-1000 ppm with an accurateness of $\pm 10\%$.

Ambient air quality studies in urban areas are most essential as they serve a variety of facets to ensure sustainable eco-friendly urban development. These include monitoring of public health aspects, compliance with air pollution control norms, mobility planning, enhanced quality of life etc. [41], [42]. Figures 6 to 10 depicts sensors used for ambient air quality monitoring. The relevance of the parameter's selection is in the circumstance that 4 out of 5 ambient air quality parameters being monitored fall under the category of criteria air pollutants [43], [44]. Additionally, noise is being monitored as it is an emerging threat in the urban

scenario [45]. Figure 6 depicts an MQ-7 CO sensor, which can measure carbon monoxide (CO) concentrations in the wide range of 10 to 10,000 ppm. Figure 7 depicts a Fermion MEMS NO₂ gas sensor, which can measure nitrogen dioxide (NO₂) concentrations in the wide range of 0.1-10 ppm. Figure 8 depicts a PMS5003 Dust sensor which can measure particulate matter (SPM 10, RSPM 2.5, RSPM 1.0) concentrations in the ambient air. Equipped with a resolution of 1 $\mu\text{g}/\text{m}^3$, its range of measurement is 0.3-1.0; 1.0-2.5; 2.5-10 μm respectively. The total response time is ≤ 10 seconds.

Figure 9 depicts a DFRobot Gravity factory calibrated Electrochemical SO₂ sensor which can measure Sulphur dioxide (SO₂) gas levels in the range 0-20 ppm within ambient air. Figure 10 depicts an LM393 Sound sensor detection module for Arduino. Herein it detects noise by deciding whether sound has exceeded a threshold value in the immediate vicinity, based on land-use and time of the day [45].



Fig 1. Water Temperature Sensor



Fig 2. DO Sensor



Fig 3. Turbidity Sensor



Fig 4. pH Sensor



Fig 5. TDS Sensor



Fig 6. CO Sensor



Fig 7. NO2 Sensor



Fig 8. Dust Sensor



Fig 9. SO2 Sensor



Fig 10. Sound Sensor

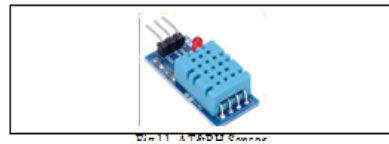


Fig 11. AT&RH Sensor



Fig 12. CO2 Sensor

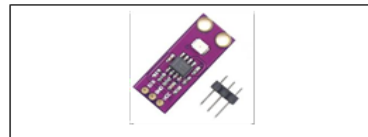


Fig 13. Sunlight UV Ray Intensity Sensor

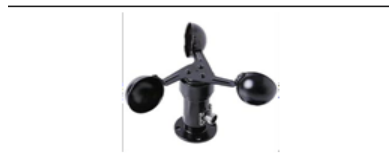


Fig 14. Wind Speed Sensor

With the advent of global warming and climate change, and cities being the epicenter with several causative factors; climate studies become mandatory. The outcome of the studies would invariably help to cope with challenges related to urban heat island effect, urban livability, thermal comfort factor, climate change adaptation, renewable energy planning etc. [46]. By understanding climate patterns, policymakers and urban planners can hence make knowledgeable pronouncements that improve living conditions and reduce environmental impacts [24], [47]. Figures 11 to 14 depicts sensors used for climate monitoring. Figure 11 depicts a DHT11 Air Temperature (AT) and Relative

Humidity (RH) sensor. It measures relative humidity and ambient air temperature, and operates in the humidity range of 20% to 90%, temperature range of 0°C to 50°C, and has a precision of $\pm 1^\circ\text{C}$ and ± 1 . Figure 12 depicts an Mg811 CO₂ sensor, which can sense carbon dioxide (CO₂) in the air for concentration levels between 350 ppm to 10,000 ppm. Figure

Figure 13 depicts a CJMCMU-GUVA-S12SD Sunlight UV Ray Intensity sensor which can detect sunlight intensity in the range 240-370 nm. Figure 14 depicts a Wind Speed sensor current type (4 mA to 20mA) Anemometer capable of measuring wind velocity in the range of 0-30 m/s. Details and specifications of all these deployed sensors have been sourced from the web portal of <https://robu.in> [48].

C. Development of the System and its Logic

Figure 15 in the form of a block diagram illustrates the architecture of the evolved IoT-based comprehensive environmental quality and climate monitoring system. As can be observed, the system consists of multiple sensors. The figure also depicts a microcontroller (ESP32), an analog-to-digital converter (ADC), and various output interfaces. As many of the sensors deployed in the present study produce output as analog signals, ADC was necessary to convert the signals into digital form. This is important, as the microcontroller can only process digital signals. In the current developed system, the ADC hence played a critical role in ensuring precision-based data representation for

digital processing [11], [12]. The details of other hardware components, software algorithms and cloud services are discussed further on.

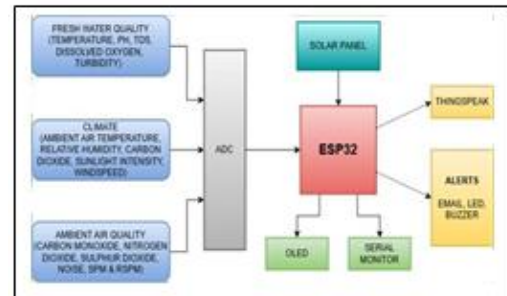


Fig 15. Block Diagram of Proposed System

As the hardware integration is achieved using a universal PCB prototype board, a hypothetical circuit diagram (Figure 16) was also pre-formulated to ensure proper wiring and functionality. All the sensors were interfaced with the ESP-32 microcontroller, which was selected on basis of its integrated Bluetooth and Wi-Fi, low power consumption, dual-core processing capabilities, and sufficient GPIO pins to interface with multiple sensors [11], [12].

As a powerful device, ESP32 can handle data collection and data processing. For the former function, it receives digital data from ADC, which in the present multi-disciplinary research encompasses various environmental parameters obtained from the multiple sensors. For the latter function, it processes the incoming data, checking for abnormalities or threshold exceedances. Sensors usually provide raw data (as voltage or resistance). The ESP32 reads this data viz. its ADC for analog sensors. Libraries such as Adafruit_Sensor (from the Arduino IDE) was used as they simplify the process by facilitating ready-to-use functions for sensor

communication. Libraries within the developed system hence served to handle sensor initialization and support seamless reading of the raw values. For example, when using the Adafruit_PH library, the raw pH sensor value can easily be retrieved from an analog pin [11], [12].

In the current model, ESP32 was powered by a solar panel, and by doing so the system has demonstrated that it is self-sufficient by running on renewable energy and thereby exhibiting the capability to operate in remote or off-grid locations. The application enabled provision of power to charge the battery viz. the TP4056 module, with a Rocker switch, i.e. a single-pole single-throw switch to control power flow [11], [12].

Overall, this facet highlights the research and system's inclination towards eco-friendliness and sustainability, by decreasing its reliance on conventional electrical energy power sources. As can also be observed from figure 16, GND connects the ground pins of ESP32 and sensors; and VCC connects the positive power pins of sensors, LED, to the 3V3 pin of ESP32 through a Rocker Switch and a 4700-ohm resistor. The details of power management is presented in

Power Management		
Solar Panel	+ to TP4056 pin IN+	- to TP4056 pin IN-
TP4056 (Battery Charging Module)	+ to 18650 Li-ion Battery x 2 pin + OUT+ to Rocker Switch pin 1	- to 18650 Li-ion Battery x 2 pin - to the common ground
18650 Li-ion Battery x 2	+ to TP4056 pin B+	- to TP4056 pin B-

Table1. TABLE I: NETWORK CONSIDERATIONS PARAMETER CONSIDERATIONS

Power Management

Solar Panel + to TP4056 pin IN+ - to TP4056 pin IN-

TP4056

(Battery Charging Module) B+ to 18650 Li-ion Battery x 2 pin + B- to 18650 Li-ion Battery x 2 pin -

OUT+ to Rocker Switch pin 1

OUT- to the common ground

18650 Li-ion Battery

x 2 + to TP4056 pin B+ - to TP4056 pin B-

Further, all the sensors (specific to air and climate studies) were subjected to calibration [49]. Sensors (specific to studying freshwater quality) were calibrated according to the procedures of “Standards Methods” prescribed by APHA- AWWA-WEF [50]. Calibration is of utmost importance as data accuracy remains a critical facet, as inaccuracies can lead to incorrect assessments. Apart from physical calibration, the sensors also required conversion of raw data into meaningful measurements. Libraries such as MG811 in CO2 sensors automatically include functions that apply calibration constants automatically, thereby adjusting the raw data to accurate values based on known sensor characteristics [11], [12].

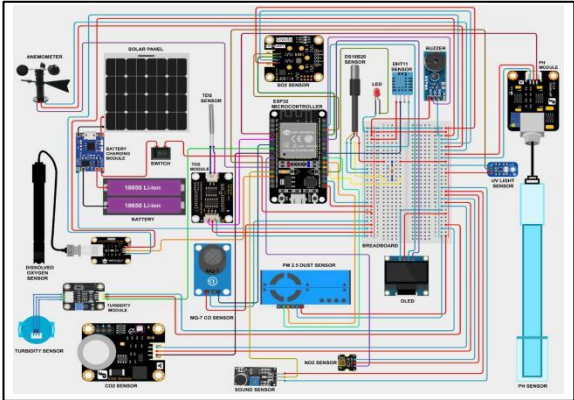


Fig. 16 Circuit Diagram of Proposed System

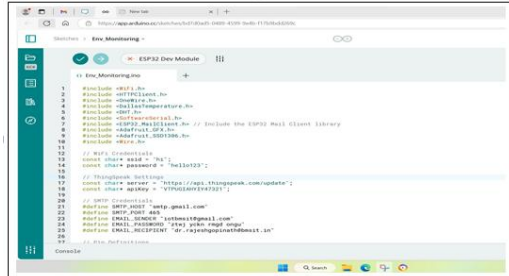


Fig 17. Uploading and testing of code in Arduino IDE

“Development Environment platform” Arduino IDE

1.8.16 (www.arduino.cc) [51] was used to code the microcontroller for data acquisition and its transmission, with “Embedded C” as the programming language. The serial monitor as showcased in figure 17, served to assist in de- bugging, testing concepts and sending command to control the program. Thereby it allowed users to communicate viz. serial ports. To satisfy the variable requisites, the resultant output (processed data) of the system was deliberated upon with multiple output interfaces. Arduino IDE “Serial Monitor” facilitated the real-time feed of the data and system messages onto a remotely connected computer.

ThingSpeak, a cloud-based IoT analytics platform (<https://thingspeak.com>) [52] was deployed for data storage, analysis, and visualization. The process concludes with the end of the data collection cycle, after which the system can either enter a standby mode or continue

monitoring, for the next cycle. This continuous loop ensures that the system could monitor environmental parameters spontaneously and respond promptly to any changes in real-time. Further the processed numeric data is presented visually to stakeholders in the form of simple charts, to engage easy understanding. This setup also ensures that the sensor data can be remotely accessed and observed for effective monitoring of environmental conditions briefly through the designated web interface.

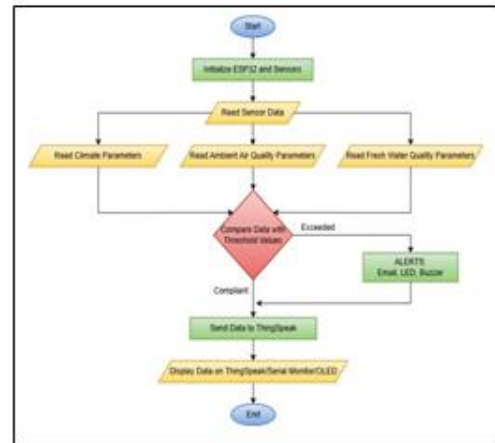


Fig 18. Logic-based workflow of the proposed system.

In addition to sending data to cloud, the integrated system also has a 0.96" OLED screen which facilitates real-time in- situ alpha-numeric information display for locally-based users (on-site task force/public). This system also promotes an automated warning system, i.e. triggering alerts / notifications to caution appropriate stakeholders. This was accomplished viz. high tone alarms and viz. repeated LED blinking wherein the immediate vicinity stakeholders could be alerted. The third mechanism was viz. ESP32

sending email to designate recipients/users, hence thereby notifying even remotely located decision makers. A stable Wi-Fi connection ensures the alerts are sent on time. The trigger happens whenever the parametric variable level exceeds the pre-defined statutory thresholds (safe limits) as per the laws of the Indian Government [53], and statutory norms of European Union [54], American Society of Heating, Refrigerating and Air- conditioning Engineers [55], Bureau of Indian Standards [29],

and World Health Organization [31]. This feature is crucial for remote monitoring and for equipping corrective and remedial measures in the event of quick environmental changes. Figure 18 depicts the afore-discussed logic-based workflow of the system.

D. Implementation of the System

To determine the accuracy and efficiency of the prototype for all aforementioned parameters, following measures were in place. Firstly, both the conventional/traditional and developed prototype, were simultaneously deployed to monitor water quality variables in laboratory-based studies under controlled indoor-environmental conditions (figure 19) and at a lake (figure 20). While water quality of lake was analyzed on-site, the off-site studies in the laboratory included grab sampled water sourced from a residential bore-well, rooftop harvested rain water, municipal tap water and synthesized test sample.



Fig 19. Lab-based set-up studies.



Fig 20. Studies for Lentic Water Ecosystem.



Fig 21. Studies in (outdoor) Parking Lot.



Fig 22. Studies at Green Campus.



Fig 23. Studies at Arterial Road.

Further both traditional/conventional apparatus and the developed prototype, were simultaneously deployed for continuous ambient air quality and climate studies in distinct outdoor environment for 10 hours with monitoring interval of 30 minutes. The outdoor locations included a parking space with high vehicular variable density (figure 21) and a green campus with rich canopy (figure 22). The observations have been presented under results and discussion section.

The ulterior objective was also to understand if there was a significant deviation in the inherent performance of the prototype from the conventional means. This was achieved with statistical analysis by means of Two-Sample T-test. Popularly also referred to as ‘Independent samples T-test’, the method is basically used to compare the means of any two independent groups. In the context of the present research, it encompasses the parameters monitored by both the conventional methods and developed prototype.

The tool herein assumes a normal distribution for data, and essentially computes a statistic ‘p’ value. Herein, a statistically significant p-value (typically < 0.05) indicates that there is a significant difference between the parameters monitored by both the conventional methods and developed prototype [56].

For the present research, the hypothesis were framed as follows:

- i. Null Hypothesis (H_0): There is no significant difference in the performance of the two systems (conventional method and developed prototype) with respect to any parameter.
- ii. Alternate Hypothesis (H_a): There is a significant difference in the performance of the two systems (conventional method and developed prototype) with respect to any parameter.

The resultant deviation aspects are as well discussed in the results and discussion section. Finally, upon validation, the prototype was deployed at an arterial road with moderate traffic volume as part of its trail run (figure 23). The resultant outcome is also depicted under results and discussion section.

III. RESULTS AND DISCUSSION
Statistical analysis of data is essential for extracting meaningful insights, detecting patterns, and helping to make informed decisions, before implementation of the model in real-time for data acquisition to address the capabilities of the developed prototype. In this context, the first set of validations were obtained by checking simultaneous data and their mean, for both conventional and developed prototype.

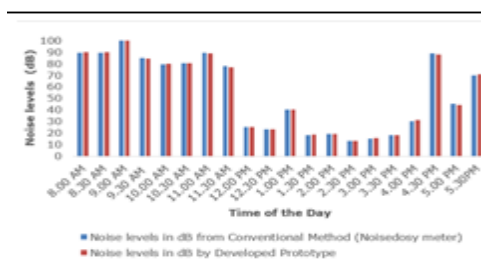


Fig 24. Noise variation levels as observed from both conventional and developed prototype.

Showcased as a sample, figure 24 clearly depicts that there is no major variation among the observations and trend alike, in the context of real-time ambient noise levels. Similar observations was drawn for all other air-related parameters. This was also comprehended from Table 2 which depicts the results of Two-Sample T-test for noise and other air parameters. As can be observed from Table 2, since the p- value is greater than 0.05, therefore the Null Hypothesis may not be rejected at 5% level of significance. Thus, it can be concluded that there is no significant difference in the monitoring performance of both the conventional and developed prototype) with respect to the Noise parameter. Similarly, it was found that the p-values for the other parameters of Air quality also lie between 0.9661 and 1. Hence as these are clearly greater than 0.05, therefore the Null Hypothesis may not be rejected at 5% level of significance.

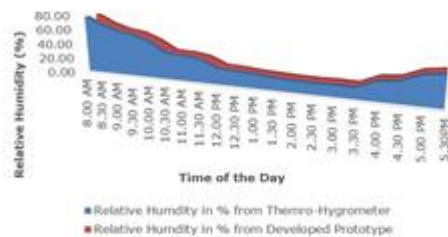


Fig 25. Relative Humidity variation levels as observed from both conventional and developed prototype.

TABLE II: RESULTS OF THE TWO-SAMPLE T-TEST FOR NOISE MEASUREMENT.

Attribute	Noise levels in dB from Conventional Method (Noisedosy meter)	Noise levels in dB by Developed Prototype
Mean	54.7900	54.8400
Variance	1047.0220	1035.3015
Observations	20.0000	20.0000
Pooled Variance	1041.1617	
Hypothesized Mean Difference	0.0000	
df	38.0000	
t Stat	-0.0049	
P(T<=t) one-tail	0.4981	
t Critical one-tail	1.6860	
P(T<=t) two-tail	0.9961	
t Critical two-tail	2.0244	

Attribute Noise levels in dB from Conventional Method (Noisedosy meter) Noise levels in dB by Developed Prototype

Mean 54.7900 54.8400

Variance 1047.0220 1035.3015

Observations 20.0000 20.0000

Pooled Variance 1041.1617

Hypothesized Mean Difference 0.0000

df 38.0000

t Stat -0.0049

P(T<=t) one-tail 0.4981

t Critical one-tail 1.6860

P(T<=t) two-tail 0.9961

t Critical two-tail 2.0244

Similarly showcased as a sample in figure 25, there is no major variation among the observations and trend alike, in the context of real-time relative humidity levels. Similar observations was drawn for all other climatic parameters. This was also comprehended from Table 3 which depicts the results of Two-Sample T-test for relative humidity and other climate parameters. As can be observed from Table 3, since the p-value is

greater than 0.05, therefore the Null Hypothesis may not be rejected at 5% level of significance. Thus, it can be concluded that there is no significant difference in the monitoring performance of both the conventional and developed prototype) with respect to the relative humidity monitoring. Similarly, it was found that the p-values for the other parameters of Air quality also lie between 0.9110 and 0.9993. Hence as these are clearly greater than 0.05, therefore the Null Hypothesis may not be rejected at 5% level of significance.

Attribute	Noise levels in dB from Conventional Method (Noisedoymeter)	Noise levels in dB by Developed Prototype
Mean	32.8777	32.8690
Variance	363.4566	365.6235
Observations	20.0000	20.0000
Pooled Variance	364.5401	
Hypothesized Mean Difference	0.0000	
df	38.0000	
t Stat	0.0014	
P(T<=t) one-tail	0.4994	
t Critical one-tail	1.6860	
P(T<=t) two-tail	0.9989	
t Critical two-tail	2.0244	

TABLE III: RESULTS OF THE TWO-SAMPLE T-TEST FOR NOISE MEASUREMENT.

As can be observed from Figure 26, all the p-value for parameters of water lie within 0.6131-0.9774. As these resultant 'p' values are greater than 0.05, therefore the Null Hypothesis may not be rejected at 5% level of significance. Thus, it can be concluded that there is no significant difference in the monitoring performance of both the conventional and developed prototype) with respect to the water quality.

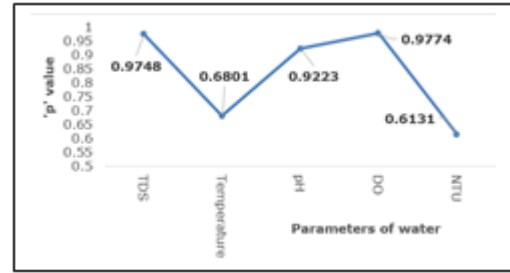


Fig 26. p-values for all water related parameters

With the statistical validation of the measurements proved, the results of deployment for trial run is discussed further. As can be observed from figure 27 and 28, the verifiable real-time primary data from the monitoring was accessible in the form of alpha-numeric based and chart- based respectively viz. Serial monitor of ThingSpeak. The cloud-based service allowed seamless remote monitoring, storage, and graphical representation of trends and anomalies. By implementing robust algorithms, the model was also trained upon to validate regulatory compliance. Showcased as a sample representation, figure 29 clearly depicts the off-site (figure 29a) and on-site (figure 29b) pictorial Air Quality Index based on logical computation [44], [54] from the real-time ambient air quality data. Similar provisions were also in place for depiction of logic- based Fresh Water Classification [30] and Human Thermal Comfort [34], [55].

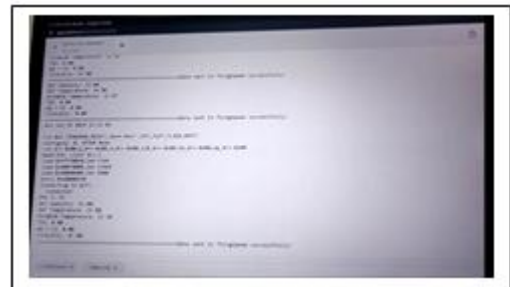


Fig 27. Real-time observation as numeric based in Serial Monitor.

As can be observed from figure 30, the violations as per statutory norms were also remotely communicated in the form of email notifications. On-site it was observed viz. alarm buzzing and blinking of LED. Hence, the integrated AI in the form of ‘live’ serial monitoring and cloud-based analytics has significantly enhanced the performance and precision accuracy of the system thereby demonstrating the practical feasibility.

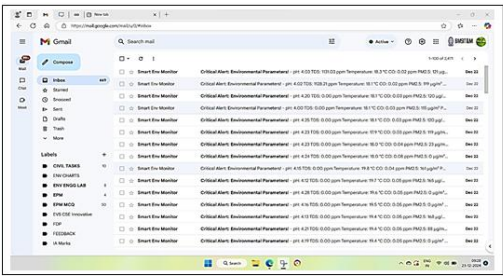


Fig 30. Real-time alerts (notifications) to designated Email ID

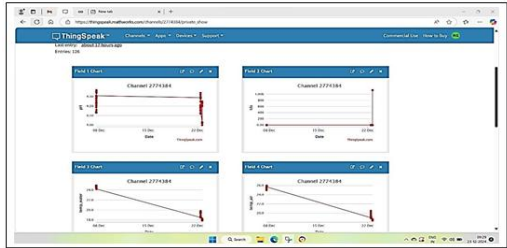


Fig 28. Real-time visualization as charts in ThingSpeak.



Fig 29(a). Resultant representation off-site



Fig 29(b). Resultant representation on-site

A. System Benevolence

The study hence shows that the system is compatible for integration with dashboards by inter-linking and networking the deployed multi-sensor system to official govt. based environmental monitoring platforms. The product can also be easily perceived for customized specific industrial environmental monitoring such as for EMS compliance. The system’s benevolence (as per the existing framework) not only serves to facilitate the detection of point-source pollution sources, but when imbibed with deep learning could also aid in determining non-point sources. Integrated Sensors with AI potential allows for predictive analysis for smarter environmental management. The current research also postulates that future studies can explore logistical and financial barriers pertaining to data security and the interoperability of devices in the resource-constrained regions. It may hence be inferred that the developed prototype can empower potential stakeholders to enforce timely actions to protect public health by monitoring environmental quality round the clock.

IV. CONCLUSIONS

The present study divulges details of

the developed integrated system that can serve to monitor and manage environmental quality. Unlike conventional systems, the system is trained to simultaneously monitor multiple attributes of air, water, and climate conditions, thereby providing a holistic environmental assessment in the form of Air Quality Index, Fresh Water Classification and Thermal Comfort. By leveraging the ESP32 microcontroller, pre-selected sensors and solar panel, the developed system is sustainable and efficient. Statistical analysis has also served to decipher validation in terms of reliability. As it was found that the p-values for all measured/monitored parameters were found to be greater than 0.05, therefore the Null Hypothesis may not be rejected at 5% level of significance. The IoT-enabled remote monitoring product is also equipped with different modes of on-site and off-site real-time early warning system, and thereby capable of providing valuable insights into environmental conditions. Data security is complied with automatic uploading to ThingSpeak, thereby enabling cloud storage and remote access. The final outlook is hence an advanced, efficient, real-time, and sustainable solution for comprehensive environmental monitoring with scalability.

V. FUTURE SCOPE OF WORK

The model finds application with all probable end-users and beneficiaries such as environmental agencies, industries, urban planners, scientists, public and public health departments. The vast primary environmental data collected can be of extensive use for

researchers to perceive vital insight upon trends and contemplate critical areas which would require immediate intervention.

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VIII. AUTHOR CONTRIBUTIONS

The study is multi-inter-disciplinary and the following are the contributions by each author. Dr Rajesh Gopinath and Mr Sitaram Govindrao Suryawanshi have conceptualized the study and framed the entire work-flow logic. Dr Rajesh Gopinath has also drafted, reviewed the manuscript and is the corresponding author. Dr Jojoy Joseph Idicula has undertaken the detailed statistical analysis for validation studies. The students (Nitish KS, Sri Srujan Hari T, Tarun Patil) have diligently accomplished conceptualization, fabrication, implementation, and testing across the various phases of the study at varied locations.

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AN EXPLAINABLE HYBRID DEEP LEARNING AND GRADIENT BOOSTING FRAMEWORK FOR AD CLICK FRAUD DETECTION

1Salma Banu S, 2Dr Jagadeesha R

1,2Department of computer science and engineering (CSE) Impact college of engineering and applied sciences, Karnataka, India

1banus6422@gmail.com , 2Jagdish.mtech@gmail.com

Abstract— Regrettably, one of the biggest issues of the digital advertising world is click fraud. It is very expensive and renders online marketing statistics less dependable. Old methods of detection of fraud do not always detect new fraud patterns and sophisticated user actions. In this research Ad Click Fraud Detection Dataset on Kaggle is utilized. It has records on the way the users reacted to both real and fabricated ad hits. In the preprocessing stage, the unnecessary characteristics were discarded and class imbalance was corrected with the help of RUS and SMOTE. This was in order to ensure the quality of data and impartiality. Some of the ML and DL models that were developed and experimented with include CNN, DNN, RNN, LR, DT, RF, KNN, ANN, Gradient Boosting, LightGBM, XGBoost, NB and SVM. In order to make the predictions even more accurate, we employed LSTM, GRU, LSTM +GRU, and a Voting Classifier (XGBoost with Bagging DT). XAI (LIME and SHAP) was also used by us to simplify the results. The application of the learned models was also developed into a Flask-based web interface to predict ad click fraud in real time. Due to tests, the Voting Classifier achieved 100% accuracy,

precision, recall, and F1-score, which is powerful and can be used as an effective method of detecting fake ad clicks.

“Keywords— Click fraud, machine learning, deep learning, online-advertising, bot detection, pay-per click, fraud”.

I. INTRODUCTION

The online advertisement is a significant aspect of business marketing in the contemporary digital economy, as it enables enterprises to access the right individuals both on the computer and phones. Current systems of online marketing are founded on the PPC model where the advertisers pay each time a person clicks on one of their ads [1]. The more companies invest in digital advertisements, the more they will rely on user click statistics to determine the success of their campaign and the amount of money they are earning back. However, such reliance has also created massive security gaps particularly regarding click scam where the PPC systems are deceived to generate money [2].

One of the major issues that affect the digital advertising business is click fraud, a process where an individual clicks an advertisement without their authorization or with ill motives [3]. Such activities are normally performed

by software robots, farm of clicks, or rivalry, which results in deformed interaction metrics and wasted cash [4]. The common methods of identifying fraud can be heuristic or statistical techniques and they cannot always catch up with the emerging forms of fraud [5]. VPNs, proxy servers, and distributed botnets allow fraudsters to conceal their names, posing as actual users, thus complicating the process of catching them [6]. Consequently, the gap in the research on designing models capable of altering and being cognized to discern faked clicks in a changing real world context continues to exist significantly [7].

The paper proposes an intelligent analytical approach to detecting ad click fraud with the help of user interaction with advertising data. This is aimed at making sure that legal and illegal activities are rightly differentiated and that the system can be understood and used in real time [8]. The proposed model is expected to produce a scalable, transparent, and data-driven detection system due to the employment of behavioural characteristics and contact patterns. XAI is another feature added to make things more understandable and make the prediction made by the model more understandable and appealing to the marketer [9].

Eradication of fraud and safeguarding advertisers funds, promotion of healthy competition are some of the things that this research contributes to the improvement of online advertisement. Ultimately, it establishes trust, reliability and sustainability in online

marketing space [10].

II. RELATED WORK

Over the last several years, much research was conducted on the methods of ML and AI to identify fake clicks on online advertisements. Shaik and Kakulapati [11] developed a feature based ML strategy of detecting fake ad clicks, demonstrating that trained models have the capability to classify user click behavior accurately. Their study was however limited by a small data and failure to keep up with changing fraud trends. The traditional classifiers were also employed to detect click fraud online by Aljabri and Mohammad [12], as data-based approaches are superior to rule-based ones. Although they achieved some good results, their work was more about accuracy than being able to be interpreted and scaled right away which are significant in the application in the real world in advertising networks.

Sisodia and Sisodia [13] developed a generalization stack architect on predicting publisher behavior where the datasets are highly skewed. The trick behind this framework was to use more than one base learner in order to achieve better classification. Nevertheless, the algorithm consumed a significant amount of computational resources and it was not clear what features were most significant. This work was extended by Sisodia, Sisodia, and Singh [14], who focused on the significance of important features in the process of bad publisher identification and highlighted the usefulness of feature selection in fraud detection. Instead, their research merely examined fixed data sets and did not examine

how to counter click fraud mechanisms that always evolve. Alzahrani and Aljabri [15] have conducted an entire research on the AI- based approaches to detecting ad click fraud. They highlighted XAI and ensemble learning as the fields that require further research in the future. They found in their review that they were in a recurring issue on balancing between producing very accurate models and models that are easy to understand and apply to real-life applications.

The scam detection systems have become more powerful with the help of DL techniques. In PPC campaigns, Batool

and Byun [16] proposed an ensemble DL system to locate click frauds. This architecture was closer to the truth and it was less susceptible to being misled by malevolent user actions, however it was harder to execute in real time since it had so many complications. Sisodia and Sisodia [17] developed a model based on K-nearest neighbor using quad divide prototype selection to recognize an uneven dataset. The model minimizes the computational burnt out yet sensitive to noises and fraud tendencies that are not apparent. Similarly, Chari et al. [18] considered several ML algorithms applying behavioural and feature engineering methods. They achieved good results and when using large datasets problems of scalability and overfitting occurred. Also besides the work of ads research, large studies of fraud detection have provided us with valuable information. Dekou et al. [19] considered ML approaches to identifying fraud in

online marketplaces, with the domain adaptation and generalizability to discover the various forms of fraud in platforms. Also Sisodia and Sisodia [20] applied gradient boosting to identify fake publishers, but this was more precise compared to the conventional classifiers but had issues with timing data and interpretation of the model.

III. MATERIALS AND METHODS

The idea behind the proposed system is to generate a scalable, intelligent system of detecting fake ad clicks that is intelligible and precise. The approach involves pre-processing the Ad Click Fraud Detection Dataset on Kaggle that contains annotated records of user interaction and feature optimization, feature encoding, and normalization to ensure the quality of inputs to be used to train the model. Data mismatch is corrected with the help of RUS and SMOTE to produce more general results. Several various ML and DL models are applied, and to perform the predictions even more precise, ensemble learning is applied with a Voting Classifier that includes XGBoost, Bagging, and DT. The advanced designs of LSTM, GRU and hybrid LSTM +GRU networks are applied to understand the changes in user behavior over time. XAI techniques such as LIME and SHAP are also designed to enable the model to be more understandable and a Flask-based deployment interface allows fraud to be detected in real time. This comprehensive approach ensures that this ad click fraud detection is more scalable, reliable, and powerful.

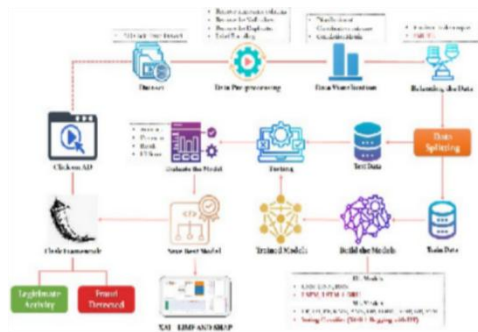


Fig. 1. System Architecture

Figure 1 demonstrates the system design, which indicates a full workflow of the ad click fraud work finding. The first step is to obtain the AD Click Fraud data. Secondly is data pre-processing which involves cleaning, removal of nulls, removal of duplicates and label encoding. Correlation visualization and analysis of data help us understand the trends, and the use of such techniques as SMOTE ensures the even distribution of the data. The data has been divided into a train and test set. A model is built then by using ML and DL. Plain models are tested, graded with metrics, saved, and deployed with the use of Flask. This allows XAI to describe real-time fraud with LIME and SHAP.

A) Dataset Collection

The data set of the present research is the Ad Click Fraud Detection Dataset of the Kaggle webpage. This data consists of 5,000 entries of user interaction obtained in various forms of online ads. The dataset contains 21 features as well as categorical, numerical, and time-related, such as device type, browser, duration of clicking, and behavioral indicators. The is fraudulent column decides whether it is true or false. This data includes diverse realistic user actions and a skewed class distribution that reflects the occurrence of fraud in the real

world. It is a highly diverse and versatile model of user- machine interactions and time series, and thus can be used to test sophisticated ML and DL models to detect counterfeit ad clicks.

	device_type	browser	operating_system	click_duration	scroll_depth	mouse_movement	key strokes_detected
0	Desktop	Safari	Android	0.75	60	171	8
1	Desktop	Opera	iOS	0.61	25	152	20
2	Desktop	Safari	Linux	0.42	16	131	16
3	Desktop	Edge	macOs	4.25	29	112	81
4	Desktop	Opera	Windows	2.75	94	98	2

Fig. 2. Ad Click Fraud Dataset

B) Pre-Processing

In the data preparation phase, cleaning, encoding, balancing, correlation analysis and split are some of the steps that are undertaken in a planned manner to ensure the data quality and model reliability is upheld. This would enable proper and equitable training of the fraud detector model.

Data Cleaning: The step entailed identifying and eliminating values of null and duplications of records in a preconceived manner in order to ensure that the data was complete and reliable. Through this process, the only valid and unique data instances were retained to study. Pre- treatment of the data enhances the quality of the overall data, reduces the likelihood of spurious trends, and prevents potential weaknesses in learning the model. The step maintains the purity of the data, on which the preprocessing will be reliable and the evaluation of the models will be accurate.

Categorical Data Encoding: Categorical features which symbolized written or qualitative data were converted to numbers in order to simplify training a ML model. It is a conversion that ensures that programs can be able to correctly interpret and consume

categorical variables without being biased by non-numeric data. Encoding allows the encoding of various attributes into one space of features. This not only makes the process of computation quicker, but also assists models to discover valuable patterns across nominal dimensions of the data. Class Balancing (Random Under-Sampling): Random Under-Sampling was employed in order to correct the issue

of a discrepancy in class between real and fake clicks. This approach equalizes the number of the majority with the minority class, resulting in no bias of the models to strong categories. The balance of the information ensures equal learning of both classes, and increases the predictability and stability of the predictions. It is quite a significant contribution to more accurate, recallable, and generalizable scam detection models particularly when skewed real-world data is involved.

Feature Correlation Analysis: To examine the relationship between the numerical aspect of each other, the use of feature correlation analysis was directed at identifying

and provides the correct measures of feature importance to be easily interpreted [27].

$$Gini = 1 - \sum_{i=1}^C (P_i)^2 \quad (3)$$

KNN is an algorithm which classifies instances into sets with the majority class of the most similar instances in the feature space. It is able to manage complex data distributions; detect

minute variations in the behavior of fraud patterns because it learns in a distance and achieves this [21].

$$distance(x, X) = \sqrt{\sum_{j=1}^d (x_j - X_{i,j})^2} \quad (4)$$

the potential of a multicollinearity. The step can assist in determining the most significant variables to the prediction job and the dependencies between features. By extracting the patterns of correlation, the traits that are not necessary or correlated strongly will be eliminated and this will result in a simplified model that is easier to comprehend. Such analysis enhances the reliability of the model, reduces the chances of overfitting, and ensures that the most practical attributes are brought out in the course of training.

C) Training and Testing

In order to simplify the process of testing and checking the model, the balanced dataset had been divided into training and testing groups. Much attention was paid to the testing set that allowed observing the extent to which the model learned using the training set and was applied to new data. Their separation in this manner prevents overfitting, and also ensures that the evaluation measures are a proper

ANN has multiple layers of neurons which are connected and learns nonlinear features relations through weights optimization. Since it has the ability to represent complex relationships and extract the latent representations, it is more precise in classification and useful in massive, divergent datasets.

$$y = \sigma \quad wL \cdot aL-1 + bL \quad (5)$$

Naïve Bayes assuming that traits are conditionally independent, is a probabilistic classifier founded on the Bayes theorem. It is very easy, however, and can scale well to a large amount of data, classifying quickly, in scale, and reliably, as well as with reasonable baseline performance [23].

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad (6)$$

representation of the ability of the model to predict the real world. This will ensure that the trial results maintain the validity because it will maintain the right train-test ratio and also it will enable the fair comparisons of the various detection models.

D) Algorithms

LR is a simplified and binary classification that employs a logistic equation to estimate the possibility of various events. It can compute fast and be easily comprehended as well as be statistically sound. These properties render it applicable to benchmarking and determining how features influence the scam detection activities [22].

Gradient Boosting makes a good student out of the weak models one after another that correct their errors, which the preceding models made. This monotonic accuracy enhancement identifies the complex feature interactions, enhances the generalization and reduces overfitting through controlled learning updates [25].

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x) \quad (7)$$

LightGBM executes gradient boosting in a manner that is very fast and effortless and was created to be scaled.

It processes large datasets in a short period of time and precisely

$$\hat{y}_i = \sigma(w^T x + b) = \frac{1}{1 + e^{-(w^T x + b)}} \quad (1)$$

and minimizes training time and leaf-wise tree development and histogram computation.

XGBoost is a graded boosting algorithm that employs

DT is a checked learning strategy that divides the figures more than once and more with respect to the feature values to create comprehensible decision rules. The way it is assembled is obvious, which is why it is not difficult to examine decision paths and the most significant characteristics. This assists in classification which does make sense in both numeric and qualitative properties [24].

$$I(\hat{d}) = 1 - \sum_{i=1}^k p_i^2 \quad (2)$$

regularization, parallel processing, and shrinkage to ensure that it is faster. It is very effective with large classification tasks as it is powerful, can be scaled and it can make more accurate predictions [28].

SVM optimize the hyperplane which maximizes the margins between the classes. It is effective with nonlinear boundaries and it generalizes well through the use of kernel functions. This is suitable in cases of binary classification tasks that have few or skewed data.

n

RF is a majority voting based ensemble learning algorithm which employs a combination of multiple DT to make predictions more stable. It prevents

overfitting of the model, manages noises, and identifies nonlinear associations

$$\underset{W}{\text{minimize}} \frac{1}{2} \|W\|^2 + c \sum_{i=1}^n \xi_i \quad (8)$$

CNN automatically extracts hierarchical and spatial information of structured data by convolution and pooling layers. It can learn powerful representations, which increase the reliability of classification, reduces sensitivity to noise, and improves the performance of anomaly detection [29].

$$S(i, j) = \sum_m \sum_n I(i + m, j + n) \cdot K(m, n) \quad (9)$$

DNN introduces additional layers to ANN designs in order to be able to learn higher-order feature abstractions. It is capable of representing complex relationships with a high degree of accuracy because of its deep hierarchical representations. This improves the precision of predictions and generalization with large sets of data.

RNN permits the establishment of feedback loops which allow you to learn both sequential and temporal data. It is good at modelling dynamic trends and better predicting behavior in time dependent tasks in behaviour analysis by maintaining contextual information over time steps.

LSTM is a state-of-the-art form of RNN which employs memory cells and gating mechanisms to solve vanishing gradient problems. It is effective in long-term time series relations, thus, making sequential and time-series prediction tasks more predictable and precise to forecast their outcomes [26].

$$h_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \cdot \tanh(C_t) \quad (10)$$

GRU is a revised recurrent design which regulates the passage of time information using update and reset gates. It offers a good tradeoff between learning and working and has higher convergence speed and successful sequence modeling with reduced computational complexity.

The hybrid LSTM–GRU The model has long-term memory retention and speed of computation. It considers both the short-term and long-term time correlations through the basis of complementary gating mechanisms. This results in increased performance of sequence learning and improved generalization.

The Voting Classifier combines XGBoost and Bagging using DT to exploit the best of the two. It reduces bias and randomness in the form of majority vote, which provides consistent, reliable, and overarching fraud detection capabilities.

enhances confidence and responsibility in the results of models.

The Flask framework is also used to do real-time deployment and create an interactive web interface that allows adding new data and provides the results of fraud detection immediately, as well as explanations provided by XAI. The system is applicable in real life experiences, where online advertising keeps on varying due to this combination which makes it scalable, transparent, and readily accessible.

IV. EXPERIMENTAL RESULTS

Accuracy: The degree to which a test can distinguish between unwell and healthy individuals is referred to as its

accuracy. In order to obtain an idea of the accuracy of a test we want to determine the percentage of cases which are true positives and true negatives. Mathematically this can be expressed as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (12)$$

Precision: Precision is the ratio of the number of cases or samples correctly classified to that which were correctly classified as positives. The way to determine the precision is, then, the following:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (13)$$

Recall: Recall, which is a measure used in ML, is the ability of a model to locate all the important examples of a particular class. It demonstrates the degree to which a model represents the example of a particular class. It is estimated by dividing the correct predictions of positive observations with the real positives.

$$Recall = \frac{TP}{TP + FN} \quad (14)$$

F1-Score: F1 score is a method of quantifying the accuracy of a ML solution. It sums the accuracy and recalls scores of a model. The accuracy measure gives the number of times, in the entire dataset, a model made a correct guess.

$$F1\ Score = 2 * Recall * Precision * 100 \quad (15)$$

Recall + Precision

ML Model	Accuracy	Precision	Recall	F1-Score
CNN	0.9839	0.9837	0.9846	0.9839
DNN	0.9799	0.9797	0.9805	0.9799
RNN	0.9678	0.9685	0.9691	0.9678
Logistic Regression	0.9738	0.9741	0.9749	0.9738
DT	0.9638	0.9637	0.9637	0.9637
RF	0.6781	0.6875	0.6821	0.6766
KNN	0.5272	0.5269	0.5269	0.5268

ANN	0.9336	0.9335	0.9342	0.9336
Gradient Boosting	0.8632	0.8889	0.8687	0.8619
LightGBM	0.9598	0.9612	0.9614	0.9598
XGBoost	0.8652	0.8902	0.8707	0.8640
NB	0.9718	0.9722	0.9730	0.9718
SVM	0.4809	0.4877	0.4900	0.4603
LSTM	0.9953	0.9952	0.9955	0.9953

Table. 1. Performance Evaluation

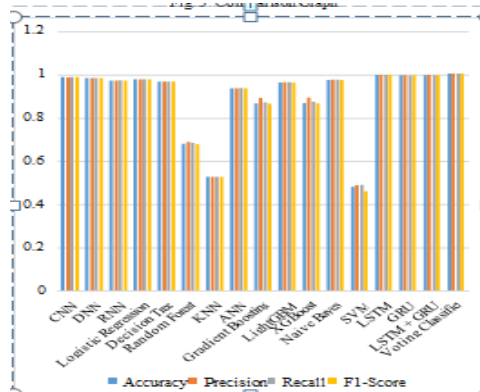
$$\hat{y} = \underset{c}{\operatorname{argmax}} \left(\sum_{i=1}^n I_{\hat{y}_i = c} \right) \quad (11)$$

E) Integration of XAI and Flask Framework

The ad click fraud detection system can be explained with the added Explainable XAI techniques such as LIME and SHAP, which allows one to see the model predictions in a clearer way. Using waterfall chart, LIME allows providing local explanations of the influence of various features on certain predictions. SHAP on the other hand provides a global perspective as it demonstrates the significance of features to both fraudulent and legal classes. These approaches combined assist users and analysts in understanding the reasoning behind decision making which

Table.1 compares the performance of models with the accuracy, precision, recall, and the F1-score. It demonstrates that the Voting Classifier achieved the highest scores, being more successful than any other ML and DL models.

Fig. 3. Comparison Graph



As the Fig.3 comparison graph shows, the Voting Classifier is superior to all of them in accuracy, precision, recall and F1-score. The LSTM and LSTM + GRU structures rank second and third respectively.



Fig.4 Click on Ad

Fig.4 has the input interface with a live fraud detection demo that allows users to select and test various real-time fraud detection applications.

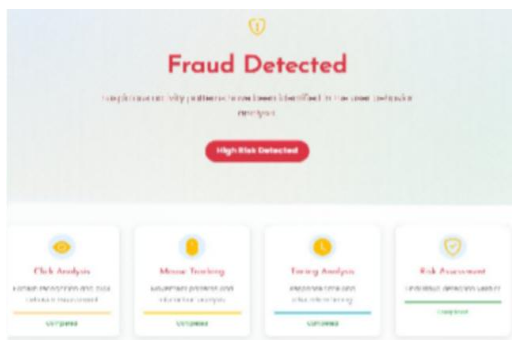


Fig.5 Predicted Result

Figure 5 provides the forecast output in the form of "Fraud Detected" indicating that behavior analysis identified high risk suspicious activity.

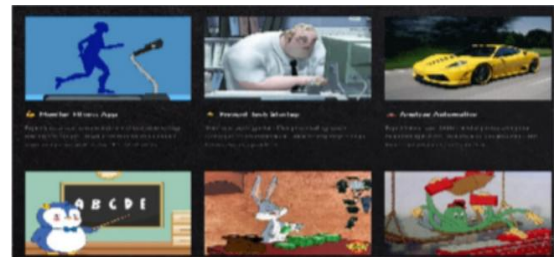


Fig.6 Click on Ad

Figure 6 demonstrates the input screen that allows the user to select among the various fraud detection tools that include fitness, tech startups, and automotive analysis.

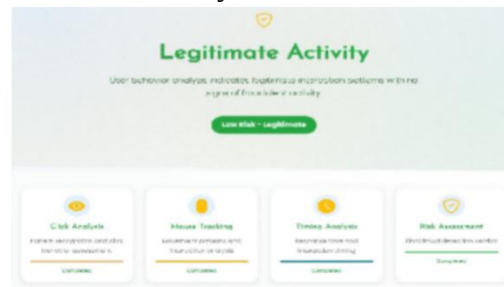


Fig.7 Predicted Result

Legitimate Activity is the result of the prediction that appears on the output interface of Fig.7. This implies that the individual is behaving normally and no indications of fraud.

V. CONCLUSION

Ultimately, this paper aimed to apply advanced DL and ML techniques to develop an intelligent and trustworthy platform to detect ad click fraud in online advertising. The system relied on the Ad Click Fraud Detection Dataset that has been used by Kaggle and consists of user interaction data that displays the real and fake ad hits.

Thorough preprocessing included RUS and the SMOTE to ensure that the data that would be fed into the model was of high quality and fair. Many various algorithms have been taken and tested with different standard classification metrics. Such algorithms involved not only traditional classifiers such as LR, DT, and RF but also the DL models such as CNN, DNN, and RNN. To achieve improved future prediction, hybrid and

ensemble models, such as LSTM, GRU, LSTM+GRU, and Voting Classifier which integrates XGBoost, Bagging and Decision Tree, were designed. The Voting Classifier performed better than all standard models with precision rate, recall rate and F1-score of 100 percent accuracy rate. It was also easier to understand and use, with XAI (LIME and SHAP) methods, and a Flask-based web deployment. In general, the proposed structure demonstrates a powerful, distinct, and implementable method of decreasing ad click fraud within real-life online advertising environments.

The system can further be optimized by fusing real-time data streams of the various ad platforms to make it more flexible. This will simplify the aspect of identifying shifting fraud trends. The inclusion of more advanced forms of feature engineering and reinforcement learning might improve decisions further and scale the system, as well. The inclusion of cross-platform behavioral analytics and unsupervised anomaly identification in the model would help to make it more general with a wider range of datasets.

Application of the framework in the cloud or on the edge might also assist in the detection of fraud on a huge scale, and latency. This would enable round the clock monitoring and automated response mechanisms that would streamline the operations of digital advertising ecosystems.

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Contact: 99000 00480 / 9701737404