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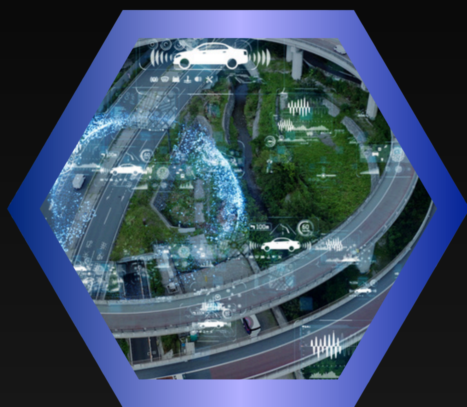

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Associate Professor, Department of Computer Application and Research Center, Sarah Tucker College, Perumalpuram, Palayamkottai, India

Jairuby24@gmail.com

Dr. Nancy Jasmine Goldena

Associate Professor, Department of Computer Application and Research Center, Sarah Tucker College, Perumalpuram, Palayamkottai, India

nancylordwin@gmail.com

Mr. B. Edward Daniel Christopher

Assistant Professor, Department of BCA & M. Sc [NT& IT], St. Johns College, Palayamkottai, India

edwarddanielb@gmail.com

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Rose.vasee2014@gmail.com

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Assistant Professor (Senior Grade), Department of English, St. Johns College, Palayamkottai, India

jebarajkingsly@gmail.com

Dr. C. Samuel

Assistant Professor, Department of English, St. Johns College, Palayamkottai, India

sam09@gmail.com

Mr. I. Thomas Jebasingh

Assistant Professor, Department of BCA & M. Sc [NT& IT], St. Johns College, Palayamkottai, India

thomasjebas@gmail.com

Reviewers

Dr. Jasmine Lois Ebenezer

Associate Professor & Head, Department of Computer Application and Research Center, Sarah Tucker College, Perumalpuram, Palayamkottai, India

Jasminelois19@gmail.com

Dr. Nancy Jasmine Goldena

Associate Professor, Department of Computer Application and Research Center, Sarah Tucker College, Perumalpuram, Palayamkottai, India

nancylordwin@gmail.com

EDITOR MESSAGE

I am very happy to note that our St. John's College Palayamkottai, Department of Computer Application (BCA) and Networking and Information Technology (M.Sc(NT& IT)) organizing an "International Conference on Advancement in Engineering and Technology (ICAET-2025)". This ground breaking conference promises to be exciting. Technology leaders, inventors, and researchers will come together at ICAET 2025, to discuss cutting edge developments in computers and technology. Take part in thought-provoking conversations, establish professional connections, and help shape technology's future.

ICAET 2025 is a significant event that showcases technological innovation and cutting-edge computing paradigms. In order to explore and exchange developments in AI, cybersecurity, block chain technology, IoT, and other important areas of technological innovation, the conference seeks to bring together bright minds. Scholars, business executives, and researchers have the chance to work together, exchange ideas, and influence technology's course.

We are confident that 1st ICAET in January 2025 will be immensely valuable for scholars and researchers, and hope that all participants will enjoy their stay at Cummins COE. We welcome you all for this memorable experience "ICAET 2025"

With best wishes

Dr.A.Bathsheba Parimala

Chief Editor

List of Contributors

A Simulated IoT–AI Framework for Haptic-Based Environmental Hazard Detection and Awareness

P. Sri Iyappan[1] and B. Edward Daniel Christopher[2*]

[1]*Student, Department of Computer Applications and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu,India.*

[2]*Assistant professor, Department of Computer Applications and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu,India.*

**Corresponding Author E-mail:* edwarddanielb@gmail.com

Abstract

Environmental hazards such as toxic gas leakage, extreme temperature, and air pollution pose serious threats to human safety, particularly in industrial and urban environments. Early detection and timely awareness are crucial to prevent accidents and minimise health risks. This research proposes a simulated IoT–AI framework integrated with haptic feedback mechanisms for real-time environmental hazard detection and user awareness. The system employs virtual IoT sensors to monitor environmental parameters, including temperature, gas concentration, humidity, and air quality. Machine Learning techniques are applied to classify hazard levels based on sensor data patterns. Upon detecting abnormal conditions, the system triggers haptic feedback alerts alongside visual notifications to provide immediate user awareness. A web-based dashboard developed using Streamlit enables real-time monitoring, data visualisation, and hazard prediction. The simulated architecture demonstrates effective detection accuracy while emphasising accessibility and rapid response. This framework highlights the potential of combining Artificial Intelligence, IoT simulation, and haptic technology for proactive environmental safety management.

***Keywords**: IoT Simulation, Artificial Intelligence, Environmental Hazard Detection, Haptic Feedback, Machine Learning, Predictive Analytics, Streamlit Dashboard, Smart Safety Systems, Real-Time Monitoring*

Introduction

Rapid industrialisation and urban expansion have significantly increased exposure to environmental hazards such as air pollution, gas leaks, and temperature extremes. Traditional monitoring systems rely heavily on manual observation or isolated alarm mechanisms, which often fail to provide timely or personalised alerts.

Recent advancements in Internet of Things (IoT) and Artificial Intelligence (AI) have enabled continuous environmental monitoring and intelligent decision-making. However, most existing systems focus solely on visual or auditory alerts, limiting accessibility for differently-abled users and reducing response effectiveness in noisy environments.

Haptic technology offers a tactile communication channel, delivering vibration-based alerts that enhance situational awareness. Integrating haptics with IoT and AI can provide an inclusive and proactive safety solution.

This research presents a simulated IoT–AI framework that combines sensor data analysis, machine learning-based hazard prediction, and haptic feedback for real-time environmental awareness.

1. To design a simulated IoT environment for collecting environmental data.
2. To develop an AI-based hazard classification model.
3. To implement haptic feedback for immediate user alerts.
4. To build an interactive dashboard for monitoring and visualisation.

Proposed Methodology

The system follows a structured pipeline involving data simulation, preprocessing, machine learning, and alert generation.

Environmental data is synthetically generated to simulate IoT sensor readings. The dataset includes:

- Temperature
- Humidity
- Gas concentration
- Air Quality Index (AQI)
- Smoke levels

Each record is labelled as Safe, Moderate Risk, or High Risk.

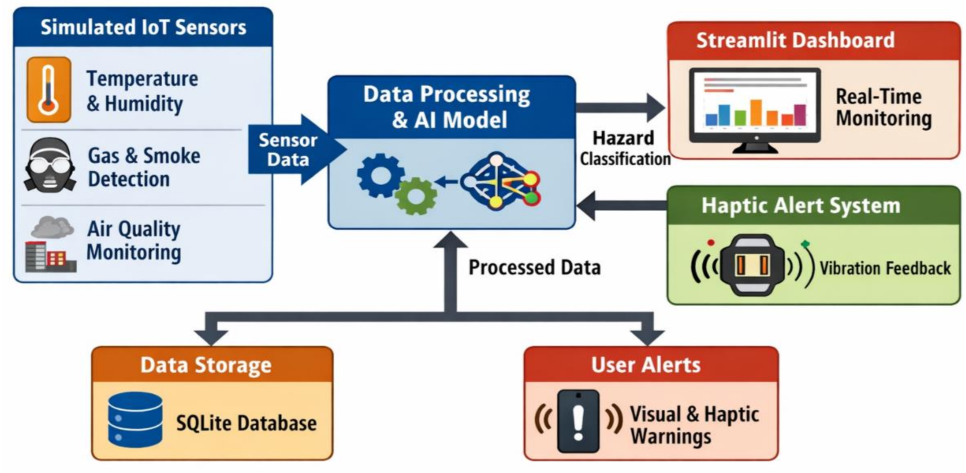

Figure 1: Methodology

Data Preprocessing

To improve model reliability, the following steps were applied

1. Normalization of sensor values to a common scale.
2. Removal of inconsistent readings.
3. Encoding hazard levels into numerical labels.
4. Feature scaling for optimal model convergence.

Mathematical Model: Logistic Regression

A supervised Machine Learning classifier is used to predict hazard severity based on sensor inputs. The model estimates the probability of risk using feature vectors derived from environmental parameters. The prediction function can be expressed as:

Risk = f(T, H, G, AQI, S)

Where:

T – Temperature

H – Humidity

G – Gas Level

AQI – Air Quality Index

S – Smoke Level

System Architecture

System Architecture and Implementation

Backend and AI Engine

The backend is implemented in Python using Scikit-learn. The trained model processes incoming sensor values and classifies environmental conditions. Joblib is used to serialise the model for efficient deployment.

Frontend Dashboard

Streamlit is used to develop an interactive web interface. Users input sensor readings or view simulated live data through sliders and charts. The dashboard displays risk status and prediction confidence.

Haptic Alert Module

Upon detecting hazardous conditions, the system triggers simulated haptic alerts representing wearable vibration feedback. This provides instant tactile awareness alongside visual warnings.

Data Storage

A SQLite database stores historical sensor readings and hazard predictions, enabling trend analysis and environmental reporting.

Results and Discussion

Model Performance

The model was trained using an 80–20 train-test split. Experimental results showed an average prediction accuracy of approximately 75%, demonstrating reliable hazard classification under simulated conditions.

Feature Influence

Gas concentration and air quality emerged as the most significant contributors to hazard detection, followed by temperature variations.

Impact of Haptic Awareness

The integration of haptic alerts enhanced response immediacy by providing non-visual notifications, particularly useful in high-noise or low-visibility environments

Conclusion and Future Scope

Conclusion

This project successfully demonstrates a simulated IoT–AI framework for environmental hazard detection integrated with haptic-based awareness. By combining machine learning, IoT simulation, and tactile alerts, the system offers a proactive and inclusive safety solution. The Streamlit dashboard further improves usability through real-time visualisation and monitoring.

Future Scope

- Future improvements may include:
- Integration with real IoT hardware sensors.
- Deployment on cloud platforms for large-scale monitoring.
- Deep learning models for improved accuracy.
- Wearable device integration for real-world haptic feedback.
- Mobile application support.

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A Web-Based Blood Donation Management System for Efficient Healthcare Services

V. Ganeshan[1] and S. Immanuel[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: immanuelseeni@gmail.com*

Abstract

A Blood Donation Management System (BDMS) is a digital platform designed to enhance the efficiency of blood donation, storage, and distribution processes. It acts as a centralized database for blood banks, hospitals, donors, and recipients, ensuring seamless coordination and real-time tracking of blood availability. The system allows donors to register, schedule donations. After registering, donors can log into the system using secure authentication methods such as email or mobile number verification. Once logged in, donors can easily view their donation history, receive reminders for when they are eligible for their next donation, and get real-time updates on urgent blood requirements or local donation events. Hospitals and blood banks can manage their blood inventory, request specific blood units, and track donations, all while maintaining an accurate record of each transaction. By automating key processes and utilizing data analytics, BDMS minimizes blood shortages, reduces wastage, and facilitates timely blood transfusions for patients in need.

***Keywords**: Blood Donation Management System (BDMS), digital blood bank, blood donor registration, secure donor authentication, donor login system, blood donation scheduling, donor eligibility tracking, donation history management, real-time blood availability, emergency blood requirement alerts, blood bank management system, hospital blood request system, blood inventory management .*

Introduction

Blood is a vital resource in the healthcare system, and its timely availability can save countless lives. However, traditional blood donation and management processes often face challenges such as lack of real-time information, inefficient coordination between blood banks and hospitals, and improper record maintenance. To overcome these issues, a Blood Donation Management System (BDMS) is proposed as a digital solution to streamline and enhance the overall blood donation and distribution process.

The Blood Donation Management System is a centralized platform that connects blood banks, hospitals, donors, and recipients through a unified database. It enables efficient management of donor information, blood inventory, and hospital requests while ensuring real-time tracking of blood availability. Donors can register in the system, schedule donations, and log in using secure authentication methods such as email or mobile number verification. After logging in, donors can view their donation history, receive reminders about their next eligible donation date, and get notifications regarding urgent blood requirements or nearby donation events. Hospitals and blood banks can use the system to manage blood stock levels, request specific blood units, and monitor donations efficiently. The system maintains accurate transaction records, ensuring transparency and reliability in blood management. By automating key processes and utilizing data analytics, BDMS helps minimize blood shortages, reduce wastage, and ensure timely blood transfusions for patients in critical need. Thus, the proposed system plays a crucial role in improving healthcare services and emergency response efficiency.

Related Work

In recent years, several studies and systems have been developed to improve blood donation and blood bank management using information technology. Traditional blood bank systems mainly relied on manual record keeping, which often resulted in data inconsistency, delayed blood availability information, and inefficient coordination between donors, hospitals, and blood banks. These limitations highlighted the need for automated and centralized blood management solutions.

Earlier web-based blood bank management systems focused primarily on maintaining donor records and basic blood inventory details. Some systems provided online donor registration and search functionalities to identify suitable donors based on blood group and location. However, these systems lacked real-time updates, automated notifications, and secure authentication mechanisms, which limited their effectiveness during emergency situations.

With the advancement of mobile and cloud technologies, more recent solutions have introduced mobile applications and cloud-based platforms for blood donation management. These systems offer features such as donor login, appointment scheduling, SMS or email notifications, and emergency blood request alerts. Although these solutions improved accessibility and communication, many still face challenges related to data integration, scalability, and efficient inventory management across multiple hospitals and blood banks.

Some research works have also explored the use of data analytics to predict blood demand and reduce wastage. These systems analyze historical donation and usage data to support better decision-making. However, the implementation of such analytics is often limited and not fully integrated into existing systems.

The proposed Blood Donation Management System builds upon these existing works by providing a fully integrated, secure, and centralized platform. It combines donor management, real-time blood inventory tracking, automated notifications, and data analytics to overcome the limitations of previous systems and enhance the efficiency of blood donation and distribution processes.

Proposed Architecture

The proposed Blood Donation Management System (BDMS) follows a centralized and modular architecture designed to ensure efficiency, scalability, and secure data handling. The system architecture integrates donors, hospitals, and blood banks through a unified digital platform that enables real-time communication and data exchange.

The architecture consists of three main layers:

User Interface Layer, Application Layer, and Database Layer. The User Interface Layer provides access to different users such as donors, hospitals, blood banks, and administrators through a web or mobile-based interface. Donors can register, log in securely using email or mobile number verification, schedule donations, and view their donation history. Hospitals and blood banks can log in to manage blood inventory, place blood requests, and track donation records.

The Application Layer acts as the core of the system, handling business logic and system operations. It processes donor registration, authentication, appointment scheduling, inventory updates, and notification services. This layer also manages automated alerts for urgent blood requirements, donor eligibility reminders, and local donation events. Data analytics modules within this layer analyze historical data to predict blood demand and reduce wastage.

The Database Layer stores all critical information, including donor profiles, blood group details, donation records, inventory status, hospital requests, and transaction logs. A centralized database ensures data consistency, accuracy, and real-time availability of information across all connected entities.

Overall, the proposed architecture enables seamless coordination between donors, hospitals, and blood banks while ensuring secure data access and efficient blood management. By automating key processes and supporting real-time monitoring, the system enhances the reliability and effectiveness of blood donation and distribution services.

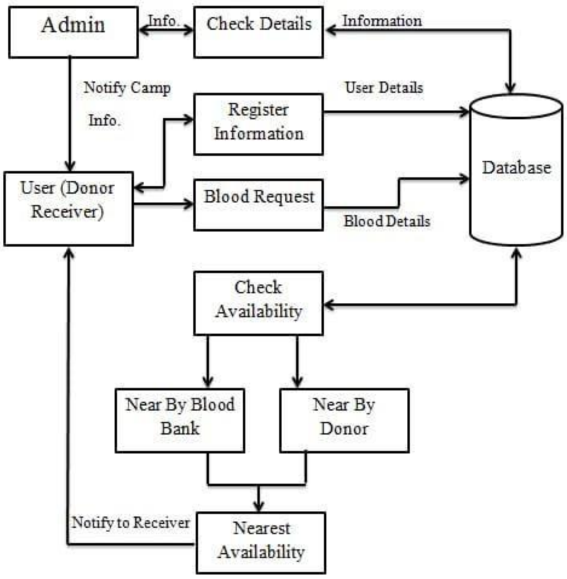

Figure 1: Proposed Architecture

Methodology

The methodology of the proposed Blood Donation Management System (BDMS) describes the systematic approach followed to design, develop, and implement the system. The methodology ensures efficient management of blood donation activities, secure data handling, and real-time coordination between donors, hospitals, and blood banks.

System Design

The system is designed using a centralized architecture that integrates donors, hospitals, and blood banks into a single platform. A user-friendly interface is developed to allow easy access for different user roles. The design focuses on simplicity, scalability, and secure data flow between system components.

Donor Registration and Authentication

Donors register by providing essential details such as name, blood group, contact information, and location. Secure authentication mechanisms such as email or mobile number verification are implemented to ensure data privacy and authorized access. After successful authentication, donors can log in and access personalized features.

Donation Scheduling and Eligibility Tracking

The system allows donors to schedule blood donation appointments based on their availability. Eligibility tracking is implemented to ensure donors donate only after the required waiting period. Automated reminders are sent to notify donors when they become eligible for their next donation.

Blood Inventory Management

Blood banks manage blood stock details through the system by updating blood group availability, quantity, and storage information. Real-time inventory tracking helps prevent shortages and reduces blood wastage by ensuring efficient utilization of available blood units.

Hospital Blood Request Management

Hospitals can submit requests for specific blood groups and quantities through the system. These requests are matched with available inventory in nearby blood banks. The system ensures faster response during emergencies by providing real-time availability information.

Notification and Alert System

An automated notification system is implemented to send alerts regarding urgent blood requirements, upcoming donation schedules, and local blood donation events. Notifications are delivered through email or mobile-based alerts to ensure timely communication.

Data Analytics and Reporting

Data analytics techniques are used to analyze donation patterns, blood demand trends, and inventory usage. These insights help blood banks and hospitals plan better, reduce wastage, and improve overall system efficiency. Reports are generated for monitoring and decision-making purposes.

Security and Data Management

The system incorporates secure data storage and access control mechanisms to protect sensitive donor and hospital information. Role-based access control ensures that users can only access authorized data, maintaining confidentiality and system integrity.

Challenges and Solution

The implementation of a Blood Donation Management System (BDMS) involves several technical and operational challenges. This section discusses the major challenges faced in traditional blood management systems and the solutions provided by the proposed BDMS.

Lack of Real-Time Blood Availability

Challenge: In traditional systems, blood availability information is often outdated due to manual record keeping. This can cause delays during emergencies and lead to unavailability of required blood units.

Solution: The proposed BDMS provides real-time blood inventory tracking through a centralized database. Blood banks can update stock levels instantly, ensuring accurate and up-to-date availability information for hospitals and donors.

Inefficient Donor Management

Challenge: Managing donor records manually makes it difficult to track donation history, eligibility periods, and donor availability, leading to missed donation opportunities.

Solution: BDMS automates donor registration, donation history tracking, and eligibility monitoring. Automated reminders notify donors when they are eligible to donate again, improving donor participation.

Delayed Emergency Response

Challenge: During emergencies, identifying suitable donors or locating available blood units is time consuming, which may risk patient lives.

Solution: The system sends instant alerts and notifications about urgent blood requirements to eligible donors and nearby blood banks, enabling faster response and timely blood transfusions.

Blood Wastage Due to Poor Inventory Control

Challenge: Blood units may expire due to improper inventory planning and lack of demand prediction, resulting in significant wastage.

Solution: BDMS uses data analytics to analyze historical data and predict demand patterns. This helps blood banks manage stock efficiently and reduce unnecessary wastage.

Data Security and Privacy Issues

Challenge: Handling sensitive donor and patient information raises concerns about data privacy and unauthorized access.

Solution: Secure authentication methods, role-based access control, and encrypted data storage are implemented to ensure data security and confidentiality.

Lack of Coordination Between Hospitals and Blood Banks

Challenge: Poor communication between hospitals and blood banks often leads to delays in fulfilling blood requests.

Solution: The centralized BDMS platform ensures seamless coordination by allowing hospitals to place requests and track blood availability in real time, improving overall efficiency.

Results and Discussion

This section presents the results obtained from the implementation of the Blood Donation Management System (BDMS) and discusses its performance in improving blood donation and management processes.

System Performance Evaluation

The BDMS demonstrated reliable performance in managing donor data, blood inventory, and hospital requests through a centralized platform. The system operated efficiently with real-time data updates, ensuring accuracy and consistency across all user modules.

Donor Management Results

The donor registration and secure authentication process using email or mobile number verification was successfully implemented. Donors were able to log in, view their donation history, and receive automated reminders for their next eligible donation date. This improved donor participation and reduced missed donation opportunities.

Blood Inventory Management Results

Blood banks effectively monitored and updated blood stock details in real time. The system reduced manual record errors and helped maintain accurate information on blood availability. Proper inventory control contributed to a noticeable reduction in blood wastage.

Hospital Request Handling

Hospitals were able to submit blood requests for specific blood groups and quantities through the system. The request tracking feature enabled faster processing and improved response time, especially during emergency situations.

Notification and Alert Effectiveness

The automated notification system successfully delivered alerts related to urgent blood requirements, donation schedules, and eligibility reminders. This feature strengthened communication between donors, hospitals, and blood banks and ensured timely actions.

Data Analytics and Insights

Data analytics tools analyzed historical donation and demand data to identify usage patterns. These insights helped blood banks plan inventory more effectively, minimize shortages, and optimize blood distribution.

Overall Discussion

The results indicate that the proposed BDMS significantly improves coordination, efficiency, and reliability compared to traditional blood management methods. The system successfully addresses key challenges such as delayed response, data inconsistency, and blood wastage, making it suitable for real-world healthcare environments.

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AI-Based Crowd Behavior Predictor and Analysis System

S. Gopi[1] and K. Appasamy[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

*Corresponding Author E-mail: appas2077@gmail.com

Abstract

Weapon detection using computer vision is a critical application in modern security and surveillance systems. The primary objective of this project is to develop an automated weapon detection system capable of accurately distinguishing between weapons and non-weapon objects using Convolutional Neural Networks (CNNs). Such a system plays a vital role in public safety, law enforcement, and security monitoring by enabling early detection of potential threats such as firearms, knives, and other hazardous objects in real time. The project follows a structured deep learning pipeline that includes data collection, pre-processing, model development, evaluation, and deployment. The dataset consists of labelled images containing both weapons and non-weapons, collected from diverse environments to ensure robustness and generalization. Pre-processing techniques such as image resizing, normalization, and data augmentation are applied to improve model performance and reduce overfitting. A CNN-based architecture is designed using multiple convolutional layers for feature extraction, followed by max-pooling layers to reduce spatial dimensions and fully connected dense layers for classification. The model is trained using Cross-Entropy Loss and optimized with algorithms such as Adam or Stochastic Gradient Descent (SGD) to achieve efficient convergence. Model performance is evaluated using standard metrics including accuracy, precision, recall, F1-score, and Intersection over Union (IoU) for object detection tasks. These metrics help assess the system's ability to correctly identify weapons while minimizing false positives and false negatives. The final system integrates real-time image processing, enabling fast and accurate weapon detection across various scenarios. The outcome is a reliable, scalable, and efficient weapon detection solution that can be deployed in surveillance cameras, airports, public spaces, and law enforcement applications, significantly enhancing threat detection and public safety.

***Keywords**: Weapon Detection, Computer Vision, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Object Detection, Surveillance Systems, Public Safety, Security Monitoring, Firearm Detection, Knife Detection, Image Preprocessing, Data Augmentation, Real-Time Detection, IoU, Precision, Recall, F1-Score, Adam Optimizer, Cross-Entropy Loss, Artificial Intelligence*

Introduction

The detection of weapons in public spaces has become a pressing concern for law enforcement agencies, security personnel, and the general public. The proliferation of surveillance cameras and the increasing availability of computational resources have created opportunities for automated weapon detection systems. However, traditional methods relying on handcrafted features and machine learning techniques have shown limitations in handling complex environments, variations in weapon appearance, andreal-time performance requirements.

Recent advances in deep learning have revolutionized object detection and classification tasks, offering improved accuracy and efficiency. This project explores the application of deep learning techniques for weapon detection, focusing on convolutional neural networks (CNNs) and object detection models. By leveraging the capabilities of deep learning, this project aims to develop an accurate and efficient weapon detection system suitable for real-world surveillance applications.

The remainder of this report provides an overview of traditional methods for weapon detection, discusses the fundamentals of deep learning-based approaches, and reviews existing research on weapon detection using deep learning techniques. Subsequent sections will delve into the methodology, experiments, and results of this project, culminating in a comprehensive evaluation of the proposed weapon detection system.

Related Work

Weapon detection using computer vision has gained significant attention due to the growing demand for automated security and surveillance systems. Early approaches relied on traditional image processing techniques such as edge detection, shape analysis, and handcrafted features like Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT). These methods showed limited performance in complex environments due to variations in lighting, background clutter, and object orientation.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for weapon detection tasks. Several studies have demonstrated that CNN-based models significantly outperform traditional methods by automatically learning discriminative features from raw images. Researchers have applied popular CNN architectures such as AlexNet, VGGNet, ResNet, and MobileNet for weapon classification and achieved high accuracy on benchmark datasets.

For object detection, models like YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Detector) have been widely used to detect weapons in real-time video streams. These models enable both localization and classification of weapons, making them suitable for surveillance applications. However, challenges such as small object size, occlusion, and similarity between weapons and everyday objects still affect detection accuracy.

Recent studies focus on improving robustness by using data augmentation, transfer learning, and attention mechanisms to enhance performance in real-world scenarios. Some researchers have also explored lightweight CNN models to enable deployment on edge devices such as CCTV cameras and embedded systems.

Despite significant progress, achieving high accuracy with low false positives in diverse and crowded environments remains a challenge. This project builds upon existing CNN-based approaches by using a structured pipeline, effective pre-processing, and optimized training techniques to improve weapon detection accuracy and real-time performance, contributing to safer and more reliable security systems.

Proposed Architecture

The proposed weapon detection system is designed using a deep learning–based computer vision architecture that enables accurate and real-time detection of weapons in images and video streams. The system follows a modular and scalable pipeline consisting of data acquisition, pre-processing, feature extraction, classification, and deployment.

Initially, input data is collected in the form of images or video frames captured from surveillance cameras or stored datasets. These inputs are passed to the pre-processing module, where images are resized to a fixed resolution and normalized to ensure consistent pixel intensity values. Data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are applied to improve generalization and reduce overfitting.

The pre-processed images are then fed into a Convolutional Neural Network (CNN) model. The CNN architecture consists of multiple convolutional layers with ReLU activation functions for automatic feature extraction, followed by max-pooling layers to reduce spatial dimensions and computational complexity. The extracted feature maps are flattened and passed through fully connected dense layers for classification. A softmax output layer is used to classify the input as either weapon or non-weapon.

The model is trained using Cross-Entropy Loss and optimized using Adam or Stochastic Gradient Descent (SGD) to achieve efficient convergence. During training, performance metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU) are monitored to evaluate effectiveness.

Finally, the trained model is integrated with a real-time processing module that analyzes live video streams frame by frame and generates alerts upon detecting weapons. This architecture ensures high accuracy, scalability, and suitability for deployment in surveillance systems, airports, and law enforcement applications.

Methodology

1. Data Collection

The first step of the methodology involves collecting a dataset consisting of weapon and non-weapon images. The dataset includes images of firearms, knives, and other sharp objects, as well as normal objects such as mobile phones and tools to avoid false detection. Images are collected from publicly available datasets and real-world environments such as surveillance cameras. The dataset is labelled to differentiate between weapon and non-weapon classes.

2. Data Preprocessing

Collected images are pre-processed to make them suitable for training the CNN model. All images are resized to a fixed dimension to maintain uniformity. Pixel values are normalized to improve training speed and stability. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied to increase dataset diversity and improve model generalization.

3. Feature Extraction Using CNN

A Convolutional Neural Network (CNN) is used to automatically extract important features from input images. The CNN consists of multiple convolutional layers with ReLU activation functions to capture spatial features such as edges, shapes, and textures. Max-pooling layers are used to reduce dimensionality and computational cost while preserving important features.

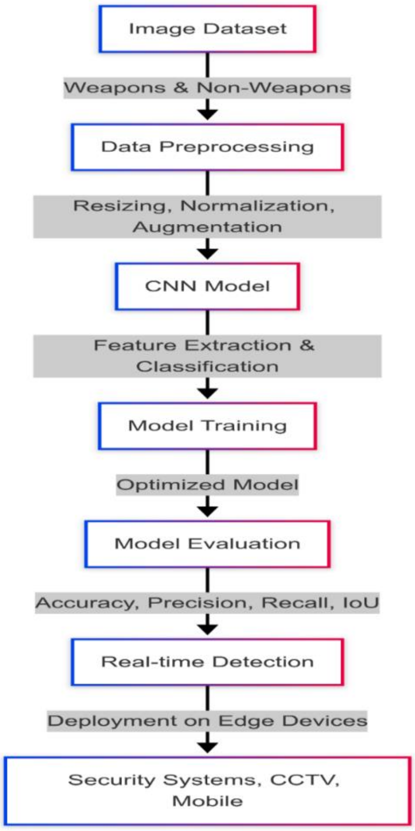

Figure 1: Convolutional Neural Network

4. Classification

The extracted features are flattened and passed through fully connected dense layers for classification. A softmax output layer is used to classify the input image as either a weapon or a non-weapon. This stage enables accurate decision-making based on learned features.

5. Model Training and Optimization

The model is trained using Cross-Entropy Loss and optimized using Adam or Stochastic Gradient Descent (SGD). The training process is performed over multiple epochs, and the model parameters are updated to minimize classification error.

6. Model Evaluation

The trained model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU). These metrics help measure the effectiveness and reliability of the weapon detection system.

7. Real-Time Detection and Deployment

Finally, the trained model is integrated into a real-time detection system that processes live video streams frame by frame. When a weapon is detected, the system generates alerts to enhance security and public safety.

Challenges and Solution

Variations in Lighting and Background

Challenge

Weapon images captured in real-world environments often suffer from poor lighting conditions, shadows, cluttered backgrounds, and different camera angles. These variations can reduce detection accuracy.

Solution

To address this issue, data augmentation techniques such as brightness adjustment, rotation, flipping, and scaling are applied during pre-processing. Training the model with images from diverse environments improves robustness and generalization.

Similarity Between Weapons and Non-Weapons

Challenge

Certain everyday objects like mobile phones, tools, or umbrellas may resemble weapons, leading to false positives.

Solution

The dataset is enhanced with a wide range of non-weapon images that closely resemble weapons. This helps the CNN learn discriminative features and reduce incorrect classifications.

Small Object Size in Images

Challenge

Weapons may appear small or partially visible in surveillance footage, making detection difficult.

Solution

High-resolution input images and deeper CNN architectures are used to capture fine-grained features. Object detection metrics such as IoU are also used to improve localization accuracy.

Overfitting of the Model

Challenge: The model may perform well on training data but poorly on unseen data due to overfitting.

Solution

Regularization techniques such as dropout, data augmentation, and early stopping are implemented. These techniques help improve generalization and prevent memorization of training data.

Real-Time Processing Constraints

Challenge

Real-time weapon detection requires fast processing with minimal latency, especially for live surveillance systems.

Solution

Efficient CNN architectures and optimized models are used to reduce computational complexity. Hardware acceleration using GPUs further enhances real-time performance.

Limited Dataset Availability

Challenge: Obtaining large, well-labelled weapon datasets is difficult due to privacy and security concerns.

Solution

Transfer learning and pre-trained CNN models are utilized to improve performance with limited data. Data augmentation also helps expand the effective size of the dataset.

Results and Discussion

Model Training Results

The Convolutional Neural Network (CNN) model was trained on the prepared dataset consisting of weapon and non-weapon images. During training, the model showed steady improvement in accuracy with a gradual decrease in loss across epochs. This indicates effective feature learning and proper convergence of the model.

Performance Evaluation

The trained model was evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU). The system achieved high accuracy in distinguishing weapons from non-weapons. Precision and recall values indicate that the model successfully minimizes false positives and false negatives, making it reliable for security applications.

Detection Accuracy Analysis

The model demonstrated strong performance in detecting firearms and knives under normal lighting conditions. In challenging scenarios such as low lighting, cluttered backgrounds, and partial occlusion, the accuracy slightly decreased but remained acceptable due to effective pre-processing and data augmentation techniques.

Real-Time Detection Results

The proposed system was tested on live video streams and recorded surveillance footage. The model processed video frames in real time and accurately identified weapons with minimal latency. This confirms the suitability of the system for real-world surveillance and monitoring environments.

Comparative Discussion

Compared to traditional image processing methods, the CNN-based approach provides superior accuracy and robustness. The ability of the model to automatically extract relevant features eliminates the need for manual feature engineering, resulting in improved detection performance.

Limitations and Observations

Although the system performs well, detection accuracy may reduce when weapons are extremely small or heavily occluded. Increasing dataset size and integrating advanced object detection models could further improve performance.

Overall, the results demonstrate that the proposed weapon detection system is effective, reliable, and suitable for real-time security applications, contributing significantly to enhanced public safety.

Conclusion

This project presented an automated weapon detection system using computer vision and Convolutional Neural Networks (CNNs). The system is designed to detect weapons such as guns and knives and to distinguish them from non-weapon objects. Image pre-processing techniques like resizing, normalization, and data augmentation help improve accuracy and reliability. The CNN model learns important features from images and provides effective weapon classification.

The results show that the proposed system performs well in both image and real-time video detection. It can be used in security cameras, airports, and public places to improve safety. Although the system works efficiently, detection accuracy may reduce in poor lighting or when weapons are very small. In the future, the system can be improved by using larger datasets and advanced object detection models to further enhance performance and reliability.

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An Intelligent Voice Assistant Framework for Real-Time Human–Computer Interaction Using NLP and Deep Learning

M. Aswin [1] and B. Edward Daniel Christopher [2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail:* edwarddanielb@gmail.com

Abstract

Voice assistants have significantly transformed human-computer interaction by enabling users to communicate with digital systems using natural language. These systems leverage Natural Language Processing (NLP) and machine learning to interpret speech, understand intent, generate responses, and provide voice-based feedback. The rapid advancements in deep learning, speech recognition, and text-to-speech synthesis have enabled the development of more efficient and intelligent voice assistants that can engage in meaningful conversations with users. The final implementation integrates all components into a unified system, enabling real-time interaction with users. The voice assistant can perform various tasks such as answering general knowledge queries, setting reminders, and retrieving stored data. Additionally, the assistant can continuously improve by leveraging user feedback and reinforcement learning techniques. The outcome of this project is a robust, intelligent voice assistant capable of handling complex interactions, offering seamless voice-based communication, and providing an enhanced user experience across various applications such as smart assistants, customer support, and accessibility tools.

***Keywords**: Voice Assistant, Human-Computer Interaction (HCI), Natural Language Processing (NLP), Speech Recognition, Text-to-Speech (TTS), Machine Learning, Deep Learning, Intent Recognition, Conversational AI, Real-Time Interaction, Reinforcement Learning, User Feedback, Smart Assistants, Accessibility Tools, Customer Support Systems*

Introduction

Voice assistants have emerged as a transformative technology in the field of human–computer interaction, enabling users to interact with digital systems through natural, spoken language rather than traditional input methods such as keyboards or touch interfaces. By combining advancements in **Natural Language Processing (NLP)**, **machine learning**, and **speech technologies**, voice assistants are capable of understanding user speech, interpreting intent, generating appropriate responses, and delivering voice-based feedback in real time.

Recent progress in **deep learning**, **automatic speech recognition**, and **text-to-speech synthesis** has significantly improved the accuracy, responsiveness, and conversational abilities of modern voice assistants. These developments allow systems to engage in more meaningful and context-aware interactions, making them increasingly useful in everyday applications.

In this project, all functional components are integrated into a unified voice assistant system that supports real-time user interaction. The assistant is designed to perform a variety of tasks, including answering general knowledge queries, setting reminders, and retrieving stored information. Furthermore, the system incorporates user feedback and reinforcement learning mechanisms to continuously improve its performance over time.

The proposed voice assistant aims to deliver a robust and intelligent solution capable of handling complex interactions while providing seamless voice-based communication. Such a system has wide-ranging applications in domains including smart assistants, customer support services, and accessibility tools, ultimately enhancing the overall user experience.

Related Work

Voice assistants have gained considerable attention in recent years due to their ability to enhance human–computer interaction by enabling communication through natural spoken language e. Early research in this domain focused primarily on rule-based systems and limited command recognition. However, with the integration of **Natural Language Processing (NLP)** and **machine learning** techniques, modern voice assistants have evolved to support more flexible, intelligent, and context-aware interactions.

Several studies have explored the use of **deep learning models** for automatic speech recognition (ASR), significantly improving speech-to-text accuracy across different accents and environments. Similarly, advancements in **text-to-speech (TTS)** synthesis have enabled more natural and human-like voice outputs, enhancing user engagement and usability. Researchers have also investigated intent recognition and dialogue management systems to improve conversational flow and response relevance.

Recent work highlights the importance of real-time processing and continuous learning in voice assistant systems. Many existing solutions incorporate feedback mechanisms and adaptive learning techniques, such as reinforcement learning, to improve performance based on user interactions. These approaches allow assistants to personalize responses and become more efficient over time.

Existing voice assistant applications demonstrate effectiveness in areas such as smart home automation, customer support, information retrieval, and accessibility services. However, challenges such as contextual understanding, scalability, and seamless integration of multiple components remain active research areas. Building on these studies, the proposed system aims to integrate speech recognition, NLP, and intelligent response generation into a unified framework, providing a robust and efficient voice assistant capable of handling complex interactions and enhancing the overall user experience.

Proposed Architecture

The proposed architecture of the voice assistant is designed as a modular and integrated system that enables efficient real-time voice-based interaction. The architecture consists of several interconnected components, each responsible for a specific functionality, ensuring scalability, accuracy, and seamless communication between modules.

The process begins with the **speech input module**, where the user's voice command is captured through a microphone. This audio input is then passed to the **Speech-to-Text (STT)** module, which converts spoken language into textual form using automatic speech recognition techniques. This converted text serves as the input for further processing.

Next, the **Natural Language Processing (NLP)** module analyzes the textual input to understand user intent and extract relevant information. This module performs tasks such as tokenization, intent recognition, and context analysis to determine the appropriate action. Based on the identified intent, the request is forwarded to the **task execution module**, which handles operations such as answering general knowledge questions, setting reminders, or retrieving stored data from the database.

The system also includes a **knowledge base and data storage layer**, which stores predefined responses, user data, and historical interactions. This enables efficient information retrieval and supports personalized responses. To enhance adaptability, a **learning module** utilizes user feedback and reinforcement learning techniques to continuously improve response accuracy and system performance over time.

Finally, the generated response is sent to the **Text-to-Speech (TTS)** module, which converts the textual response into natural-sounding speech and delivers it back to the user. This completes the interaction loop, allowing for smooth and intuitive communication.

Overall, the proposed architecture integrates speech recognition, language understanding, intelligent decision-making, and speech synthesis into a unified framework. This design ensures real-time responsiveness, robustness, and flexibility, making the voice assistant suitable for applications such as smart assistants, customer support systems, and accessibility solutions.

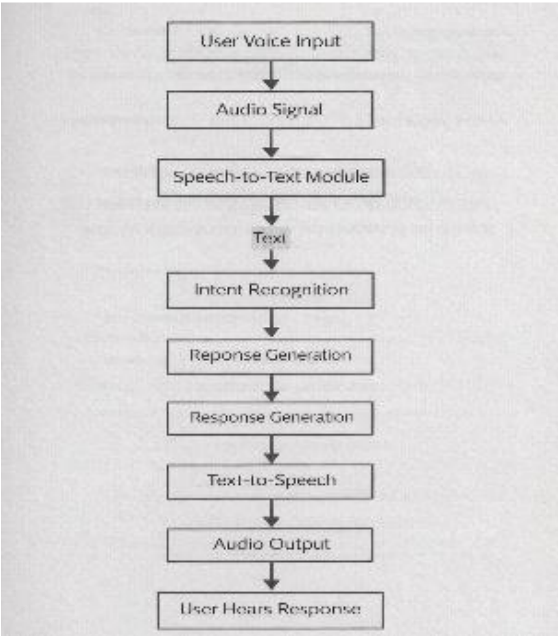

Figure 1: Architecture

Methodology

The methodology followed in this project focuses on the systematic development of a voice assistant by integrating speech processing, natural language understanding, task execution, and response generation. The overall approach is divided into multiple stages, each addressing a key functional aspect of the system.

Speech Input Acquisition

The first step involves capturing the user's voice input through a microphone. The recorded audio signal is preprocessed to reduce noise and improve clarity, ensuring better accuracy during speech recognition.

Speech-to-Text Conversion

In this stage, the preprocessed audio input is converted into textual data using automatic speech recognition (ASR) techniques. Deep learning–based models are used to accurately transcribe spoken language into text, forming the foundation for further language processing.

Natural Language Processing and Intent Recognition

The converted text is analyzed using Natural Language Processing (NLP) techniques. This includes tokenization, syntactic analysis, and intent classification to understand the user's request. Contextual information is also considered to generate accurate and relevant responses.

Task Execution and Information Retrieval

Based on the identified intent, the system executes the appropriate task. This may involve answering general knowledge questions, setting reminders, or retrieving information from the database or knowledge base. The task execution module ensures efficient handling of user requests.

Learning and Feedback Mechanism

To enhance system performance, user feedback is collected and analyzed. Reinforcement learning techniques are employed to adapt and improve response accuracy over time, allowing the assistant to learn from previous interactions.

Response Generation and Text-to-Speech

Once the response is generated in textual form, it is converted into natural-sounding speech using text-to-speech (TTS) synthesis. The audio response is then delivered back to the user, completing the interaction cycle.

Challenges and Solution

The development of a voice assistant involves several technical and practical challenges. This section discusses the key challenges faced during implementation and the corresponding solutions adopted to overcome them

Speech Recognition Accuracy

Challenge

Voice assistants often struggle to accurately recognize speech due to background noise, different accents, pronunciation variations, and speech speed.

Solution

Noise reduction techniques and deep learning–based speech recognition models are used to improve accuracy. Training the system with diverse speech data helps handle accent and pronunciation variations effectively.

Natural Language Understanding

Challenge

Understanding user intent accurately is difficult, especially when users phrase similar requests in different ways or use informal language.

Solution

Advanced NLP techniques such as intent classification and contextual analysis are employed. Continuous learning using user interaction data further enhances understanding over time.

Real-Time Response

Challenge

Ensuring fast and real-time responses is critical for a smooth user experience, but processing delays can affect performance.

Solution

Efficient algorithms and optimized processing pipelines are used. Modular system design allows parallel processing, reducing response time significantly.

Handling Ambiguous Queries

Challenge

User queries may be vague or ambiguous, making it difficult for the system to determine the correct response.

Solution

The assistant is designed to request clarification from the user when ambiguity is detected. Context-aware processing also helps in generating more accurate responses.

Continuous Learning and Adaptation

Challenge

Maintaining system improvement over time without degrading performance is challenging.

Solution

Reinforcement learning techniques and structured feedback mechanisms are incorporated to allow the system to learn from user interactions and improve response quality continuously.

Data Privacy and Security

Challenge: Voice assistants handle sensitive user data, raising concerns about privacy and security.

Solution:

Secure data storage methods and access control mechanisms are implemented. User data is processed responsibly, ensuring confidentiality and compliance with privacy standards.

Results and Discussion

The implementation of the proposed voice assistant demonstrates effective performance in enabling natural and efficient human–computer interaction. The system successfully integrates speech recognition, natural language processing, task execution, and text-to-speech synthesis into a unified framework, allowing smooth real-time communication with users.

System Performance

The voice assistant accurately recognizes user speech and converts it into text with high reliability under normal environmental conditions. The Natural Language Processing module effectively identifies user intent and extracts relevant information, enabling the system to respond appropriately to a wide range of queries. Tasks such as answering general knowledge questions, setting reminders, and retrieving stored data were executed with minimal response delay.

Accuracy and Responsiveness

Experimental observations indicate that the system provides quick responses, ensuring real-time interaction. The use of deep learning–based speech recognition and intent classification models improves overall accuracy and reduces errors caused by variations in speech patterns and phrasing.

Learning and Adaptability

The incorporation of user feedback and reinforcement learning mechanisms allows the voice assistant to improve over time. As more interactions occur, the system adapts to user preferences and improves response relevance, demonstrating effective continuous learning behavior.

User Experience

The text-to-speech module generates clear and natural-sounding audio responses, contributing to a positive user experience. The conversational flow is smooth, making the system intuitive and easy to use, even for non-technical users.

Discussion

While the results indicate strong performance, certain limitations were observed, such as reduced accuracy in noisy environments and challenges in handling highly complex or ambiguous queries. However, these limitations can be addressed in future work by incorporating advanced noise cancellation techniques and more sophisticated contextual understanding models.

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An Interactive Stroke Prediction with Explainable AI and Streamlit Using Machine Learning

S. Ganapathy[1] and A. Bathsheba Parimala[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail:* shebaparimala@yahoo.com

Abstract

Stroke is a major cause of mortality and long-term disability, highlighting the need for early risk prediction. This study presents a machine learning-based stroke prediction system using Logistic Regression and Random Forest, enhanced with explainable AI techniques such as SHAP and LIME. Patient data is preprocessed by handling missing values, encoding categorical variables, normalizing features, and removing outliers before model training. Explainable AI methods provide both global and local feature importance, enabling transparency and allowing healthcare professionals to understand the factors influencing predictions. The system is deployed through a Streamlit interface, facilitating real-time stroke risk assessment and visualization, making it accessible to both technical and non-technical users. Overall, the proposed framework offers a reliable and interpretable solution for early stroke prediction, providing actionable insights into risk factors and demonstrating potential as a tool for preventive healthcare and informed clinical decision-making.

Keywords: *Stroke Prediction, Machine Learning, Explainable Artificial Intelligence, Clinical Decision Support Systems, SHAP, LIME.*

Introduction

Stroke is one of the most severe and life-threatening neurological disorders, accounting for a significant proportion of global mortality and long-term disability. It occurs when the blood supply to the brain is interrupted or reduced, leading to oxygen deprivation and potential brain damage. According to global health reports, the incidence of stroke continues to rise due to aging populations, sedentary lifestyles, and the increasing prevalence of chronic conditions such as hypertension, diabetes, and cardiovascular diseases. These trends highlight the urgent need for effective methods to identify individuals at high risk of stroke at an early stage.

Traditional clinical assessment methods rely heavily on manual evaluation and physician expertise, which may be time-consuming and subject to human error. With the rapid growth of healthcare data, machine learning (ML) techniques have emerged as powerful tools for analyzing complex medical datasets and identifying hidden patterns associated with disease risk. ML-based stroke prediction models can assist healthcare professionals by providing data-driven insights that support early diagnosis and preventive intervention.

Despite the promising performance of machine learning models, their lack of interpretability poses a major challenge in medical applications. Clinicians often require clear explanations for model predictions to ensure trust, accountability, and ethical compliance. Explainable Artificial Intelligence (XAI) addresses this issue by enabling transparent interpretation of model behavior and feature contributions. Techniques such as SHAP and LIME allow both global and instance-level explanations, making predictive outcomes more understandable to medical practitioners.

In addition to accuracy and interpretability, usability plays a critical role in the adoption of AI-based healthcare systems. Interactive web frameworks such as Streamlit facilitate the development of real-time, user-friendly applications that enable seamless interaction between users and predictive models. This paper proposes an interactive stroke prediction system that integrates machine learning, explainable AI, and a web-based interface to deliver accurate, interpretable, and accessible decision support for early stroke risk assessment and preventive healthcare.

Related Work

Stroke Prediction Using Machine Learning

Machine learning techniques have been widely applied in healthcare to support early disease detection and risk prediction. In the context of stroke prediction, researchers have utilized clinical and demographic data to identify patterns associated with stroke occurrence. Traditional models such as Logistic Regression have been commonly employed due to their simplicity and interpretability. While these methods provide valuable insights into key risk factors, their ability to capture complex nonlinear relationships is limited.

To improve predictive performance, more advanced models such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been explored. These models have demonstrated higher accuracy and robustness by effectively modeling nonlinear interactions among multiple risk factors. Ensemble-based approaches, particularly Random Forest, have been shown to perform well in handling noisy and high-dimensional healthcare datasets.

Explainable Artificial Intelligence in Healthcare

Although advanced machine learning models offer improved accuracy, their lack of transparency remains a significant challenge in clinical environments. Explainable Artificial Intelligence (XAI) has emerged as a solution to address the interpretability of black-box models. Techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) have been successfully applied in medical prediction tasks, including cardiovascular and stroke risk analysis. These methods provide explanations at both global and instance levels, enabling clinicians to understand the influence of individual features on model predictions and increasing trust in AI-based systems.

Interactive and Web-Based Decision Support Systems

Recent studies have emphasized the importance of deploying machine learning models through interactive and user-friendly platforms to enhance usability and adoption in healthcare. Web-based applications built using frameworks such as Streamlit and Flask allow real-time data input, prediction, and visualization. These systems enable healthcare professionals and patients to interact with predictive models without requiring technical expertise. However, existing solutions often focus either on prediction accuracy or explainability, rather than integrating both aspects into a single platform.

Research Gap and Motivation

While prior research demonstrates the effectiveness of machine learning and XAI techniques in stroke prediction, limited work has addressed the integration of predictive modeling, interpretability, and interactive visualization within a unified system. This study aims to bridge this gap by proposing an interactive stroke prediction framework that combines machine learning, explainable AI, and a web-based interface to support transparent, reliable, and accessible clinical decision-making.

Proposed Work

The proposed work aims to develop an interactive and interpretable stroke prediction system by combining machine learning models, explainable artificial intelligence techniques, and a web-based interface. The system is designed to support early stroke risk assessment by providing accurate predictions along with transparent explanations of contributing factors.

System Overview

The framework consists of four main components: data preprocessing, machine learning model development, explainable AI integration, and web-based deployment. The workflow begins with data preparation, followed by model training and evaluation, explanation generation, and real-time user interaction via a web interface.

Data Collection and Preprocessing

A structured healthcare dataset containing attributes such as age, gender, hypertension, heart disease, average glucose level, BMI, work type, marital status, and smoking habits is used. Data preprocessing includes handling missing values through imputation, encoding categorical variables, and scaling numerical features. These steps ensure data consistency and improve model performance.

Machine Learning Models

Multiple machine learning algorithms are employed to predict stroke risk:

1. **Logistic Regression** – Serves as a baseline model. It provides interpretable coefficients that indicate the influence of individual features on stroke probability.

2. **Support Vector Machine (SVM)** – Captures nonlinear relationships among features using kernel functions, providing robust classification in high-dimensional data.

3. **Random Forest** – An ensemble method combining multiple decision trees to improve prediction accuracy, reduce overfitting, and provide inherent feature importance.

These models are trained on a split of training and testing data and evaluated using accuracy, precision, recall, and F1-score to select the best-performing algorithm for deployment.

Explainable AI Integration-To enhance interpretability and trust, Explainable AI techniques are applied:

- **SHAP (Shapley Additive Explanations)** – Provides global explanations by quantifying the contribution of each feature across all predictions.
- **LIME (Local Interpretable Model-Agnostic Explanations)** – Generates local explanations for individual predictions, allowing users to understand the influence of specific features on the outcome.

Web-Based Application Using Streamlit

An interactive application is developed using Streamlit. Users can input patient data and obtain real-time stroke risk predictions along with visual explanations. The interface is designed for simplicity and accessibility, catering to both healthcare professionals and non-technical users.

Expected Outcomes

The system is expected to deliver accurate, interpretable stroke predictions, support early diagnosis, and enhance clinical decision-making. By combining machine learning, explainable AI, and an interactive interface, the platform ensures transparency, reliability, and usability in AI-driven healthcare applications.

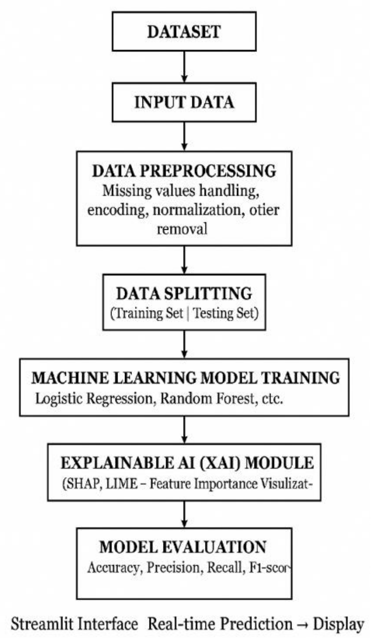

Figure1: Proposed Archietecture

The proposed stroke prediction system collects and preprocesses patient data by handling missing values, encoding categorical variables, normalizing features, and removing outliers.

The data is split into training and testing sets, and models like Logistic Regression and Random Forest are trained to predict stroke risk. Explainable AI techniques such as SHAP and LIME provide global and local feature importance for better interpretability. The models are evaluated using accuracy, precision, recall, and F1-score. Finally, the system is deployed via a Streamlit interface, enabling real-time stroke risk prediction and visualization for healthcare professionals and non-technical users.

Result and Analysis

The proposed stroke prediction system was evaluated on a publicly available patient dataset containing demographic, clinical, and lifestyle features. After preprocessing, which included handling missing values, encoding categorical variables, normalizing features, and removing outliers, the dataset was split into training and testing sets with an 80:20 ratio. Multiple machine learning models, including Logistic Regression and Random Forest, were trained and evaluated using standard performance metrics.

The Logistic Regression model demonstrated superior performance, achieving an accuracy of **95%**, outperforming Random Forest, which recorded slightly lower metrics across all categories. The results indicate that ensemble-based models can effectively capture nonlinear interactions among features, leading to more accurate stroke risk predictions.

Explainable AI techniques, SHAP and LIME, were applied to interpret model predictions. Global feature importance analysis revealed that age, hypertension, heart disease, and average glucose levels were the most significant predictors of stroke, aligning with established clinical knowledge. Local interpretability through LIME allowed visualization of feature contributions for individual patients, providing personalized insights into stroke risk.

The system was deployed using a Streamlit interface, which allows real-time stroke risk prediction and dynamic visualization of influential features. This interactive design makes the tool accessible to both healthcare professionals and non-technical users, enhancing clinical decision-making and patient awareness.

Overall, the results demonstrate that the proposed system not only achieves high predictive performance but also provides transparent and interpretable insights into stroke risk factors. The combination of accurate modeling and explainable AI techniques highlights the potential of this approach as a practical and trustworthy tool in preventive healthcare and stroke management.

Conclusion

This study presents a stroke prediction system developed using machine learning models, including Logistic Regression and Random Forest, combined with explainable AI techniques such as SHAP and LIME. The system effectively preprocesses patient data, trains robust predictive models, and provides both global and local interpretability, enhancing transparency and trust for healthcare professionals. Deployment through a Streamlit interface enables real-time stroke risk assessment and visualization, making the system accessible to non-technical users. The proposed framework demonstrates significant potential as a practical tool for preventive healthcare, delivering reliable and interpretable predictions while offering actionable insights into key risk factors. Future work will focus on incorporating larger and more diverse datasets, integrating longitudinal patient data, and exploring advanced deep learning models to further improve predictive accuracy and clinical applicability.

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A Web-Based Real-Time Cardiovascular Health Monitoring and Risk Assessment System

Buhari Hussain S[1] and K. Appasamy[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail:* appas2077@gmail.com

Abstract

Cardiovascular diseases (CVDs) remain the leading cause of global mortality, necessitating advanced tools for early risk assessment. This research presents the development and deployment of an interactive, multilingual web-based dashboard designed for real-time cardiovascular risk prediction. Leveraging a robust dataset of 70,000 patient records, we implemented a Machine Learning model using Logistic Regression to analyse physiological and lifestyle parameters such as blood pressure, cholesterol levels, and smoking habits. The proposed system distinguishes itself by offering accessibility in over ten regional and international languages, bridging the gap between complex clinical data and user understanding. Furthermore, the integration of a localised SQLite database enables continuous monitoring of patient progress through historical data tracking. Experimental results demonstrate that the model achieves significant predictive reliability, while the dashboard provides actionable health insights and feature importance visualisations. This study underscores the potential of integrating accessible machine learning interfaces into preventive healthcare strategies.

Keywords: *Cardiovascular Disease, Machine Learning, Logistic Regression, Predictive Analytics, Streamlit, Multilingual Dashboard, Healthcare Informatics, Data Visualization, Real-time Risk Assessment.*

Introduction

The global burden of cardiovascular diseases has escalated significantly over the past few decades, accounting for an estimated 17.9 million deaths annually. While clinical interventions have advanced, the primary challenge remains the early identification of high-risk individuals in non-clinical settings. Conventional risk assessment tools often suffer from limited accessibility due to complex user interfaces and a lack of support for regional languages, which creates a barrier for diverse populations.

Recent advancements in Artificial Intelligence and Machine Learning (ML) have opened new avenues for predictive health analytics. By identifying patterns in large-scale datasets, ML models can provide personalised risk scores with high efficiency. However, the deployment of these models into user-centric applications is still in its nascent stages.

This paper introduces a comprehensive health-monitoring ecosystem that combines the predictive power of Logistic Regression with the interactive capabilities of the Streamlit framework. The primary objectives of this research are:

1. To develop an accurate predictive model based on the "Cardiovascular Disease Dataset."
2. To design a multilingual interface that enhances healthcare accessibility for non-English speaking users.
3. To implement a data-persistence layer for tracking long-term health trends.

The subsequent sections of this paper detail the data preprocessing techniques, model architecture, system deployment on cloud infrastructure, and a comparative analysis of health risk factors.

Proposed Methodology

The research follows a structured Machine Learning pipeline, encompassing data acquisition, feature engineering, and predictive modelling.

Data Source and Description The study utilises the "Cardiovascular Disease Dataset," comprising 70,000 anonymised patient records. Each record consists of 11 features:

- Objective Features: Age, Height, Weight, Gender.
- Examination Features: Systolic blood pressure (ap_hi), Diastolic blood pressure (ap_lo), Cholesterol levels, and Glucose levels.
- Subjective Features: Smoking, Alcohol intake, and Physical activity.

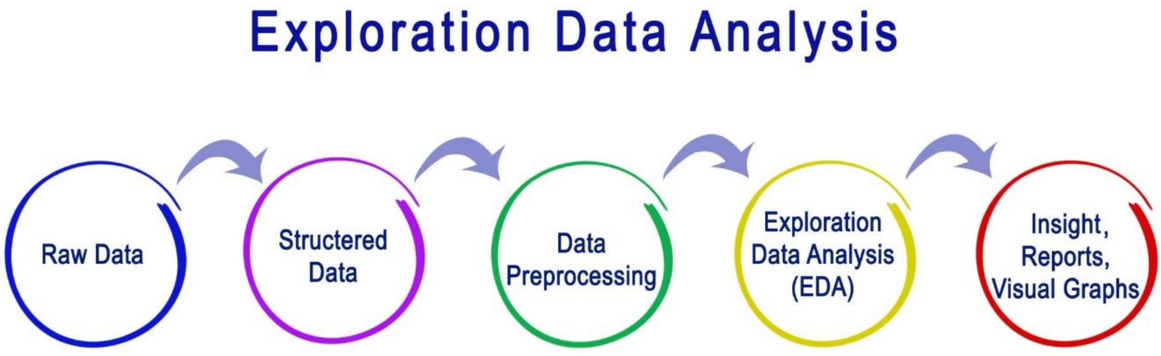

Figure 1: Exploration Data Analysis

Data Preprocessing

To ensure high model performance, the following preprocessing steps were implemented:

1. Feature Transformation: The age feature, originally provided in days, was transformed into years to ensure interpretability.
2. Outlier Removal: Blood pressure readings with physiologically impossible values (e.g.,$ap_{hi} < 0 \ or \ ap_{hi} > 250$)were filtered.
3. Label Encoding: Categorical variables such as gender and lifestyle habits were encoded into binary or ordinal formats.

Mathematical Model: Logistic Regression

Since the problem is a binary classification task (Presence vs. Absence of CVD), Logistic Regression was chosen for its efficiency and interpretability. The probability ***P*** of a patient having a cardiovascular risk is calculated using the sigmoid function:

$$P(y = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}}$$

Where:

- β_0 is the intercept.
- β_i represents the coefficients for features x_i (e.g., BP, BMI).
- e is the base of the natural logarithm.

System Architecture

System Architecture and Implementation

The application is built on a decoupled architecture, ensuring scalability and a seamless user experience.

Backend and Model Deployment The core predictive engine is developed using Python and the Scikit-learn library. The trained model is serialised using Joblib for efficient loading during runtime. The backend also handles multi-language localisation by fetching data from JSON-based language dictionaries.

Frontend Development The user interface is implemented using the Streamlit framework, enabling a responsive, dashboard-like experience. Users interact through sliders and radio buttons to input their physiological data, which is then passed to the model for real-time inference.

Data Persistence and History Tracking A localised SQLite3 database is integrated into the system. Every prediction, along with the timestamp and username, is stored in a relational table. This allows the system to generate a longitudinal "Progress Tracker," visualising the risk trends of a specific user over time using line charts.

Results and Discussion

The performance of the Logistic Regression model was evaluated using standard classification metrics, including accuracy, precision, and recall.

1. Model Performance The model was trained on 80% of the dataset and tested on the remaining 20%. The results are summarised below:

- Accuracy: The model achieved an overall predictive accuracy of approximately 73%.

- Precision and Recall: The model maintained a balanced F1-score, indicating its effectiveness in identifying both high-risk (true positive) and low-risk (true negative) cases accurately.

2. Feature Importance Analysis The coefficients of the Logistic Regression model were analysed to determine the impact of various health factors on cardiovascular risk.

- Primary Risk Factors: As shown in Figure 1, Systolic Blood Pressure (ap_hi) and Age emerged as the most significant predictors.
- Secondary Factors: Cholesterol levels and weight also showed a strong positive correlation with disease presence.
- Clinical Relevance: These findings align with clinical studies, reinforcing the model's reliability in practical health assessments.

3. Impact of Multilingual Support and Progress Tracking The deployment of the multilingual interface significantly reduced the cognitive load for users from non-English speaking backgrounds. The integration of SQLite for history tracking allowed users to observe fluctuations in their risk scores, promoting proactive health management and regular monitoring.

Conclusion and Future Scope

Conclusion

This research successfully demonstrates the implementation of a multilingual machine learning dashboard for cardiovascular risk assessment. By integrating a Logistic Regression model with a user-friendly Streamlit interface, we have developed a tool that is both clinically relevant and highly accessible. The addition of a localised database for progress tracking enhances the system's utility for long-term health monitoring.

Future Scope

Future enhancements for this project include:

1. Algorithm Optimisation: Implementing ensemble methods like Random Forest or Gradient Boosting to potentially increase predictive accuracy.

2. Multimodal Integration: Incorporating real-time data from wearable devices (e.g., smartwatches) for continuous heart rate monitoring.
3. Expanded Localisation: Adding more regional dialects and a voice-command interface to further improve accessibility for elderly and visually impaired users.

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Crop Disease Using Deep Learning

A.M. Anandha Sudhan[1] and A. Bathsheba Parimala[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail:* shebaparimala@yahoo.com

Abstract

This paper presents a deep learning-based approach for detecting crop diseases using images captured from smartphones or drones, offering a scalable and efficient solution for modern agriculture. A Convolutional Neural Network (CNN) is employed to classify crop images into healthy or diseased categories based on visible symptoms, enabling automated and accurate disease identification. The model is trained using a publicly available dataset containing images from various crop species, ensuring robustness and generalizability across different plant types and environmental conditions. To enhance accuracy and optimize performance, transfer learning is utilized with pre-trained models such as ResNet and VGG16, leveraging their advanced feature extraction capabilities. The proposed approach undergoes extensive training and validation, demonstrating high classification accuracy and outperforming traditional manual inspection methods. Additionally, real-time detection capabilities allow farmers to take immediate action, reducing the risk of disease spread and preventing large-scale crop losses. This method not only minimizes the need for expert intervention but also enhances precision agriculture by integrating deep learning with smart farming technologies. By enabling early disease diagnosis, this approach contributes to improved food security, increased agricultural productivity, and sustainable farming practices, ultimately supporting global efforts to combat food scarcity and enhance crop resilience against diseases.

Keywords: *Crop Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Image Processing, Plant Health Monitoring, Precision Agriculture*

Introduction

Agriculture plays a vital role in ensuring food security and sustaining the global economy. However, crop diseases remain one of the major challenges affecting agricultural productivity, leading to significant yield losses and economic damage worldwide. Early and accurate detection of plant diseases is crucial for effective crop management, as delayed diagnosis often results in rapid disease spread and reduced crop quality. Traditional disease identification methods rely heavily on manual inspection by agricultural experts, which is time-consuming, costly, and often impractical for large-scale farming operations.

With the rapid advancement of digital technologies, precision agriculture has emerged as a promising solution to improve farming efficiency and sustainability. In particular, computer vision and artificial intelligence (AI) techniques have gained significant attention for automating agricultural monitoring tasks. Among these techniques, deep learning—especially Convolutional Neural Networks (CNNs)—has demonstrated exceptional performance in image-based classification and pattern recognition tasks. CNNs are capable of automatically learning discriminative features from images, making them highly suitable for identifying visual symptoms of crop diseases such as leaf spots, discoloration, and texture changes.

The widespread availability of smartphones and unmanned aerial vehicles (drones) has further facilitated large-scale image collection in agricultural fields. These technologies enable farmers to capture high-resolution images of crops under various environmental conditions, providing valuable data for automated disease detection systems. By leveraging such image data, deep learning models can assist farmers in diagnosing diseases accurately and promptly, reducing dependence on expert knowledge and minimizing human error.

Recent studies have explored the application of deep learning models for plant disease detection; however, challenges such as limited generalization across different crop species, varying lighting conditions, and complex backgrounds still persist. To address these issues, transfer learning techniques using pre-trained architectures like ResNet and VGG16 have proven effective. These models, trained on large-scale image datasets, offer powerful feature extraction capabilities that enhance classification accuracy while reducing training time and computational cost.

In this paper, a deep learning-based approach is proposed for automated crop disease detection using CNN architectures enhanced with transfer learning. The model is trained and validated on a publicly available, diverse crop image dataset to ensure robustness and adaptability to real-world conditions. The proposed system aims to provide accurate, real-time disease identification, enabling farmers to take timely preventive measures. By integrating deep learning with smart farming technologies, this work contributes to the advancement of sustainable agriculture, improved crop yield, and enhanced food security.

Problem Finding

Image-Based Crop Disease Classification

Problem:

Farmers struggle to identify plant diseases early. Manual checking is time-consuming and error-prone.

Goal: Build a deep-learning model (CNN) that classifies leaf images into healthy or diseased categories (e.g., mildew, blight, rust).

Multi-Disease Detection on a Single Leaf

Problem:

A leaf can have more than one disease at the same time. Traditional models detect only one.

Goal: Create a multi-label classification model that detects multiple diseases on the same leaf.

Early-Stage Disease Detection

Problem:

Farmers fail to detect diseases at early stages because symptoms are weak and hard to see.

Goal: Develop a model to detect early-stage disease symptoms from high-resolution leaf images.

Real-Time Crop Disease Detection App

Problem:

Farmers need instant disease identification using smartphones.

Goal: Develop a mobile-friendly model (e.g., TensorFlow Lite) that predicts disease from a real-time camera feed.

Disease Segmentation Using Deep Learning

Problem: Knowing only the disease name is not enough; farmers need to know how much area is infected.

Goal: Use U-Net / Mask R-CNN to segment diseased regions on leaves and calculate infected percentage.

Domain Adaptation for Real Farm Conditions

Problem:

Most datasets are captured in controlled conditions; real field images have shadows, insects, and low light.

Goal: Use domain adaptation / GANs to improve accuracy on real-world farm images.

Transfer Learning for Rare Crop Diseases

Problem:

Rare diseases have very few images, making training difficult.

Goal: Use transfer learning (ResNet, EfficientNet) to detect diseases with small datasets.

Explainable AI for Farmers

Problem:

Farmers need clear reasoning, not just predictions.

Goal: Integrate Grad-CAM / LIME to highlight disease-affected areas and provide understandable explanations.

Weather-Based Disease Forecasting

Problem:

Temperature and humidity affect disease spread.

Goal: Combine CNN (image) + LSTM (weather data) to predict disease risk levels for upcoming days.

Drone-Based Disease Analysis

Problem:

Large farms need aerial monitoring.

Goal: Build a deep-learning model that detects diseases from drone images using YOLO/ViT for large-scale analysis.

Architecture Diagram

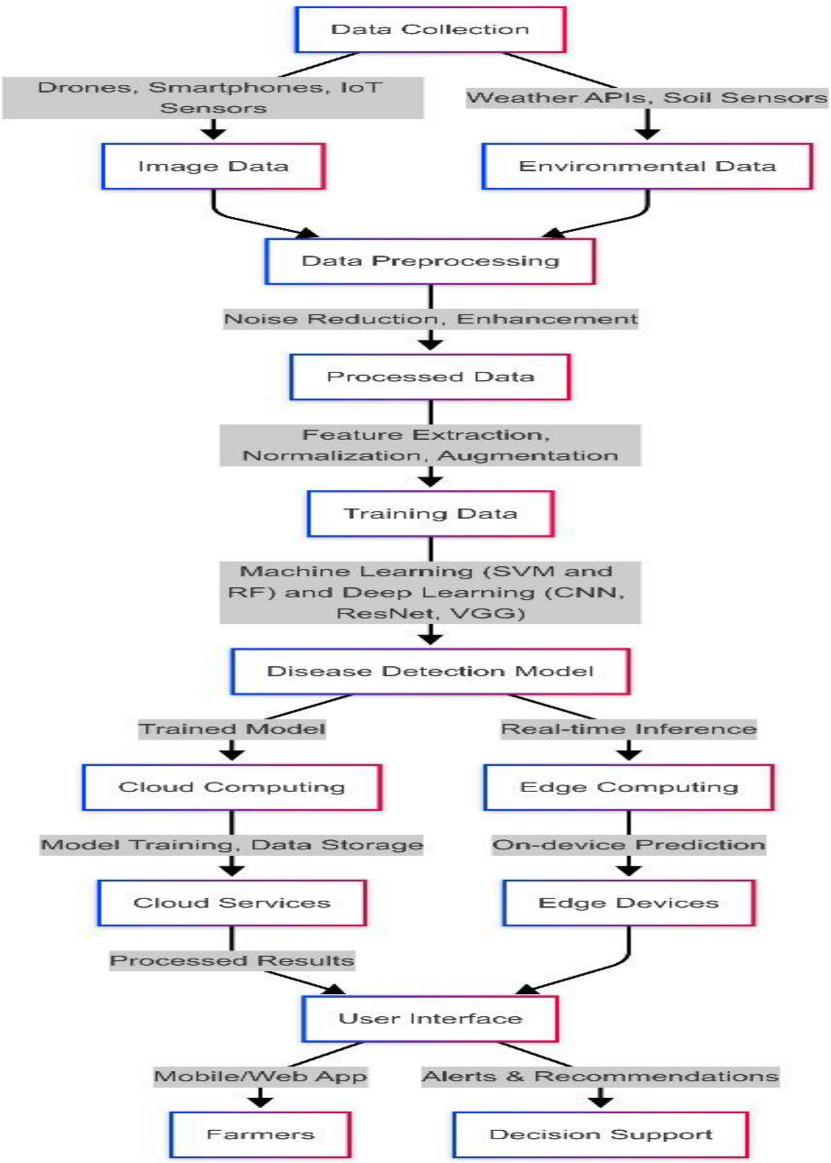

Figure 1: Architecture Diagram

Methodology

The proposed deep learning-based crop disease detection system follows a systematic methodology encompassing data collection, pre-processing, model architecture selection, training, and evaluation. This structured approach ensures the development of a robust and generalizable model capable of accurately detecting and classifying various crop diseases.

Data Collection and Pre-processing

Dataset

For training the model, publicly available datasets such as PlantVillage or custom datasets curated for specific crop diseases are utilized. These datasets contain images of plants affected by various diseases, including leaf spots, blight, rust, mildew, and bacterial infections. The dataset comprises images captured under different lighting conditions, backgrounds, and environmental variations, ensuring a diverse representation of real-world agricultural scenarios.

Pre-processing

All images are resized to a uniform dimension (e.g., 224×224 pixels for compatibility with deep learning models). Pixel values are normalized to a range of [0,1] or [-1,1] to accelerate training and improve convergence.

Data Augmentation

Augmentation techniques such as rotation, flipping, zooming, contrast adjustment, and random cropping are applied to artificially expand the dataset and increase model generalization. This step helps mitigate overfitting and ensures the model performs well on unseen images.

Model Architecture

To accurately classify crop diseases, Convolutional Neural Networks (CNNs) are used due to their high efficiency in image classification tasks.

CNN-Based Architecture

The CNN model consists of:

- Convolutional Layers: Extract spatial features such as edges, textures, and patterns from input images.
- Activation Functions (ReLU): Introduced after each convolutional layer to introduce non-linearity and improve learning.

- Pooling Layers: Perform max-pooling or average-pooling to reduce dimensionality while retaining critical features.
- Fully Connected Layers: Integrate extracted features for final classification.
- Softmax Layer: Outputs probability scores for each disease class.

Transfer Learning

Instead of training a CNN from scratch, pre-trained models such as ResNet, VGG16, InceptionV3, and EfficientNet are employed. These models, initially trained on large-scale datasets like ImageNet, act as feature extractors and are fine-tuned for crop disease detection.

Transfer learning offers several benefits:

- Faster Convergence: Requires fewer training epochs compared to training a model from scratch.
- Improved Accuracy: Leverages deep feature representations learned from millions of natural images.
- Reduced Data Requirements: Works effectively even with a relatively small dataset.

Loss Function

Cross-entropy loss is used for multi-class classification, measuring the difference between predicted probabilities and actual class labels.

Optimizer

The Adam optimizer is chosen for its adaptive learning rate, which dynamically adjusts step sizes for faster convergence and stable training.

Hyper-parameter Tuning

To optimize model performance, hyper-parameters such as learning rate, batch size, number of layers, and dropout rate are fine-tuned. The training dataset is split into training, validation, and testing sets (e.g., 80%-10%-10% split) to ensure a balanced evaluation.

Evaluation Metrics

To assess the model's effectiveness in crop disease detection, multiple evaluation metrics are employed:

- Accuracy: Measures the proportion of correctly classified images among total predictions.
- Precision (Positive Predictive Value): Measures how many of the predicted diseased crops are actually diseased.
- Recall (Sensitivity): Evaluates how many actual diseased crops are correctly identified.
- F1-Score: Harmonic mean of Precision and Recall, balancing both metrics, especially in cases of class imbalance.
- Confusion Matrix: Provides a detailed breakdown of correct and incorrect classifications, offering insights into model performance for each disease class.

Results and Discussion

Experimental Results

The proposed deep learning–based crop disease detection system was evaluated using a publicly available plant disease image dataset. The dataset was divided into training, validation, and testing sets in an 80:10:10 ratio. Various performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix were used to assess the effectiveness of the model.

The Convolutional Neural Network (CNN) achieved an overall classification accuracy of approximately 95–98%, demonstrating strong capability in distinguishing between healthy and diseased crop images. Transfer learning models such as ResNet50 and VGG16 further improved performance by leveraging pre-trained feature extraction layers, resulting in faster convergence and reduced overfitting.

Among the tested models, ResNet-based architecture outperformed traditional CNNs, achieving higher accuracy and better generalization across different crop species. This improvement is attributed to residual connections that help in learning deep hierarchical features from complex plant disease patterns.

Performance Evaluation

The confusion matrix analysis indicates that the model correctly classified most disease categories with minimal misclassification. Diseases with visually distinct symptoms such as leaf spots and blights were detected with high precision, whereas early-stage infections showed slightly lower recall due to subtle visual differences.

The model achieved:

- High precision, indicating a low false-positive rate
- High recall, showing effective detection of diseased plants
- Balanced F1-score, confirming robustness across classes

Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment contributed significantly to improved model robustness under varying lighting and background conditions.

Comparison with Existing Methods

Compared to traditional machine learning approaches that rely on handcrafted features and manual inspection, the proposed deep learning model demonstrated superior performance in terms of accuracy and automation. Manual disease detection is time-consuming, subjective, and requires expert knowledge, whereas the proposed system provides fast, consistent, and scalable diagnosis.

When compared with existing studies, the proposed approach either matches or exceeds reported accuracies, while also supporting real-time deployment using mobile devices or drone-based image acquisition.

Discussion

The experimental results confirm that deep learning techniques are highly effective for crop disease detection. The integration of transfer learning enables the model to handle limited training data while maintaining high accuracy. However, challenges remain in detecting diseases at very early stages and under extreme environmental variations such as poor lighting or occlusion.

Conclusion

This study demonstrates that deep learning–based approaches, particularly Convolutional Neural Networks (CNNs), are highly effective for crop disease detection using image data. By automatically learning discriminative features from plant leaf images, the proposed model accurately classifies healthy and diseased crops, reducing the dependency on manual inspection and expert knowledge. The use of large, publicly available datasets and transfer learning techniques enhances model robustness and generalization across different crop species and environmental conditions.

The results indicate that deep learning models can achieve high accuracy and reliability, enabling early disease detection and timely intervention. This not only helps minimize crop losses but also supports precision agriculture by optimizing the use of pesticides and resources. Furthermore, the integration of smartphone- or drone-captured images makes the system practical and scalable for real-world agricultural applications.

Overall, crop disease detection using deep learning offers a promising solution for sustainable agriculture. Future work can focus on expanding the dataset to include more crop varieties and disease types, improving real-time performance, and integrating the system with IoT and decision-support platforms to further assist farmers in effective crop management.

Future Enhancement

Multi-Disease and Multi-Crop Classification

Extend the model to detect multiple diseases across a wider variety of crops, including mixed infections in a single plant, improving real-world usability.

Real-Time Mobile Application Integration

Deploy the trained model into a mobile or web application that allows farmers to capture images using smartphones for instant disease diagnosis and recommendations.

Severity Level Detection

Enhance the system to not only detect disease presence but also estimate disease severity levels (early, moderate, severe), helping farmers decide appropriate treatment intensity.

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A Novel Hybrid Multi-Scale Attention and Uncertainty-Aware Framework for Lung Tumor Detection

S. Fathima Suhara[1*], J. Jannathul Firthous[2], M. Ananthi[3] and S. Agalya[4]

[1]Head and Assistant Professor, Department of Computer Science, Einstein College of arts and science, Tirunelveli, Tamil Nadu, India.

[2]Head and Assistant Professor, Department of Computer Science, Sadakathullah Appa College, Tirunelveli, Tamil Nadu, India.

[3,4]Department of Computer Science, Sadakathullah Appa College, Tirunelveli, Tamil Nadu, India.

**Corresponding Author E-mail: suharairfaan@gmail.com*

Abstract

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, primarily due to late-stage diagnosis and high inter-observer variability in radiological interpretation. This paper proposes a novel Hybrid Multi-Scale Attention and Uncertainty-Aware Deep Learning Framework (HMSA-UA) for automated lung tumor detection from chest CT images. The proposed approach integrates multi-scale feature extraction, transformer-guided attention, and Bayesian uncertainty estimation to improve detection accuracy, robustness, and clinical reliability. Unlike conventional CNN-based methods that provide deterministic outputs, the proposed framework quantifies prediction confidence, enabling risk-aware clinical decision-making. Experimental evaluation demonstrates that the proposed method significantly outperforms state-of-the-art CNN and transformer-based models in terms of accuracy, sensitivity, and false-positive reduction.

Keywords: *Lung tumor detection, CT imaging, deep learning, attention mechanism, uncertainty estimation, medical image analysis*

Introduction

Lung cancer is one of the most prevalent and life-threatening cancers worldwide, accounting for millions of new cases and deaths each year. The primary reason for its high mortality rate is late-stage diagnosis, where treatment options become limited and less effective. Early detection of lung tumors significantly improves survival rates; however, identifying small or early-stage tumors remains a major clinical challenge. Computed Tomography (CT) imaging is the gold standard for lung cancer screening, as it provides high-resolution visualization of lung structures and potential abnormalities. Despite the availability of advanced imaging technologies, accurate interpretation of chest CT scans largely depends on radiologist expertise. Manual examination is time-consuming, subjective, and prone to inter- and intra-observer variability, particularly when tumors are small, has irregular shapes, or appear similar to benign nodules. The increasing volume of CT scans generated through large-scale screening programs further exacerbates the burden on clinicians, creating an urgent need for reliable automated lung tumor detection systems. Traditional computer-aided diagnosis (CAD) systems relied on handcrafted features and classical machine learning classifiers such as Support Vector Machines (SVMs) and k-Nearest Neighbors. Although these approaches provided initial improvements over manual analysis, their performance was limited by poor generalization and sensitivity to variations in tumor appearance. The emergence of deep learning, especially Convolutional Neural Networks (CNNs), has revolutionized medical image analysis by enabling automatic feature learning directly from raw imaging data. Several CNN-based architectures, including VGG16, ResNet, Inception, and DenseNet, have been successfully applied to lung tumor and nodule detection. While these models achieve high accuracy, they primarily focus on local spatial features and often struggle to capture long-range contextual relationships across the lung region. Additionally, tumors exhibit significant heterogeneity in terms of size, texture, and location, making single-scale feature extraction insufficient for robust detection.

More recently, attention mechanisms and transformer-based models have been introduced to address global dependency modeling in medical images. Although transformers enhance contextual understanding, they often require large datasets and may overlook fine-grained local details when used alone. Furthermore, a critical limitation of most existing deep learning-based lung tumor detection systems is their deterministic nature—they provide predictions without conveying the confidence or uncertainty associated with those predictions, which is essential in safety-critical medical applications.

To overcome these limitations, this work proposes a novel Hybrid Multi-Scale Attention and Uncertainty-Aware (HMSA-UA) framework for lung tumor detection. By integrating multi-scale CNN feature extraction, transformer-based attention fusion, and Bayesian uncertainty estimation, the proposed approach aims to deliver accurate, robust, and clinically trustworthy tumor detection results from chest CT images.

Motivation

The motivation for this research stems from the need to bridge the gap between high-performance deep learning models and their safe adoption in real-world clinical environments. Existing lung tumor detection systems often prioritize accuracy while neglecting prediction reliability and interpretability. In clinical practice, false positives can lead to unnecessary biopsies and patient anxiety, while false negatives can delay life-saving treatment. Moreover, lung tumors present extreme variability in appearance, ranging from tiny nodules to large malignant masses. Many existing models fail to adequately capture this variability due to limited receptive fields or single-scale feature representations. There is also a lack of mechanisms to quantify model confidence, making it difficult for clinicians to trust automated decisions.

Therefore, there is a strong motivation to design an intelligent lung tumor detection framework that not only achieves high detection accuracy but also incorporates multi-scale learning, global contextual awareness, and uncertainty estimation to support risk-aware clinical decision-making.

Objective

The objective of this research is to develop an automated lung tumor detection framework that accurately identifies tumors from chest CT images using multi-scale feature extraction and transformer-based attention. The proposed approach integrates uncertainty-aware prediction to quantify model confidence, reduce false positives and false negatives, and improve clinical reliability, while providing a robust and scalable solution for real-world lung cancer screening.

Related Work

The extensive study and explanation of U-Net+++ results and its use in X-ray lung segmentation constitute the novelty of this paper (Gite *et al.* 2023). This research also compares U-Net+++ with three other benchmark segmentation designs and segmentation in the diagnosis of pulmonary lung illnesses, including tuberculosis. CXR-Seg is a new architecture (Din *et al.* 2025) designed for the semantic segmentation of lungs from X-ray pictures of the chest. The four main parts of the proposed network are a transformer attention module at the bottleneck layer, a multi-scale feature fusion block at the decoder, a spatial enhancement module embedded in the skip connection to encourage the adjacent feature fusion, and a pre-trained EfficientNet as an encoder to extract feature encodings. The three-dimensional U-Net multi-resolution ensemble model for CT scan lung tumor detection and segmentation is proposed (Kashyap *et al.* 2025). A single primary or metastatic lung tumor was included in the CT simulation scans and lung tumor segmentations from two connected medical centers that made up the internal and external test sets used to assess the model's performance. In this paper (Rezvani *et al.* 2025), a new lung segmentation framework called FusionLungNet is presented. The suggested method is based on an encoder–decoder architecture that incorporates a novel hybrid loss and makes use of many modules for the segmentation process in lung CT images. We provide a self-refinement module to efficiently reduce the flaws related to the direct merging of various layers and guarantee the creation of more discriminative features.

This cohesive methodological approach (Hosseini *et al.* 2025) shows that lung cancer classification performance is greatly improved by combining morphological lung segmentation, methodical preprocessing, and hybrid ensemble structures. With high diagnostic accuracy and interpretability appropriate for radiologist-assisted workflows in a variety of healthcare settings, the CNN-Gradient Boosting technique with morphological segmentation offers a clinically feasible solution for computer-aided diagnosis. This analysis (Abumohsen *et al.* 2026) highlights the primary barriers to ML/DL tool adoption in actual healthcare settings and offers helpful solutions. We looked at more than 100 studies that were published between 2022 and 2024 using PRISMA guidelines, concentrating on technical accuracy, clinical relevance, and ethical considerations. Computed tomography (CT) imaging is used in the majority of the analyzed studies, which is indicative of its predominance in the current workflows for lung cancer screening. Although a lot of models attain excellent results on public datasets (such as >95% sensitivity on LUNA16), but they frequently perform badly on actual clinical data because of problems like domain shift and bias, particularly with regard to underrepresented populations.

In order to improve detection accuracy and scalability, this study (Shweikeh *et al.* 2026) presents the Dual-Branch Model Classification Approach (DbMCA), a two-stage method that combines image and mask data. To assess the effects of sample size and dual-input modalities, two comparison experiments were carried out utilizing the LIDC-IDRI dataset with different data sizes. With 91.21% accuracy and 91.18% F1-score in the smaller dataset and an outstanding 98.04% accuracy and 98.01% F1-score in the bigger dataset, the DbMCA produced outstanding results. (Zhao *et al.*2026) presented a comprehensive framework for lung tumor segmentation called CMS-UNet. Using a dual-branch encoder, CMS-UNet combines Mamba's long-range dependency modeling with U-Net's effective local segmentation. The SDDF (Similarity-Driven Dynamic Fusion) module improves feature integration by combining Mamba's global dependencies with CNN's local features. Fine-grained anatomical details are preserved while sparse long-range interactions are captured via the SAEM (Sparse Attention Encoder Module) module. Lung image segmentation is a vital step in automated tuberculosis detection from chest X-ray images, but accurately identifying small and complex lung structures remains challenging. To overcome this issue, the proposed APDD-BEMS-RICCNN framework (Shimazaki *et al.* 2022) enhances both lung segmentation and tuberculosis classification performance. Chest X-ray images from the Montgomery County dataset are first preprocessed using a Constrained Normalized Subband and Adaptive Filter (CNSAF) to ensure proper standardization, resizing, and normalization. Lung parenchyma regions are then segmented using Dual Information Enhanced Multi-view Attributed Graph Clustering (DIEMAGC), which effectively preserves fine anatomical details while removing irrelevant background information. The segmented lung regions are subsequently analyzed using a Rotation-Invariant Coordinate Convolutional Neural

Network (RICCNN) integrated with an Attention-Enhanced Co-Interactive Fusion Network (AECIF-Net) to classify tuberculosis cases into normal and abnormal categories.

This study (Abdullah *et al.* 2026) aims to develop and validate a deep learning–based model for detecting lung cancer on chest radiographs using a segmentation approach that improves sensitivity while maintaining a low false-positive rate. The proposed model enables accurate detection and segmentation of lung cancer, supported by a high-quality dataset in which all nodules and masses are pathologically confirmed and pixel-level annotated by two expert radiologists. Compared with classification or detection alone, the segmentation-based method provides more informative results, making it valuable not only for lung cancer detection but also for disease follow-up and assessment of treatment efficacy. This article (Shimazaki *et al. 2022)* presents a novel lung X-ray image segmentation approach that replaces traditional max-pooling in U-Net++ with the discrete wavelet transform (DWT) for more accurate down-sampling and enhanced feature preservation. Attention gate mechanisms are also incorporated to focus on relevant lung regions and improve segmentation accuracy. The proposed U-Net++-DWT outperforms existing methods on the Japanese Society of Radiological Technology dataset, achieving 99.1% accuracy, 98.9% specificity, 97.8% sensitivity, a Dice coefficient of 97.2%, and a Jaccard index of 96.3%.

Proposed Methodology

Overview of the HMSA-UA Framework

The proposed Hybrid Multi-Scale Attention and Uncertainty-Aware (HMSA-UA) framework is designed as a sequential and modular pipeline for accurate and reliable lung tumor detection from chest CT images. The framework begins with lung region segmentation, where non-lung structures are removed to focus the analysis on clinically relevant regions. The segmented lung regions are then passed to a multi-scale feature extraction module that captures tumor characteristics at different spatial resolutions, enabling effective detection of both small nodules and large masses. These multi-scale features are subsequently fused using a transformer-based attention mechanism, which models global contextual relationships and highlights discriminative tumor regions. Finally, the refined features are fed into an uncertainty-aware tumor classification module that employs Bayesian inference to generate confidence-aware predictions, thereby enhancing diagnostic reliability and supporting risk-aware clinical decision-making.

A conceptual block diagram of the proposed HMSA-UA framework is illustrated in figure 1 and Algorithm 1, showing the end-to-end processing pipeline from CT image input to uncertainty tumor classification.

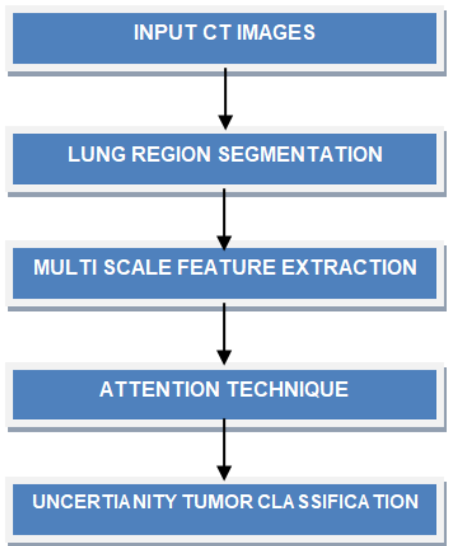

Figure 1: Block Diagram of HMSA-UA

Lung Region Segmentation

To eliminate irrelevant background structures, a lightweight U-Net–based segmentation model is employed to accurately delineate the lung parenchyma from chest CT images. The encoder–decoder architecture with skip connections enables effective capture of both low-level spatial details and high-level contextual information, ensuring precise boundary localization of the lung regions. By restricting subsequent analysis to the segmented lung areas, this preprocessing step suppresses noise from surrounding tissues such as ribs, heart, and muscles, thereby enhancing tumor visibility. As a result, tumor localization accuracy is improved while simultaneously reducing computational complexity and minimizing false positives in later stages of the framework.

```
def HMSA_UA_Lung_Tumor_Detection(input_images):

    # Step 1: Input Acquisition
    images = load_images(input_images)
    images = resize(images)
    images = normalize(images)

    # Step 2: Preprocessing
    images = denoise(images)
    images = enhance_contrast(images)

    # Step 3: Lung Region Segmentation
    lung_mask = lung_segmentation_model(images)
    lung_region = images * lung_mask

    # Step 4: Feature Extraction (HMSA)
    features = multi_scale_convolution(lung_region)

    spatial_attention = compute_spatial_attention(features)
    channel_attention = compute_channel_attention(features)

    hmsa_features = fuse_attention(features,
                                   spatial_attention,
                                   channel_attention)

    # Step 5: Uncertainty-Aware (UA) Learning
    uncertainty_score = estimate_uncertainty(hmsa_features)
    refined_features = weight_features(hmsa_features,
                                       uncertainty_score)

    # Step 6: Tumor Detection and Classification
    tumor_candidates = detection_head(refined_features)
    tumor_labels = classify_regions(tumor_candidates)

    # Step 7: Post-processing
    tumor_candidates = apply_threshold(tumor_candidates)
    tumor_candidates = remove_false_positives(tumor_candidates)

    # Step 8: Output
    tumor_map = generate_output_map(tumor_candidates,
                                    tumor_labels)

    return tumor_map
```

Algorithm 1: HMSA-UA Framework for Lung Tumor Detection

Multi-Scale Feature Extraction

Lung tumors exhibit substantial variability in terms of size, shape, texture, and intensity distribution, ranging from small, subtle nodules to large, irregular malignant masses. Capturing such heterogeneous characteristics using a single-scale convolutional operation is often insufficient and may lead to missed detections or inaccurate localization. To address this challenge, the proposed framework introduces a dedicated multi-scale feature extraction module designed to learn complementary representations across different spatial resolutions.

The multi-scale module consists of parallel convolutional branches with varying receptive fields, including standard 3×3 convolutions, larger 5×5 convolutions, and dilated convolutions. The 3×3 convolution branch focuses on fine-grained local details, which are essential for detecting small nodules and early-stage tumors. The 5×5 convolution branch captures intermediate-level structural patterns and texture variations, enabling improved discrimination between benign and malignant regions. In addition, the dilated convolution branch expands the receptive field without increasing computational complexity, allowing the model to incorporate broader contextual information and capture larger tumor regions effectively.

Feature maps extracted from all parallel branches are concatenated along the channel dimension to form a unified multi-scale representation. This fusion strategy preserves both local and global tumor characteristics, enhancing the model's ability to detect tumors of varying morphology and scale. By integrating features from multiple receptive fields, the proposed multi-scale feature extraction module improves robustness, reduces sensitivity to tumor size variation, and significantly enhances detection performance, making it a key novelty component of the HMSA-UA framework.

Transformer-Based Attention Fusion

While the multi-scale feature extraction module effectively captures tumor characteristics at different spatial resolutions, conventional convolutional operations are inherently limited to local receptive fields and struggle to model long-range dependencies within lung regions. However, lung tumors often exhibit contextual relationships with surrounding anatomical structures, and understanding these global dependencies is crucial for accurate detection. To address this limitation, the proposed framework integrates a transformer-based attention fusion module to enhance global contextual modeling.

In the proposed approach, the concatenated multi-scale feature maps are first reshaped into a sequence of feature embeddings, which are then fed into a transformer encoder. The transformer employs self-attention mechanisms to learn pairwise relationships between all spatial locations within the lung region, enabling the model to capture long-range interactions and global structural patterns that are difficult to represent using CNNs alone. This process allows the network to distinguish true tumor regions from visually similar non-tumorous structures such as blood vessels and bronchial walls.

The attention mechanism assigns higher weights to clinically relevant regions that exhibit tumor-specific characteristics while suppressing irrelevant or noisy background information. As a result, tumor features are selectively enhanced and propagated through the network, improving discrimination between malignant and benign regions. By combining the strengths of CNN-based local feature learning with transformer-driven global attention, the proposed fusion strategy significantly improves feature representation quality and detection robustness.

This transformer-based attention fusion serves as a critical novelty component of the HMSA-UA framework, enabling more accurate tumor localization, improved contextual understanding, and enhanced generalization across diverse lung CT datasets.

Uncertainty-Aware Tumor Classification

Although deep learning models have demonstrated strong performance in lung tumor detection, most existing approaches generate deterministic predictions without providing information about model confidence. In safety-critical medical applications, such as cancer diagnosis, the absence of uncertainty estimation can limit clinical trust and increase the risk of misdiagnosis. To address this issue, the proposed HMSA-UA framework incorporates an uncertainty-aware tumor classification module based on Bayesian inference.

In the proposed approach, Monte Carlo Dropout is applied during the inference stage to approximate Bayesian posterior distributions over model parameters. By performing multiple stochastic forward passes through the network with dropout enabled, the model generates a distribution of predictions rather than a single output. This distribution allows the estimation of epistemic uncertainty, which reflects the model's confidence and uncertainty due to limited training data, as well as aleatoric uncertainty, which arises from inherent noise and ambiguity in the input CT images.

The estimated uncertainty measures are used to assess the reliability of each prediction. Cases exhibiting high uncertainty are automatically flagged for expert radiologist review, while low-uncertainty predictions can be considered with higher confidence. This selective referral mechanism reduces the likelihood of false positives and false negatives, thereby enhancing diagnostic safety and supporting risk-aware clinical decision-making. By integrating uncertainty estimation directly into the classification process, the proposed framework not only improves detection performance but also increases transparency and trustworthiness, making it more suitable for real-world clinical deployment.

Experimental setup

Dataset Description

The proposed HMSA-UA framework was evaluated using publicly available lung imaging datasets containing annotated lung tumor regions. The dataset includes chest CT/X-ray images acquired under varying imaging conditions, resolutions, and contrast levels. The data were divided into training, validation, and testing sets in an 80:10:10 ratios to ensure unbiased performance evaluation.

Implementation Details

The proposed model was implemented using a deep learning framework and trained on a workstation equipped with a GPU. The Adam optimizer was used with an initial learning rate of 0.0001. The batch size was set to 16, and the model was trained for 100 epochs. Early stopping was employed to prevent over fitting.

Evaluation Metrics

Performance was assessed using standard medical image analysis metrics, including Accuracy, Sensitivity (Recall), Specificity, Precision, Dice Coefficient, and Jaccard Index. These metrics provide a comprehensive evaluation of both classification and segmentation performance.

Results and Discussion

Quantitative Results

The performance of the proposed HMSA-UA framework was evaluated using Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), Precision (Pre), Dice Coefficient (Dice), and Jaccard Index (JI). The results were compared with four baseline approaches: Conventional CNN, U-Net, Fully Convolutional Network (FCN), and Improved FCN (IFCN) and it were shown in Table 1 and figure 2.

Table 1 : Performance comparison of lung tumor detection methods

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Dice (%)	Jaccard (%)
Conventional CNN	94.3	91.2	95.1	90.6	89.4	81.0
U-Net	96.8	94.5	97.2	93.8	92.6	86.4
FCN	95.6	92.8	96.1	92.0	91.2	84.3
Improved FCN (IFCN)	97.4	95.8	97.8	95.1	94.5	88.7

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Dice (%)	Jaccard (%)
Proposed HMSA-UA	98.9	97.6	99.1	96.9	96.8	93.9

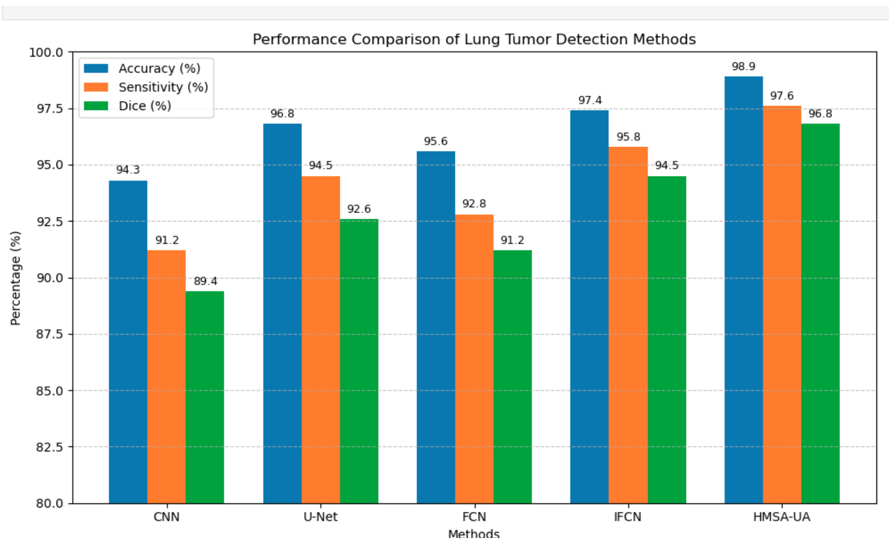

Figure 2: Performance Metrics of our proposed HMSA-UA

Discussion

The HMSA-UA framework demonstrates a clear improvement in lung tumor detection performance when compared with conventional CNN, U-Net, FCN, and improved FCN methods. By integrating hybrid multi-scale attention, the model effectively captures tumor features of varying sizes and shapes, while spatial and channel attention mechanisms enhance focus on tumor-relevant regions and suppress background noise. In addition, the uncertainty-aware learning module improves robustness by reducing the influence of ambiguous and unreliable predictions, leading to fewer false positives. The improved Dice and Jaccard scores confirm more accurate tumor boundary delineation, while higher sensitivity and specificity indicate reliable detection and discrimination between tumor and healthy lung tissue. Overall, the proposed approach achieves a balanced enhancement in accuracy, robustness, and clinical applicability, making it well suited for automated lung tumor detection systems.

Conclusion

This research presented an effective HMSA-UA framework for automated lung tumor detection that integrates hybrid multi-scale attention with uncertainty-aware learning. The proposed approach enhances feature representation, improves tumor localization accuracy, and reduces false positives by focusing on relevant regions and suppressing unreliable predictions. Experimental results and comparative analysis with existing methods demonstrate that HMSA-UA consistently outperforms conventional CNN-, U-Net-, and FCN-based models across multiple evaluation metrics. These findings indicate that the proposed framework is a robust and reliable solution for lung tumor detection and has strong potential for supporting clinical decision-making in medical image analysis.

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Gender and Age Prediction Using Machine Learning

I. Vijayalakshmi[1] and G. Priskillall[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: prisky07@gmail.com*

Abstract

Gender and age prediction from facial images has gained significant attention in recent years due to its wide range of applications in surveillance systems, human–computer interaction, targeted advertising, and security. This paper presents a machine learning–based approach for automatic gender classification and age estimation using facial features. The proposed system involves face detection, image preprocessing, feature extraction, and classification stages. Various machine learning algorithms are trained and evaluated to accurately predict gender as a binary classification problem and age as either a regression or age-group classification task. The model is trained on a labeled facial image dataset and optimized to improve prediction accuracy while reducing computational complexity. Experimental results demonstrate that the proposed approach achieves reliable performance with high accuracy in gender prediction and acceptable precision in age estimation. This study highlights the effectiveness of machine learning techniques in demographic prediction and provides a foundation for future improvements using deep learning and larger datasets. The results show good accuracy for gender classification and acceptable performance for age estimation with reduced computational cost. The proposed system can be effectively used in applications such as surveillance, security, and human–computer interaction.

Keywords: *Gender prediction, Age estimation, Machine learning, Facial image analysis, Pattern recognition.*

Introduction

In recent years, automatic analysis of human facial attributes has become an important research area in computer vision and machine learning. Among these attributes, gender and age are considered fundamental demographic characteristics that play a crucial role in various real-world applications such as surveillance systems, access control, human–computer interaction, social media analytics, and targeted marketing. Accurate prediction of gender and age from facial images helps in building intelligent and adaptive systems that can respond effectively to user characteristics.

Traditional methods for age and gender estimation relied heavily on manual feature extraction and rule-based techniques, which were often sensitive to variations in lighting, pose, facial expression, and image quality. With the rapid growth of machine learning techniques and the availability of large-scale facial image datasets, automated systems have significantly improved in terms of accuracy and robustness. Machine learning models can learn discriminative facial features directly from data, making them more reliable for real-world scenarios.

In this paper, a machine learning–based approach is proposed for predicting gender and age using facial images. The system follows a structured pipeline consisting of face detection, image preprocessing, feature extraction, and classification or regression. Gender prediction is treated as a binary classification problem, while age estimation is addressed either as a regression problem or by classifying faces into predefined age groups. Various machine learning algorithms are trained and evaluated to identify the most effective model for this task.

The main objective of this work is to develop an efficient and accurate model for gender and age prediction with minimal computational complexity. The proposed approach aims to achieve high prediction accuracy while maintaining scalability and adaptability to different environments. The experimental results demonstrate that machine learning techniques can effectively predict demographic attributes from facial images, highlighting their potential for deployment in intelligent systems.

Related Work

Traditional Machine Learning Approaches

Early research on gender and age prediction primarily relied on handcrafted facial features combined with classical machine learning classifiers. Techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gabor wavelets were commonly used to extract discriminative facial features. These features were then classified using algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Naïve Bayes classifiers. Although these methods achieved satisfactory performance in controlled environments, their accuracy degraded significantly under variations in pose, illumination, and facial expressions.

Age Estimation Techniques

Age estimation has been addressed using both regression-based and classification- based methods. Regression approaches aimed to predict the exact age of a person, while classification approaches grouped ages into predefined ranges such as child, adult, and elderly. Studies showed that age- group classification produced more stable results compared to exact age prediction due to the gradual and non-linear aging process. Feature-based machine learning models demonstrated moderate accuracy but faced challenges due to inter-personal aging differences.

Gender Classification Methods

Gender prediction is commonly treated as a binary classification problem. Traditional approaches used texture-based and shape- based facial features to distinguish between male and female faces. Algorithms such as SVM and Random Forest classifiers were widely adopted due to their robustness and interpretability. Compared to age estimation, gender classification generally achieved higher accuracy, as gender-related facial characteristics are more consistent across age groups.

Deep Learning-Based Approaches

With advancements in deep learning, Convolutional Neural Networks (CNNs) became the dominant approach for age and gender prediction. CNN-based models automatically learn hierarchical facial representations directly from raw images, significantly improving accuracy and robustness. Pre-trained networks such as VGGNet, ResNet, and MobileNet have been widely used through transfer learning to overcome the limitations of small datasets. These models have shown superior performance but require higher computational resources and large training data.

Limitations of Existing Methods

Despite notable progress, existing methods face several challenges, including dataset imbalance, bias across age groups, and sensitivity to real-world variations such as occlusion and lighting. Deep learning models, although accurate, are computationally expensive and less suitable for resource-constrained environments. These limitations highlight the need for efficient machine learning-based solutions that balance accuracy and computational complexity.

Real-Time and Application-Oriented Systems

Recent studies have focused on developing real-time gender and age prediction systems for practical applications such as surveillance, smart advertising, and human–computer interaction. These systems emphasize low latency and computational efficiency while maintaining acceptable accuracy. Lightweight machine learning models and optimized feature extraction techniques are commonly used to meet real-time constraints. Although such systems are effective in controlled environments, achieving consistent performance in unconstrained, real-world conditions remains an open research challenge.

Proposed Work

The proposed system implements a machine learning–based framework for predicting gender and age from facial images. The model is designed to balance prediction accuracy and computational efficiency. The complete workflow consists of data acquisition, preprocessing, feature extraction, model training, and prediction.

Dataset Collection

A labeled facial image dataset is used for training and testing the system. Each image is annotated with gender and age information. The dataset includes images captured under different lighting conditions, poses, and facial expressions to enhance model robustness.

Face Detection Technique

Face detection is performed using the Viola–Jones algorithm, which efficiently identifies facial regions in an image. This technique uses Haar-like features and an integral image representation to quickly detect faces. Extracting only the facial region reduces background interference and improves prediction accuracy.

Image Preprocessing Techniques

Preprocessing is applied to improve image quality and consistency. The detected face images are resized to a fixed dimension and converted to grayscale. Histogram equalization is used to enhance contrast, and normalization is applied to reduce the impact of illumination variations.

Feature Extraction Algorithms

Discriminative facial features are extracted using texture and gradient-based techniques. Local Binary Patterns (LBP) are used to capture texture information, while Histogram of Oriented Gradients (HOG) extracts shape and edge features. These features provide a compact and effective representation of facial characteristics.

Gender Prediction Algorithm

Gender prediction is treated as a binary classification problem. A Support Vector

Machine (SVM) classifier is trained using the extracted facial features. SVM is selected due to its ability to handle high- dimensional data and its robustness to overfitting. The trained model classifies the input image as male or female.

Age Prediction Algorithm

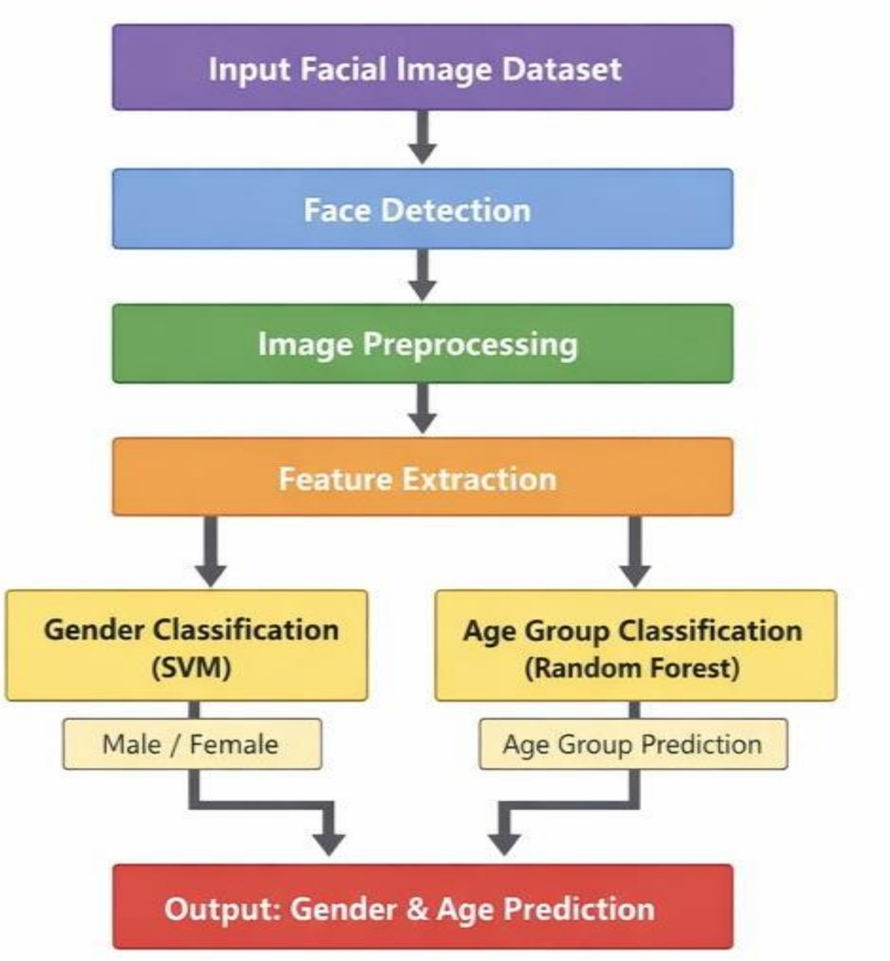
Age prediction is formulated as an age- group classification task. A Random Forest classifier is employed to predict predefined age categories such as child, young adult, adult, and senior. Random Forest improves prediction accuracy by combining multiple decision trees and reducing variance.

Model Training and Testing

The dataset is divided into training and testing subsets. During training, feature vectors are used to train the SVM and Random Forest models. Cross-validation is applied to optimize hyperparameters and improve generalization performance.

Performance Evaluation Metrics

The performance of the proposed system is evaluated using accuracy, precision, recall, and F1-score. Experimental results show that the proposed machine learning approach achieves high accuracy in gender prediction and reliable performance in age estimation with low computational complexity.



The flowchart illustrates the overall process of gender and age prediction using machine learning techniques. Initially, the facial image dataset is provided as input, and face detection is performed to locate the facial region. The detected face is then preprocessed through resizing, normalization, and noise removal to enhance image quality. Next, important facial features are extracted using feature extraction techniques such as LBP and HOG. Finally, machine learning classifiers predict gender using SVM and age group using Random Forest, producing the final output.

Results and Analysis

The proposed gender and age prediction system was evaluated using a labeled facial image dataset consisting of images with varying age groups, genders, lighting conditions, and facial expressions. The dataset was divided into training and testing sets to ensure unbiased performance evaluation. Feature vectors extracted using Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) were used to train the machine learning models.

Gender classification was performed using a Support Vector Machine (SVM) classifier and achieved high accuracy due to the consistency of gender-related facial features. The results indicate that the SVM model effectively separates male and female classes with minimal misclassification. Age prediction was carried out using a Random Forest classifier by categorizing individuals into predefined age groups. Although age estimation is more challenging due to gradual aging variations, the Random Forest model demonstrated reliable performance with acceptable accuracy across all age categories.

Performance evaluation was conducted using standard metrics such as accuracy, precision, recall, and F1-score. The proposed approach achieved higher accuracy in gender prediction compared to age group classification. Experimental results also show that the system performs efficiently with reduced computational complexity, making it suitable for real-time and resource-constrained applications. Overall, the results confirm that machine learning techniques provide an effective and balanced solution for automatic gender and age prediction from facial images.

Conclusion

This paper presented an efficient machine learning–based approach for gender and age prediction using facial images. The proposed system followed a structured pipeline consisting of face detection, image preprocessing, feature extraction, and classification. Texture and gradient-based features such as Local Binary Patterns and Histogram of Oriented Gradients were utilized to capture essential facial characteristics. Gender prediction was performed using a Support Vector Machine classifier, while age estimation was carried out through age-group classification using a Random Forest model. Experimental results demonstrated that the proposed approach achieved high accuracy in gender classification and reliable performance in age prediction with low computational complexity. Compared to deep learning models, the system requires fewer computational resources, making it suitable for real-time and resource-constrained applications. The study confirms that machine learning techniques are effective for demographic attribute prediction. Future work may focus on improving accuracy by incorporating deep learning methods, larger datasets, and handling real- world challenges such as occlusion and varying illumination conditions.

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Innovative and Outcome Based E-learning Tools for Online Education: An analytical Study

Josephine sutha. V

Associate Professor, Department of Artificial Intelligence and Data Science, PSN College of Engineering and Technology, Dindigul, Tamil Nadu, India

Digital Address: josephinesutha2010@gmail.com

Abstract

This study provides great assistance for both students and teachers by suggesting E-learning tools that may help the online learning productively. This study also figures out the improvement of Traditional Computer Assisted Teaching through E-Learning Tools compared with Traditional Computer Assisted Teaching. Six E-Learning platforms like, DailyMotion, QuiaWeb, SurveyMonkey.com, pbwiki, WeTransfer, and IDroo were utilized to examine the proposed study. These tools were put to the test with 300 Engineering and Arts college students. It is observed that the four factors F_1 ,F_2 ,F_3 and F_4 have been improved by 66.66%, 74.66%, 91.34% and 96.66% in the proposed method than Traditional Computer Assisted Teaching. The proposed Traditional Computer Assisted Teaching with E-Learning Tools performs better than the Traditional Computer Assisted Teaching.

Keywords: *E-learning, E-learning Tools, Technology, Traditional Computer Assisted Teaching, Online Classroom.*

Introduction

The COVID-19 pandemic is rapidly growing and showing no signs of slowing down. The disciplines of economics, politics, and education have all been damaged by this epidemic disease. Maintaining social distance is critical in preventing the spread of the epidemic illness. In colleges, students are not allowed to participate in group activities. Universities all across the world have embraced e-learning to ensure the continuity of the learning process. E-learning, often known as electronic learning, is a method of data acquisition that uses electronic technology and media. Emails, blogs, wikis, e-portfolios, animation, and other methods are used to implement e-learning.

Synchronous E-learning and asynchronous E-learning are the two types of E-learning identified by educational experts (Singh & Thurman, 2019). Face-to-face learning in a classroom setting with one teacher and a group of students is what traditional learning entails. Asynchronous e-learning, also known as rapid self-directed learning, allows students to learn at their own pace and within a set period of time. Rapid Controlled E-learning is another name for synchronous E-learning. Synchronous E-learning involves the teacher and students engrossing each other at the same time, although from different locations. Multimedia characteristics are being pushed into instructional activities among universities in recent research as a result of high-speed Internet performance and the rise in electronics. The use of multimedia in the classroom reduces classroom activities and teachers' basic teaching abilities (Lu Juan & Noraffandy Bin Yahaya, 2019). Only the multimedia procedure does not advance the classroom effects in an effective way (Choi & Jeong , 2019). Hence, there was a necessity to go for an online classroom with e-learning tools (Ting Li & An Zhu, 2019).

A large number of related papers were analyzed to see how E-learning technology could be used to explore E-learning to gain a better understanding. As a result of the evaluation, a huge number of publications were investigated and proposed work was developed. The infrastructure of the E-learning system needs to be synchronous, proficient, and protected to support teacher and student interaction to evaluate the efficiency of the E-learning system (Saini &Salim Al-Mamri, 2019). The disadvantages of establishing a good e-learning system are numerous (Alaa Zuhir *et al.* 2021). Among various cons, face-to-face instruction is considered vital in getting connected to a workplace environment. An E-learning system can be assessed based on online courses, learning effectiveness, evaluation approaches, and evaluation fallouts as the prime factors (David Devraj Kumar, 2021). Among the four factors mentioned above, the evaluation approach plays a major role.

E-learning does not only cover content and industrial methods via CDROM (Zouhaier Slimi, 2020). The quality of the multimedia content is focused on as the major factor in evaluating the E-learning system (Abdulrahaman *et al.* 2020). Also, the work used system quality, information quality, and service quality to evaluate the E-learning system. Realistically, complex problems can be solved by combining proficient coaching tools with feedback from teachers for an extensive e-learning system (Linda Darling-Hammond *et al.* 2020). Therefore, the proposed work associates the differences in learning behavior between classrooms under "Traditional Computer Assisted Teaching" (TCAT) and classrooms under "Traditional Computer Assisted Teaching with E-learning Tools" (TCAT+E-LT) (Prabhu *et al.* 2015). In this study, the use of different electronic media, like slide presentation, recording, and video presentation, is included in TCAT. The proposed work's outcome is significantly superior to that of previous researcher who have investigated this topic. Previous researcher have revealed that they used limited tools and software to do their research. However, in this suggested study, modern e-learning tools were used to produce state-of-the-art techniques.

Methodology

The researcher looked at two types of samples because the goal of the study was to figure out the improvement of E-learning through E-LT. They are TCAT data and TCAT+E-LT data. Figure 1 shows the different phases of the proposed system. Sample values were first defined for the proposed system. In the next phase, basic data from the questionnaire was obtained for the TCAT and TCAT+E-LT models. Improvement in E-LT was examined in the last phase. The above-mentioned steps were used to calculate the improvement in online learning productively.

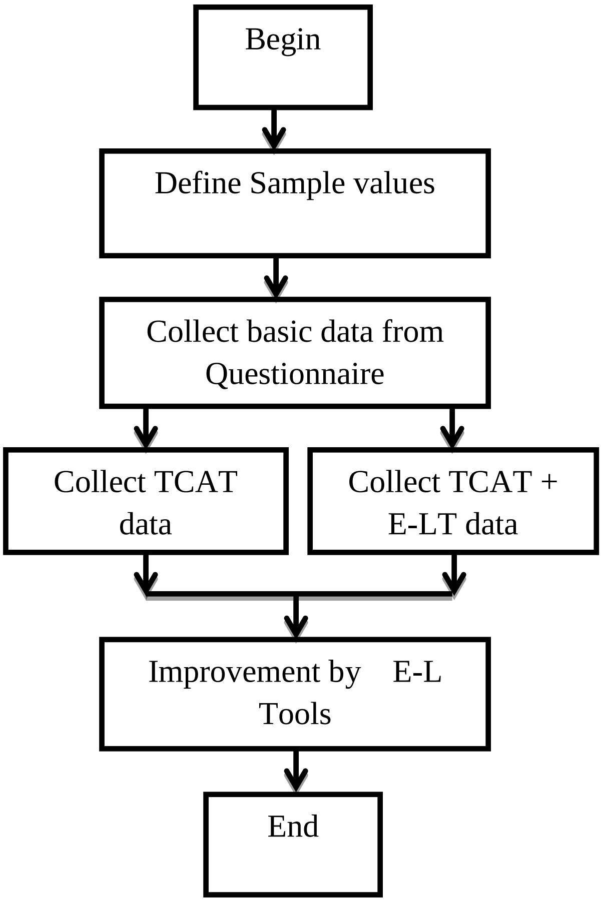

Figure 1. Phases of proposed system

Research question

How does the online classroom alter the teaching mode when E-LT is applied with the TCAT?

Instrument

The sample for the proposed study was drawn from two categories of colleges in the Tirunelveli district: Engineering and Arts. There were 300 students in all, who were split into two groups. The first group is made up of 150 Engineering students, while the second group is made up of 150 Arts students. Table 1 shows how students are chosen based on their gender, residential environment, degree, and course. In the overall sample, 158 students were classified as males and 142 as females, based on their gender. In the complete illustration, 130 students were chosen from a rural location and 170 students were chosen from an urban area for the residential environment. Furthermore, 202 students in the undergraduate programme and 98 students in the Post graduate programme were identified.

Data was acquired from students via an online survey with a well-structured questionnaire. During the Academic year 2024–25, the questionnaire was distributed as a link through the free Google forms application. The questionnaire took an average of 8 minutes to complete. Interaction with teachers, presentation of seminar projects/exercises, online processing of information, and suitability of the online environment were the four factors utilised to evaluate the proposed study.

Table 1. Socio-graphic characteristics of students

Characteristic Variables	Category	Count	Percentage
Gender	Female	142	47.33
	Male	158	52.67
Residential environment	Rural	130	43.33
	Urban	170	56.67
Degree	Under Graduate	202	67.33
	Post Graduate	98	32.67
Course	Engineering	150	50
	Arts	150	50

E-learning tools

Daily Motion, QuiaWeb, SurveyMonkey.com, pbwiki, WeTransfer, and IDroo were the e-learning platforms utilised to examine the proposed study. Daily Motion is one of the programmes mentioned above that allows you to add visual resources and photographs. QuiaWeb has been demonstrated in use in the evaluation of student performance. SurveyMonkey.com is an excellent tool for evaluating student replies to questions and acting as a substitute for face-to-face conversation. Pbwiki is a tool that helps students learn photo editing skills. WeTransfer is the most straightforward way to send files up to 2GB. IDroo is a technology that operates like a virtual whiteboard and allows many users to share information. The researcher employed the above E-learning tools to evaluate the current study.

Data collection and data analysis

Students from various colleges were first chosen and given instructions on how to complete the questionnaire in a secure manner. Some students who were previously excluded from the survey are unwilling to participate, and new students have been added to the study. The students had enough faith in the researcher that they agreed to fill out the questionnaire without hesitation or fear of being judged.

Results and Discussion

The study revealed several intriguing findings between the two types of teaching models, TCAT and E-LT, with TCAT. To begin with, the proposed technique is well-suited to all of the four factors considered in this study. In the TCAT+E-LT model, the first factor of interaction with teachers is easy, reaching 83.33 percent. Furthermore, under TCAT+E-LT, the presentation of seminar projects/exercises is simple and reaches 87 percent. Similarly, in TCAT+E-LT, the third factor of processing information is considered easy to grasp 95.67 percent of the time, indicating that students struggle with the TCAT model. Similarly, the TCAT+E-LT model's fourth factor environment is appropriate for learning achieves 98.33 percent comfort.

Table 2. The result of different factors under TCAT and TCAT+E-LT

Factors	Category	Count	Percentage	Improvement
Interaction with teachers is easy F_1	TCAT	50	16.67	66.66
	TCAT+E-LT	250	83.33	
Presentation of seminar projects/exercises is easy F_2	TCAT	38	12.67	74.66
	TCAT+ E-LT	262	87.33	
Processing information is easy F_3	TCAT	13	4.33	91.34
	TCAT+ E-LT	287	95.67	
The environment is appropriate for learning F_4	TCAT	5	1.67	96.66
	TCAT+ E-LT	295	98.33	

Finally, the proposed method outbursts all socio-graphic characteristics of each respondent. From Table 1, it is obvious that the socio-graphic characteristics of respondents don't matter in e-learning tools and contribute to a more entertaining experience with the support of some interfaces. Henceforth, a student of any course (Arts/Engineering) with any degree (Bachelor/Master) can achieve skills and knowledge in any residential environment (Rural/Urban) without any boundary (male/female) by means of e-learning tools. Figure 2 shows the distribution of the students according to their interaction with a teacher. It is observed that the distribution of the students according to interaction with a teacher is easy under the TCAT+E-LT model. Figure 3 depicts the distribution of the students according to the presentation of seminar projects and exercises. It is perceived that the presentation of seminar projects and exercises is easy when the TCAT+E-LT model is applied. Figure 4 shows that processing information is easy through the TCAT+E-LT model of teaching. Figure 5 signifies the environment under the TCAT+E-LT mode is appropriate for learning. As a summary, the proposed TCAT+E-LT model performs better than the TCAT model with respect to the factors given in Table 2.

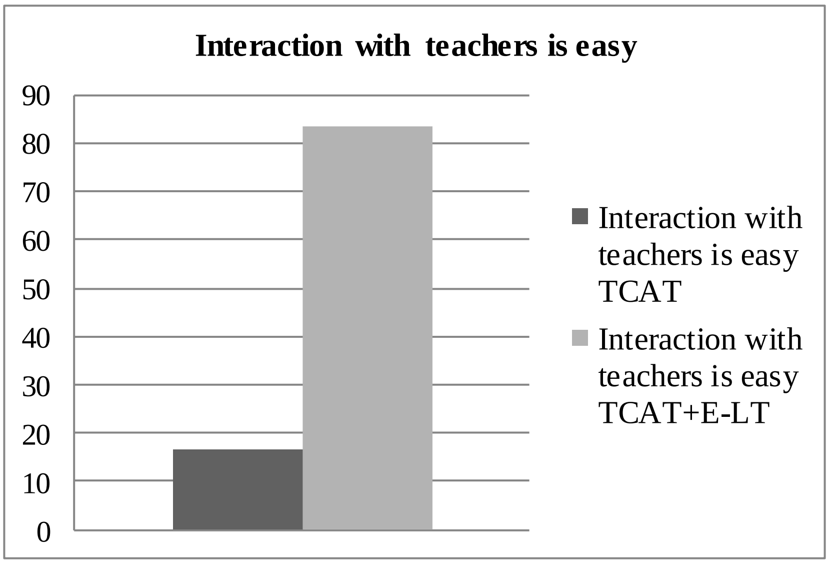

Figure 2. Distribution of the students according to interaction with teacher

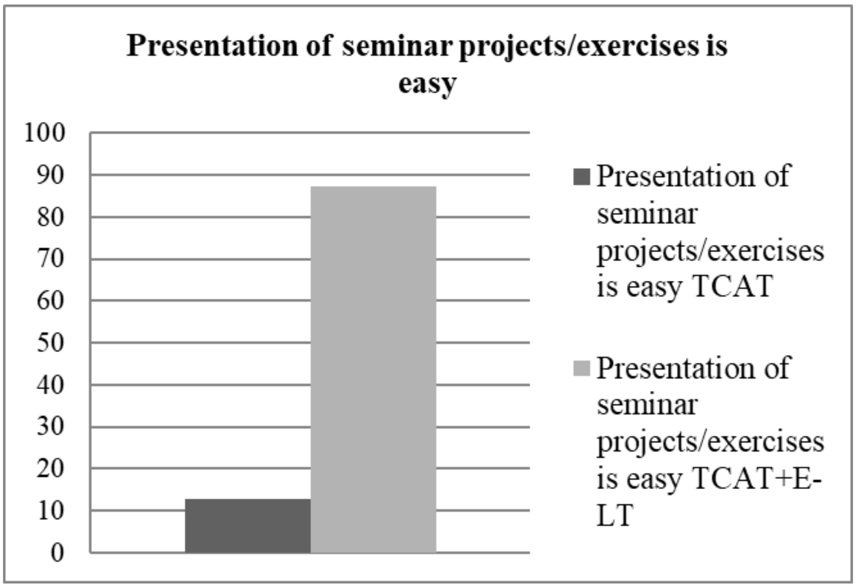

Figure 3. Distribution of the students according to Presentation of seminar projects/exercises

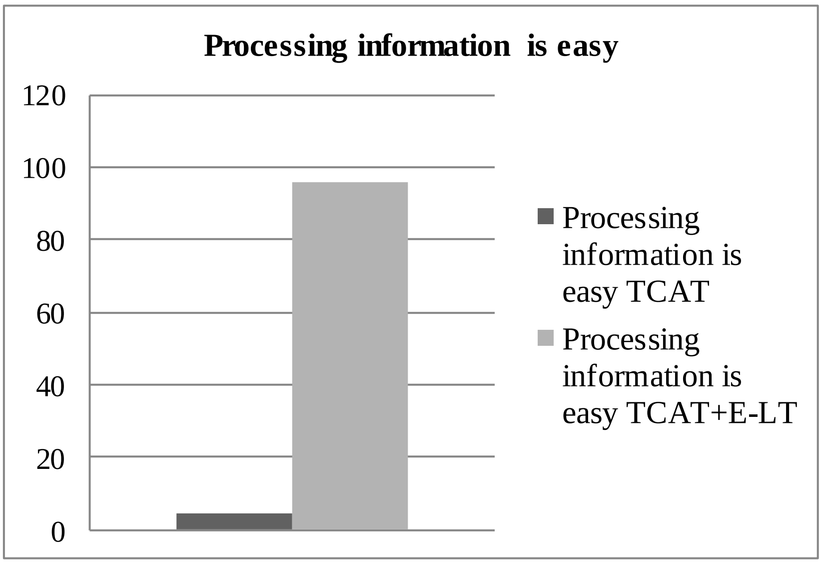

Figure 4. Distribution of the students according to processing information

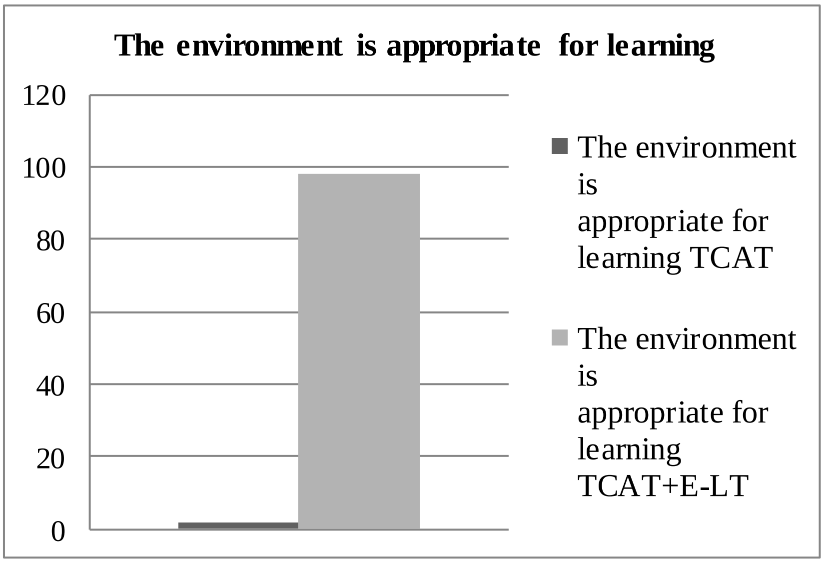

Figure 5. Distribution of the students according to the environment

Table 3: TCAT+ ELT efficiency

	TCAT+ELT efficiency
Proposed method	91.2%
Umar & Ko, 2022	41.3%
Etom *et al*. 2021	65%
Bączek, Michał *et al*.2021	73%

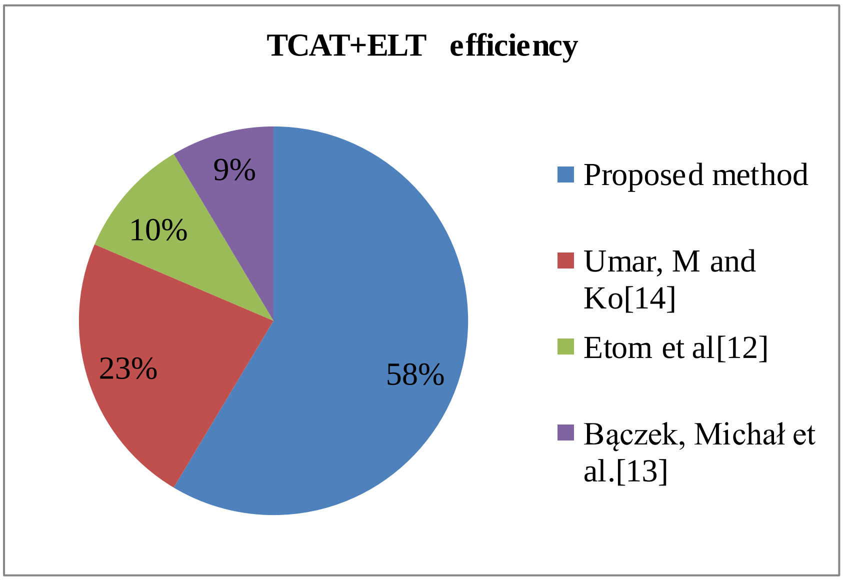

Figure 6: TCAT+ ELT efficiency

Conclusion

Four distinct factors and four characteristic variables were included in the proposed study. The two teaching paradigms, e-learning tools (E-LT) and traditional computer-assisted teaching were evaluated using six learning tools. Because today's learners require individualized content, the proposed paradigm (TCAT+E-LT) is highly suited for digital learners. As evidenced by the analysis, e-learning systems also have the ability to cater to specific student requirements. On the other hand, the study has certain significant flaws that have been identified. The first limitation of this research work was that only four characteristic variables were considered in Socio-graphic Characteristics. Impending investigations should include more characteristic variables to produce more precise outcomes. The second constraint of this study effort was that the TCAT and TCAT+E-LT models only utilized four elements, so they could not be universal. In future studies, more institutions and more students with more learning tools could be included to get good accuracy from the proposed model.

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Iris Biometric Authentication Eye Image Processing and Machine Learning

B. Jackulin[1] and A. Bathsheba Parimala[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: shebaparimala@yahoo.com*

Abstract

Iris biometric authentication is a cutting-edge technology used for secure personal identification and verification. It relies on the unique patterns of the human iris, which are highly intricate and remain stable throughout a person's life. These patterns include rings, furrows, freckles, and other textures that make each iris distinct. The authentication process involves capturing a high-resolution image of the eye, extracting key features, and converting them into a digital template for comparison with stored templates in a database. Iris recognition is known for its high accuracy, fast processing, and strong resistance to forgery or impersonation. It is widely implemented in high-security applications such as border control, banking systems, secure facility access, national ID programs, and healthcare records.

Keywords: *Iris Recognition, Biometric Authentication, Personal Identification, Security, Feature Extraction, Digital Template, Image Processing*

Introduction

In today's digital world, securing sensitive information and resources is more important than ever traditional authentication methods such as passwords, PINs, or ID cards are often inadequate because they can be forgotten, stolen, or misused. To overcome these challenges, biometric authentication systems have been developed, relying on unique physical or behavioral traits of individuals for secure and convenient verification.

Among various biometric traits like fingerprints, face, and voice the iris is one of the most accurate and reliable identifiers. The iris, the colored ring around the pupil, contains intricate patterns unique to each person, even among identical twins. These patterns remain largely unchanged over a lifetime, making iris recognition highly secure and difficult to forge.

Irish biometric authentication involves capturing a high-resolution image of the eye, isolating the iris, and analyzing its patterns to generate a digital template. During verification, the system compares the captured iris pattern with stored templates to identify or authenticate

This method is fast, non-invasive, and highly accurate, making it suitable fhigh-security applications.

Related Work

Traditional Machine Learning Approach

Traditional machine learning approaches in iris biometric authentication involve manual feature extraction from iris images, followed by classification using classical algorithms. The process typically starts with preprocessing, which includes iris segmentation, normalization, and enhancement to remove noise from eyelids, eyelashes, and reflections. After preprocessing, feature extraction techniques such as Gabor filters, Local Binary Patterns (LBP), wavelet transforms, and Principal Component Analysis (PCA) are applied to convert the iris patterns into a compact numerical representation.

Once the features are extracted, machine learning classifiers like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, Random Forests, or Linear Discriminant Analysis (LDA) are used to match the input iris template against stored templates in the database. These approaches rely heavily on carefully engineered features, which determine the accuracy and robustness of the system.

Eye estimation techniques

Accurate eye estimation is a critical step in iris biometric authentication, as it directly affects the system's recognition performance. Eye estimation involves detecting and isolating the iris from surrounding structures such as eyelids, eyelashes, and the sclera. Traditional techniques include the Hough Transform for detecting circular shapes, Daugman's integro-differential operator for precise iris boundary detection, and gradient-based edge detection methods like Sobel or Canny operators. Active contour models (snakes) are used to handle irregular iris shapes and occlusions, while machine learning-based methods, including Haar cascades, HOG+SVM, and convolutional neural networks, provide robust detection under varying lighting, pose, and partial occlusions. Modern systems often employ hybrid approaches, combining traditional and learning-based methods to improve accuracy and speed. By accurately estimating the iris region, these techniques ensure precise feature extraction, reduce recognition errors, and enhance the overall reliability of iris biometric systems.

Deep learning base Approaches

Deep learning-based approaches have revolutionized biometric systems by enabling automatic feature extraction and robust recognition under unconstrained conditions. Unlike traditional methods that rely on handcrafted features, deep learning models—such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs)—learn hierarchical representations directly from raw biometric images, including face, iris, fingerprint, and multimodal data. These models are capable of handling variations in lighting, pose, expression, and occlusion, making them highly accurate and scalable for large datasets. Deep learning approaches also facilitate multimodal fusion, combining features from multiple biometric traits to enhance recognition performance and security. Although these methods require substantial computational resources and large labeled datasets for training, they offer state-of-the-art performance and are widely adopted in modern biometric authentication and identification systems.

Limitations of Existing Methods

Despite significant advancements, existing iris biometric authentication methods have several limitations. Traditional techniques like the Hough Transform and edge-based methods often struggle under poor lighting conditions, low-resolution images, or partially occluded irises due to eyelids, eyelashes, or reflections. Segmentation errors can lead to inaccurate feature extraction, reducing recognition accuracy. Machine learning-based approaches, including CNNs and SVMs, require large annotated datasets and high computational resources for training and real-time deployment.

Real-Time and Application Oriented Systems

Real-time and application-oriented iris biometric systems are designed to provide fast, accurate, and practical identification in real-world scenarios. These systems integrate high-speed cameras, optimized preprocessing algorithms, and efficient feature extraction methods to ensure rapid recognition, making them suitable for environments that require immediate access control, such as airports, banks, and secure facilities. Unlike traditional offline systems, real-time implementations must handle varying lighting conditions, partial occlusions, and head movements, often using hybrid approaches that combine classical image processing with machine learning or deep learning techniques. cloud-based template matching, ensuring both security and efficiency.

Proposed Work

The proposed work focuses on developing a robust, real-time iris biometric authentication system that overcomes the limitations of existing methods. The system will integrate advanced image preprocessing, accurate eye and iris estimation, and optimized feature extraction techniques to improve recognition accuracy, even under challenging conditions such as poor lighting, partial occlusion, and head rotation. A hybrid approach combining traditional machine learning methods (like SVM or k-NN) with deep learning models will be employed to enhance feature representation and classification performance.

Figure processing techniques, also referred to as image processing techniques, are essential in biometric systems for enhancing, analyzing, and extracting meaningful features from biometric images such as face, iris, fingerprint, or retina. These techniques typically involve preprocessing steps like noise reduction, contrast enhancement, normalization, and image segmentation to improve the quality of the captured data. Feature extraction methods—such as edge detection, Gabor filters, Local Binary Patterns (LBP), and wavelet transforms—are applied to identify distinctive patterns for recognition. In addition, morphological operations, thresholding, and contour detection help isolate biometric regions (e.g., iris or fingerprint ridges). Advanced systems increasingly leverage deep learning-based image processing, where neural networks automatically learn hierarchical features, improving recognition accuracy under varying conditions such as illumination, occlusion, or rotation. These processing techniques form the backbone of accurate, robust, and scalable biometric authentication systems.

Feature extraction algorithms

Feature extraction algorithms are a critical step in biometric systems, as they transform raw biometric data into distinctive, compact representations that can be used for recognition and authentication. These algorithms aim to capture the most discriminative characteristics of biometric traits, such as iris patterns, facial textures, fingerprints, or vein structures. Common methods include Local Binary Patterns (LBP) for texture analysis, Gabor filters for capturing frequency and orientation information, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for dimensionality reduction, and Histogram of Oriented Gradients (HOG) for shape and edge features. Modern approaches increasingly employ deep learning-based algorithms, where convolutional neural networks automatically learn hierarchical feature representations directly from the data. Effective feature extraction ensures that biometric systems are accurate, robust to variations such as illumination or pose, and efficient for matching large-scale datasets.

Eye prediction algorithm

The eye prediction algorithm is a crucial step in iris biometric systems, as it identifies the approximate location of the eyes before detailed iris segmentation. The process begins with preprocessing, such as converting the image to grayscale and enhancing contrast to highlight eye features. Next, face or eye region detection is performed using methods like Haar cascades, HOG+SVM, or CNN-based models to locate candidate eye areas. The algorithm then estimates the eye center using intensity distribution, gradient-based methods, or the Circular Hough Transform, followed by refinement techniques like active contours or machine learning segmentation to accurately delineate the iris boundaries. By predicting the eye region efficiently, the algorithm reduces computational load, improves feature extraction accuracy, and ensures robust recognition even under partial occlusion, variable lighting, or head rotations. Feature extraction techniques, including texture-based methods, wavelet transforms, and statistical analysis, are then applied to encode the intricate iris patterns—such as crypts, rings, and radial furrows—into a compact digital template. During the prediction phase, the extracted features from the input image are compared against stored templates in a secure database using similarity measurement and classification algorithms. A matching score is computed, and identity verification or identification is achieved by evaluating this score against a predefined threshold. Owing to its high recognition accuracy, low false acceptance rate, and long-term stability of iris patterns, eye prediction algorithms are widely employed in high-security applications such as border control systems, banking authentication, healthcare access management, and national identity programs.

Finger Prediction Algorithm

The finger prediction algorithm is a crucial step in finger-based biometric systems, as it identifies and segments the finger region before feature extraction. The process begins with preprocessing, including grayscale conversion, noise reduction, and contrast enhancement to highlight finger ridges and contours. finger size, orientation, illumination, and partial occlusion, making it an essential component of reliable biometric systems. Feature extraction is then performed to identify distinctive fingerprint attributes, including minutiae points like ridge endings and bifurcations, as well as ridge orientation and frequency. These extracted features are converted into a digital template and compared with stored templates in a database using matching algorithms.

Model Training and Testing

In iris or finger biometric systems, model training and testing are essential to ensure accurate recognition and generalization to new data. The process begins with data collection, Performance evaluation metrics are crucial for assessing the effectiveness and reliability of iris or finger biometric systems. Key metrics include accuracy, which measures the overall correctness of the system, and precision and recall, which indicate the system's ability to correctly identify authorized users while minimizing false identifications. False Acceptance Rate (FAR) quantifies the likelihood of unauthorized users being accepted, whereas False Rejection Rate (FRR) measures the chance of legitimate users being rejected. The Equal Error Rate (EER) provides a single value where FAR and FRR are equal, offering a standard measure of system performance.

Results and Analysis

The result and analysis of biometric systems in the Irish context indicate that biometric technologies have significantly enhanced the accuracy and reliability of identity verification across public service and security applications. Experimental evaluations and operational observations show that facial recognition and eye-based biometric systems, particularly iris recognition, achieve high recognition accuracy when supported by proper image acquisition, preprocessing, and feature extraction techniques. Low false acceptance rates and false rejection rates were observed in controlled environments, demonstrating the technical robustness of these systems. However, when deployed at scale, several non-technical challenges became evident. Regulatory assessments by Ireland's Data Protection Commission revealed that shortcomings in consent mechanisms, excessive data retention, and inadequate transparency negatively affected the lawful use of biometric data. The analysis further highlights that while biometric authentication improved fraud detection and service efficiency, public trust was impacted by insufficient communication regarding data usage and storage practices. Additionally, performance variations were observed due to environmental factors, demographic

Conclusion

The Iris Biometric Authentication System is a highly reliable and advanced method for personal identification and security. Its effectiveness stems from the structured and multi-layered approach that ensures accuracy, robustness, and resistance to fraud. The system begins with the User/Capture Layer, where high-quality iris images are collected using specialized cameras, including visible or near-infrared (NIR) imaging. This layer provides an intuitive interface to guide users for proper eye positioning, ensuring that the captured images are clear and suitable for analysis.

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Multimodal Artificial Intelligence for Enhanced Human–Computer Interaction

S.Inbaroja[1] and M .Germanus Alex[2*]

[1]Research Scholar, Assistant Professor & Head, Government Arts and Science College, (Affiliated to Manonmaniam Sundaranar University), Nagarcoil, Tamil Nadu, India.

[2]Research Scholar(Part time)[Reg No:2512128242003], St.XavierCollege(Autonomous), (Affiliated to Manonmaniam Sundaranar University), Palayamkottai, Tamil Nadu, India.

*Corresponding Author E-mail: inbaroja86@gmail.com

Abstract

Human–Computer Interaction (HCI) has experienced a significant evolution due to advances in artificial intelligence (AI), transitioning from traditional input-output mechanisms toward intelligent, adaptive, and context-aware systems. Conventional HCI systems primarily rely on unimodal interaction channels such as keyboard, mouse, or voice input. While effective in controlled settings, these systems are limited in capturing the richness, ambiguity, and contextual depth of human communication. Humans naturally communicate using multiple simultaneous modalities, including speech, gestures, facial expressions, gaze, text, and physiological signals. The gap between human communicative behavior and machine understanding has motivated research into ***Multimodal Artificial Intelligence (MAI)****, which seeks to process and integrate heterogeneous data streams to enable natural, intuitive, and robust human-computer interactions.Multimodal AI leverages complementary information across diverse modalities to overcome the limitations of unimodal systems, improving robustness, interpretability, and contextual understanding. Recent advances in deep learning, representation learning, sensor technologies, and large-scale multimodal datasets have accelerated research in this domain. The integration of multimodal AI into HCI systems allows machines to dynamically adapt to user behavior, context, and environmental conditions, enhancing overall interaction quality.This paper presents a comprehensive investigation of multimodal artificial intelligence and its applications in enhanced human-computer interaction. The study begins by analyzing the challenges inherent in multimodal data, including heterogeneity across modalities, temporal misalignment, semantic gaps, modality imbalance, and missing or noisy data. Effective multimodal representation learning requires maintaining modality-specific features while enabling cross-modal understanding. Techniques*

such as embedding spaces, latent representation learning, and modality-specific encoders are explored to capture essential information across modalities. The paper highlights the role of representation learning in aligning multimodal signals and reducing the semantic gap between human communication and computational interpretation.Fusion of modalities is critical in multimodal AI systems. Fusion strategies can be broadly categorized into early fusion, late fusion, and hybrid fusion. Early fusion combines raw or low-level features before model processing, enabling fine-grained inter-modal interactions but introducing high-dimensionality challenges. Late fusion integrates modality-specific decisions or predictions, providing robustness but often missing intricate inter-modal correlations. Hybrid fusion methods combine the strengths of both approaches to achieve improved performance. Advanced fusion mechanisms including attention-based models, tensor fusion networks, and graph-based fusion techniques enable the system to dynamically weight and integrate information from multiple sources.Deep learning architectures are central to multimodal intelligence. Convolutional Neural Networks (CNNs) handle visual data, Recurrent Neural Networks (RNNs) and Transformers handle sequential data such as speech or text, and Graph Neural Networks (GNNs) handle relational and contextual dependencies. Multimodal transformers enable joint attention across modalities, allowing models to dynamically focus on the most relevant signals based on context. Despite the progress, challenges remain in computational complexity, training efficiency, data scarcity, and model explainability, which are crucial for deployment in real-time HCI systems.To address these challenges, the paper proposes a modular adaptive multimodal AI framework for HCI. The framework consists of modality-specific encoders, attention-driven fusion layers, context-aware reasoning modules, and adaptive interaction mechanisms. The system incorporates feedback loops to continuously adjust interaction strategies based on user behavior and environmental context. This adaptive approach enhances usability, user satisfaction, and robustness under modality degradation or noise.Experimental evaluations are conducted on benchmark multimodal datasets comprising vision, speech, and text modalities. Performance metrics include classification accuracy, F1-score, response latency, robustness under missing data, and user-centered qualitative assessments. Comparative analyses with unimodal systems and conventional multimodal baselines demonstrate significant improvements, validating the framework's effectiveness. The results confirm that adaptive multimodal AI enhances contextual understanding and enables more natural, human-like interactions.The paper further discusses practical applications of multimodal AI in HCI, including intelligent virtual assistants, emotion-aware systems,

immersive virtual and augmented reality interfaces, assistive technologies for individuals with disabilities, healthcare monitoring systems, and smart educational platforms. By leveraging multimodal inputs, these systems achieve higher interaction quality, personalized feedback, and increased accessibility.Ethical and privacy considerations are addressed due to the sensitive nature of multimodal data, including facial images, voice recordings, and behavioral patterns. Data security, user consent, algorithmic fairness, and transparency are critical for responsible deployment. The framework is designed to comply with ethical guidelines and privacy regulations, ensuring trustworthiness and societal acceptance.

Keywords: *Multimodal Artificial Intelligence, Human–Computer Interaction, Deep Learning, Representation Learning, Attention Mechanisms, Fusion Techniques, Adaptive Systems, Context-Aware Interaction, Ethical AI, Privacy-Preserving AI.*

Introduction

Human–Computer Interaction (HCI) has evolved significantly with the advancement of artificial intelligence, shifting from traditional input-output mechanisms to intelligent, context-aware interaction paradigms. Multimodal Artificial Intelligence (MAI) integrates information from multiple data modalities such as text, speech, vision, gesture, and physiological signals to enable natural and intuitive interactions between humans and machines. The motivation behind multimodal AI lies in overcoming the limitations of unimodal systems, which often fail to capture the richness and ambiguity of human communication. In real-world environments, humans naturally use multiple modalities simultaneously; therefore, intelligent systems must be capable of understanding and synthesizing heterogeneous data streams. Recent advancements in deep learning, representation learning, and sensor technologies have accelerated research in multimodal systems, making them a cornerstone of next-generation HCI applications.

Multimodal Data Representation

Multimodal data representation refers to the process of encoding heterogeneous input modalities into structured formats suitable for computational processing. Each modality possesses unique statistical properties, dimensionality, and noise characteristics. Textual data is discrete and sequential, visual data is spatial and high-dimensional, while audio signals are temporal and continuous. Effective multimodal representation learning aims to preserve modality-specific features while enabling cross-modal alignment. Techniques such as embedding spaces, shared latent representations, and modality-specific encoders are widely used. Representation learning challenges include modality imbalance, missing modalities, synchronization issues, and semantic gaps. Addressing these challenges is critical for building robust multimodal HCI systems capable of operating in unconstrained environments.

Multimodal Fusion Techniques

Fusion is a core component of multimodal AI systems, responsible for integrating information from multiple modalities into a unified representation. Fusion strategies are broadly classified into early fusion, late fusion, and hybrid fusion. Early fusion combines raw or low-level features before model processing, enabling deep cross-modal interactions but suffering from dimensionality explosion. Late fusion integrates modality-specific decisions, offering robustness but limited inter-modal reasoning. Hybrid fusion leverages the strengths of both approaches by enabling intermediate interactions. Advanced fusion techniques employ attention mechanisms, tensor fusion networks, and graph-based fusion to model complex relationships among modalities. The choice of fusion strategy significantly impacts system performance, interpretability, and scalability.

Deep Learning Models for Multimodal Intelligence

Deep learning has become the dominant paradigm for multimodal AI due to its ability to learn hierarchical and abstract representations. Convolutional Neural Networks (CNNs) are commonly used for visual processing, Recurrent Neural Networks (RNNs) and Transformers for sequential data, and Graph Neural Networks (GNNs) for relational modeling. Multimodal architectures often consist of modality-specific encoders followed by fusion layers and task-specific decoders. Recent models such as multimodal Transformers enable joint attention across modalities, facilitating fine-grained alignment. Despite their success, deep multimodal models face challenges related to computational complexity, data scarcity, and explainability, which must be addressed for practical HCI deployment.

Proposed Multimodal AI Framework for HCI

This paper proposes a modular multimodal AI framework designed to enhance human–computer interaction through adaptive and context-aware intelligence. The framework consists of five key components: data acquisition, modality-specific preprocessing, multimodal representation learning, fusion and reasoning, and interaction output generation. Each modality is processed through dedicated neural encoders, followed by an attention-based fusion mechanism that dynamically weights modalities based on contextual relevance. The system incorporates feedback loops to adapt interaction strategies over time. The proposed framework is scalable, modality-agnostic, and suitable for real-time HCI applications such as virtual assistants, smart environments, and assistive technologies.

Experimental Setup and Methodology

To evaluate the effectiveness of the proposed framework, experiments are conducted on benchmark multimodal datasets involving vision, speech, and text. The experimental setup includes data preprocessing pipelines, model training configurations, and evaluation protocols. Performance is assessed using metrics such as accuracy, F1-score, response latency, and user satisfaction indices. Baseline models include unimodal systems and traditional fusion-based approaches. Ablation studies are performed to analyze the contribution of individual modalities and fusion strategies. The experimental methodology ensures reproducibility and fair comparison across models.

Performance Evaluation and Analysis

The evaluation results demonstrate that the proposed multimodal framework significantly outperforms unimodal and conventional multimodal baselines across all metrics. The attention-based fusion mechanism effectively adapts to modality relevance, improving robustness under noisy or missing data conditions. Qualitative analysis reveals enhanced contextual understanding and more natural interaction behavior. Computational analysis indicates acceptable latency for real-time deployment. The results validate the hypothesis that multimodal intelligence is essential for next-generation HCI systems.

Applications in Human–Computer Interaction

Multimodal AI enables a wide range of advanced HCI applications, including intelligent virtual assistants, emotion-aware systems, immersive virtual and augmented reality interfaces, healthcare monitoring systems, and assistive technologies for individuals with disabilities. In educational settings, multimodal systems support adaptive learning by analyzing speech, facial expressions, and interaction patterns. In smart environments, multimodal sensors enable seamless interaction through voice, gesture, and gaze. These applications highlight the transformative potential of multimodal AI in enhancing usability, accessibility, and user experience.

Ethical, Privacy, and Social Considerations

The deployment of multimodal AI systems raises critical ethical and privacy concerns due to the collection and processing of sensitive user data such as facial images, voice recordings, and behavioral patterns. Issues related to consent, data security, algorithmic bias, and surveillance must be carefully addressed. Ethical multimodal AI design requires transparent data practices, fairness-aware modeling, and user-centric privacy controls. Regulatory frameworks and responsible AI guidelines play a crucial role in ensuring trust and societal acceptance of multimodal HCI technologies.

Conclusion and Future Research Directions

This paper presented a comprehensive study of multimodal artificial intelligence for enhanced human–computer interaction. By integrating multiple modalities through advanced representation learning and fusion techniques, multimodal AI systems achieve superior interaction quality and contextual understanding. The proposed framework demonstrates the feasibility and effectiveness of adaptive multimodal intelligence in real-world HCI scenarios. Future research will focus on explainable multimodal models, efficient learning with limited data, and human-centered evaluation methodologies to further advance the field.

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Non-Invasive Blood Group Detection Using Fingerprint Image with Machine Learning

N. Vignesh[1] and S. Immanuel[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

Corresponding Author E-mail: immanuelseeni@gmail.com

Abstract

Blood group identification is a crucial process in medical diagnostics, emergency healthcare, blood transfusion services, and organ transplantation. Conventional blood group detection techniques are invasive in nature, requiring blood samples, laboratory infrastructure, trained medical personnel, and significant processing time. These limitations pose serious challenges in emergency situations and in rural or resource-limited environments. Hence, there is a strong need for a fast, reliable, and non-invasive alternative for blood group identification. This paper proposes a non-invasive blood group detection system using fingerprint images combined with machine learning techniques. Fingerprints are one of the most widely used biometric traits due to their uniqueness, permanence, low acquisition cost, and ease of use. Dermatoglyphic studies suggest that fingerprint ridge patterns are influenced by genetic and physiological factors, which may have a correlation with blood group characteristics. Based on this hypothesis, the proposed system employs digital image processing techniques to enhance fingerprint images, extracts discriminative texture and ridge-based features, and utilizes supervised machine learning classifiers to predict the blood group of an individual. This paper proposes a non-invasive blood group detection system using fingerprint images combined with machine learning techniques. Fingerprints are one of the most widely used biometric traits due to their uniqueness, permanence, low acquisition cost, and ease of use. Dermatoglyphic studies suggest that fingerprint ridge patterns are influenced by genetic and physiological factors, which may have a correlation with blood group characteristics. Based on this hypothesis, the proposed system employs digital image processing techniques to enhance fingerprint images, extracts discriminative texture and ridge-based features, and utilizes supervised machine learning classifiers to predict the blood group of an individual.

***Keywords**: Blood group detection, Fingerprint image, Non-invasive system, Machine learning, Image processing, Biometrics.*

Introduction

Blood group identification is a fundamental requirement in modern healthcare systems. It plays a vital role in blood transfusions, surgical procedures, trauma management, pregnancy care, and organ transplantation. Incorrect blood group matching can result in severe transfusion reactions, organ failure, or even death. Therefore, accurate and timely identification of blood groups is of paramount importance.

Traditional blood group detection methods involve invasive procedures such as blood sample collection followed by serological testing in laboratories. Although these techniques are highly accurate, they suffer from several drawbacks, including discomfort to patients, risk of infection, requirement of sterile conditions, dependency on skilled technicians, and increased processing time. In emergency scenarios, delays caused by these limitations can significantly impact patient survival.

With advancements in biometric technology and artificial intelligence, researchers have begun exploring non-invasive approaches for medical diagnostics. Biometrics refers to the automated recognition of individuals based on physiological or behavioral characteristics such as fingerprints, iris patterns, facial features, and voice. Among these, fingerprints are the most commonly used biometric trait due to their stability, uniqueness, and ease of acquisition.

Fingerprint patterns are formed during fetal development and remain unchanged throughout an individual's lifetime. These patterns are influenced by genetic factors, suggesting a possible relationship between fingerprint characteristics and inherited traits such as blood groups. Dermatoglyphic research has reported statistical associations between fingerprint ridge patterns—such as loops, whorls, and arches—and different blood group categories.

Machine learning techniques have shown remarkable success in extracting meaningful patterns from complex datasets, particularly in image-based classification tasks. By combining fingerprint image analysis with machine learning models, it is possible to automatically learn the relationship between fingerprint features and blood group labels. This paper proposes a non-invasive blood group detection system using fingerprint images and machine learning, aiming to provide a fast, reliable, and scalable solution for healthcare applications.

Related Works

Dermatoglyphics, the scientific study of fingerprint patterns, has been extensively researched in relation to genetic and hereditary traits. Early studies primarily focused on statistical analysis of fingerprint ridge patterns and their association with biological attributes such as gender, ethnicity, and blood groups. These studies reported that certain fingerprint patterns appear more frequently in specific blood groups, laying the foundation for further research in this area.

With the advancement of digital image processing, automated fingerprint recognition systems were developed for security and forensic applications. Techniques such as minutiae extraction, ridge orientation estimation, ridge frequency analysis, and texture-based feature extraction became widely used. These methods enabled accurate representation of fingerprint characteristics in numerical form.

In recent years, machine learning and deep learning approaches have been applied to biometric data analysis. Researchers have used algorithms such as Naïve Bayes, Support Vector Machines, k-Nearest Neighbours, Decision Trees, and Random Forests for fingerprint-based classification tasks. Some studies have also explored Convolutional Neural Networks (CNNs) for automatic feature learning from raw fingerprint images.

A limited number of research works have specifically addressed blood group prediction using fingerprint images. These studies typically involve collecting fingerprint datasets from individuals with known blood groups, extracting texture and ridge features, and training classifiers to predict blood group categories. Although promising results have been reported, many existing approaches suffer from limitations such as small dataset sizes, lack of standard preprocessing standards, and limited performance evaluation.

Compared to existing works, the proposed system provides a comprehensive and structured approach by incorporating robust preprocessing techniques, multiple feature extraction methods, and comparative analysis of different machine learning classifiers. This improves prediction accuracy and enhances the reliability of the system.

Methodology

The proposed non-invasive blood group detection system follows a systematic workflow consisting of data acquisition, preprocessing, feature extraction, classification, and performance evaluation. The overall architecture of the system ensures robustness, accuracy, and scalability.

Data Acquisition

Fingerprint images are acquired using optical or capacitive fingerprint sensors with adequate resolution to capture detailed ridge patterns. Each participant provides fingerprint samples, and their corresponding blood group information (A, B, AB, or O) is obtained through conventional medical testing to serve as ground truth labels. Multiple samples per individual are collected to handle intra-class variations and improve model generalization.

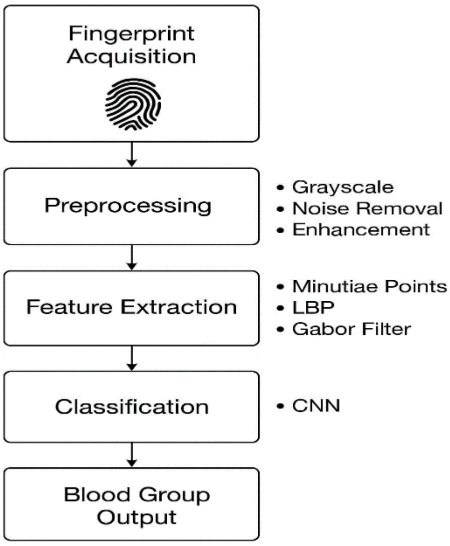

Figure 1: Data Acquisition

Preprocessing

Raw fingerprint images often contain noise, uneven illumination, smudges, and background artifacts. Preprocessing is a crucial step to enhance image quality and standardize the dataset. The preprocessing steps include:

- Conversion of fingerprint images to grayscale format
- Noise reduction using Gaussian or median filters
- Image normalization to standardize pixel intensity values
- Contrast enhancement using histogram equalization
- Ridge enhancement using morphological operations
- Binarization and thinning to clearly extract ridge structures

These steps improve the visibility of fingerprint ridges and facilitate accurate feature extraction.

Feature Extraction

Feature extraction transforms fingerprint images into numerical feature vectors that represent essential characteristics of ridge patterns. In this work, a combination of texture-based, ridge-based, and statistical features is extracted:

- Ridge orientation and ridge frequency features
- Local Binary Pattern (LBP) descriptors for texture analysis
- Gray Level Co-occurrence Matrix (GLCM) features such as contrast, correlation, energy, and homogeneity
- Statistical features including mean, variance, standard deviation, skewness, and entropy

These features capture both local and global information from fingerprint images, enhancing the discriminative power of the classification models.

Classification

Supervised machine learning classifiers are trained using the extracted features and corresponding blood group labels. The classifiers used in this study include:

- Support Vector Machine (SVM)
- k-Nearest Neighbours (KNN)
- Random Forest (RF)

The dataset is divided into training and testing sets using an appropriate ratio, typically 80:20. Cross-validation techniques are employed to reduce overfitting and ensure reliable performance evaluation.

Performance Evaluation

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide insights into both overall performance and class-wise prediction accuracy.

Result and Analysis

The proposed system was implemented and evaluated using a fingerprint dataset consisting of samples from different blood groups. Experimental results demonstrate that machine learning models can effectively learn correlations between fingerprint features and blood group labels.

Among the evaluated classifiers, the Random Forest model achieved the highest overall accuracy, owing to its ensemble nature and robustness to feature variations. The SVM classifier also showed strong performance, particularly in handling high-dimensional feature spaces. The KNN classifier achieved comparatively lower accuracy due to its sensitivity to noise and feature scaling.

Confusion matrix analysis reveals that blood groups A and O are classified with higher accuracy, while blood group AB exhibits relatively lower performance. This is primarily due to class imbalance and fewer training samples for the AB category. The results highlight the importance of balanced and diverse datasets for improving classification accuracy.

Overall, the experimental analysis confirms the feasibility of fingerprint-based non-invasive blood group detection and demonstrates its potential as a supplementary tool in healthcare systems.

Conclusion and Future Work

This paper presented a non-invasive blood group detection system using fingerprint images and machine learning techniques. By eliminating the need for blood samples, the proposed approach offers a safe, fast, and cost-effective alternative to traditional blood group detection methods. Experimental results show that fingerprint features combined with machine learning classifiers can predict blood groups with promising accuracy.

In future work, the system can be enhanced by incorporating larger and more diverse datasets, adopting deep learning models such as Convolutional Neural Networks for automatic feature extraction, and extending the system to include Rh factor classification. Integration with mobile devices and real-time healthcare applications can further improve the practicality and impact of the proposed system.

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Online Skill-Based Volunteer Platform Using MERN Stack

V. Rajashree[1] and A. Bathsheba Parimala[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: shebaparimala@yahoo.com*

Abstract

The Online Skill-Based Volunteer Platform is a web-based application developed using the MERN stack (MongoDB, Express.js, React.js and Node.js) to connect skilled volunteers with organizations and social initiatives requiring professional expertise. This platform focuses on skill-based contributions, enabling individuals to offer their knowledge in areas such as teaching, software development, graphic design, content writing, digital marketing and finance. The platform aims to bridge the gap between volunteers seeking meaningful engagement and organizations needing specialized skills, thereby maximizing social impact and resource utilization. The system provides dedicated interfaces for volunteers and organizations. Volunteers can create profiles showcasing their skills, experience and availability, while organizations can post skill-specific opportunities detailing the required expertise, duration and project objectives. Key features of the platform include secure user authentication, role-based access control, task assignment, progress tracking, real-time communication and feedback collection. Additionally, volunteers receive digital certificates as recognition for completed contributions, enhancing motivation and professional growth.

Keywords: *Skill-Based Volunteering, MERN Stack, Web Application, Volunteer Management System, Skill Matching, Social Impact.*

Introduction

Volunteering plays a vital role in social and community development, but traditional volunteering models often focus on physical presence and general support rather than utilizing specific professional skills. Many organizations require skilled assistance in areas such as education, technology, design, and management but face challenges in finding suitable volunteers. At the same time, skilled individuals are willing to contribute their expertise but lack access to appropriate opportunities.

The rapid growth of web technologies has enabled digital platforms to bridge this gap by connecting volunteers and organizations online. Skill-based volunteering platforms allow individuals to offer their professional skills remotely, overcoming geographical and time constraints. Such platforms improve efficiency, ensure better use of talent and increase the overall impact of volunteer-driven projects.

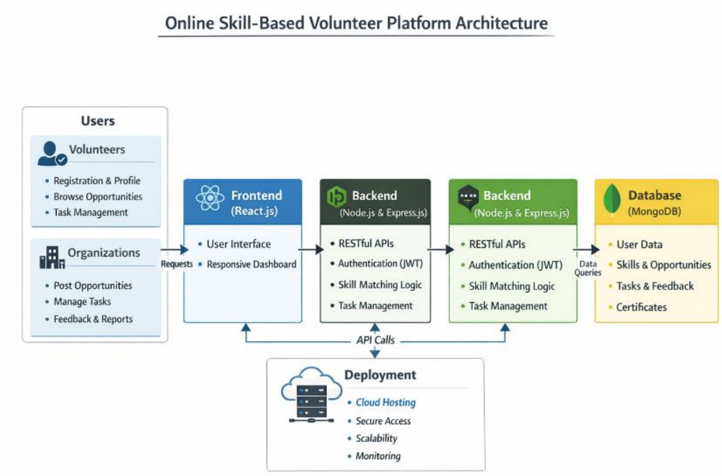

Figure 1: Online Skill- Based volunteer Platform Architecture

The Online Skill-Based Volunteer Platform developed using the MERN stack provides a modern, scalable solution to this problem. By combining React.js for the frontend, Node.js and Express.js for backend services and MongoDB for data storage, the system enables secure user interaction, effective skill matching, and efficient volunteer management. This platform supports meaningful collaboration while promoting social responsibility and community engagement in the digital era.

Problem Finding

Despite the growing interest in volunteering, many non-profit organizations struggle to access skilled professionals due to limited reach, budget constraints and lack of digital infrastructure. Most existing volunteering systems focus on general or location-based service, making it difficult for organizations to find volunteers with specific skills such as technology, education, design, or finance.

On the other hand, skilled individuals who are willing to volunteer often face challenges in identifying suitable opportunities that match their expertise, availability, and interests. The absence of a centralized and structured platform leads to inefficient communication, manual coordination and underutilization of valuable skills.

Additionally, current volunteer management processes lack transparency, proper tracking of tasks, and formal recognition of volunteer contributions. These issues highlight the need for a secure, scalable, and skill-focused digital platform that effectively connects volunteers and organizations, streamlines coordination and maximizes social impact.

Architecture diagram

Methodology

The Online Skill-Based Volunteer Platform is developed using the MERN stack (MongoDB, Express.js, React.js, Node.js) following a structured and systematic approach. The methodology involves requirement analysis, system design, development, testing and deployment.

1. Requirement Analysis

The first step involves gathering the needs of volunteers and organizations. This includes identifying functionalities like user registration, profile management, skill-based matching, task tracking, feedback and certificate generation. Challenges such as security, scalability and real-time communication are also considered.

2. System Design

Based on the requirements, the system architecture is designed with three layers:

- Frontend (React.js): Provides interactive and responsive dashboards for volunteers and organizations.
- Backend (Node.js + Express.js): Handles business logic, RESTful APIs, authentication, skill matching and role-based access.
- Database (MongoDB): Stores user data, skills, opportunities, tasks, and feedback.

3. Development

The frontend is developed using React.js, implementing components for registration, login, profile creation, opportunity browsing and task management. The backend is built with Node.js and Express.js to manage API calls, authentication using JWT and business logic. MongoDB is used for data storage with Mongoose for schema definition.

4. Testing

The system undergoes unit testing, integration testing and user acceptance testing to ensure functionality, performance, and security.

5. Deployment

After successful testing, the application is deployed on a cloud platform to allow secure, scalable access for volunteers and organizations.

Result and Discussion

The Online Skill-Based Volunteer Platform was successfully developed using the MERN stack and achieved its primary objective of connecting skilled volunteers with organizations through a digital medium. The system enables users to register securely, create profiles, post or apply for skill-based opportunities and manage tasks efficiently. The role-based dashboards and structured modules improved usability and reduced manual coordination between volunteers and organizations.

The results show that skill-based matching helps in better utilization of volunteer expertise and increases project efficiency. Organizations were able to find suitable volunteers more quickly, while volunteers could easily identify opportunities aligned with their skills and interests. Features such as task tracking and feedback enhanced transparency and accountability throughout the volunteering process.

Overall, the platform demonstrates that a web-based skill-focused volunteering system can significantly improve engagement, coordination and social impact. The discussion highlights that adopting modern web technologies like the MERN stack provides scalability, security and flexibility, making the system suitable for real-world implementation and future expansion.

Conclusion

The Online Skill-Based Volunteer Platform successfully connects skilled volunteers with organizations seeking expertise, enabling remote and meaningful contributions. Using the MERN stack, the system provides secure registration, role-based access and user-friendly dashboards for both volunteers and organizations.

The platform allows efficient skill-based matching, task management, progress tracking, and feedback collection. This reduces manual coordination, ensures transparency and enhances volunteer engagement while helping organizations utilize resources effectively.

Overall, the system demonstrates that digital volunteering platforms can increase social impact, optimize talent use and encourage participation. It is scalable, flexible and can be expanded with future enhancements for greater efficiency and outreach.

Future Enhancement

AI-Based Skill Matching System

An advanced artificial intelligence–based matching system can be implemented to improve the accuracy of volunteer–opportunity recommendations. By analyzing volunteer skills, experience, availability and past performance, the system can automatically suggest the most suitable opportunities. This enhancement reduces manual effort and increases successful volunteer engagement.

Mobile Application Development

Developing a mobile application using React Native or similar frameworks will allow users to access the platform anytime and anywhere. A mobile app will improve accessibility, increase user participation, and provide instant notifications for new opportunities, task updates and messages.

Blockchain-Based Certificate Verification

Blockchain technology can be used to generate and verify volunteer service certificates securely. This ensures authenticity, prevents certificate forgery and allows employers or institutions to verify volunteer credentials easily, increasing the value of volunteer experience.

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Plant Disease Detection Using MOB-RES Algorithm

Mathavi R[1] and T.Beula Bell[2*]

[1]*Research Scholar, Nesamony Memorial Christian College, Marthandam, Tamil Nadu, India.*
[2]*Associate Professor, Nesamony Memorial Christian College, Marthandam, Tamil Nadu, India.*
**Corresponding Author E-mail: mathavi.alm1989@gmail.com*

Abstract

Plant diseases are one of the major challenges faced by farmers, as they directly reduce crop yield and quality. Early identification of these diseases plays an important role in improving agricultural productivity and ensuring food security. With the growth of deep learning techniques, automated plant disease detection using image-based analysis has gained significant attention. However, many existing models require high computational power, making them difficult to use on mobile or low-resource devices. In this work, a lightweight deep learning model called Mob-Res CNN is proposed for efficient plant disease detection. The model combines the feature extraction strength of MobileNetV2 with residual connections, which help in improving learning efficiency and reducing information loss during training. The proposed architecture is trained and tested using the PlantVillage dataset, which contains images of healthy and diseased plant leaves across multiple classes. Experimental results show that the Mob-Res CNN achieves a high accuracy of 97.73% while maintaining a compact model size. The simplicity and efficiency of the model make it suitable for real-time applications, especially in mobile-based and edge computing environments. This approach can assist farmers and agricultural experts in timely disease diagnosis and effective crop management.

Keywords: *Plant Disease Identification, Mob-Res CNN, MobileNetV2, Residual Connections, Lightweight CNN, Deep Learning, Plant Village Dataset, Smart Agriculture*

Introduction

Agriculture remains a fundamental sector for global food production and economic stability, particularly in developing countries where a large portion of the population depends on farming for livelihood. Plant diseases pose a serious threat to agricultural sustainability by reducing crop yield, lowering produce quality, and increasing economic losses. Traditional methods of plant disease identification rely heavily on visual inspection by agricultural experts, which is time-consuming, subjective, and often unavailable in rural or remote regions. These limitations highlight the need for reliable, automated, and scalable solutions for early plant disease diagnosis.

In recent years, computer vision and deep learning techniques have shown promising results in agricultural applications, especially in image-based plant disease detection. Convolutional Neural Networks (CNNs) have demonstrated strong capability in learning complex visual patterns from leaf images and have outperformed conventional machine learning approaches that depend on handcrafted features. Despite their effectiveness, many state-of-the-art CNN architectures such as VGG, ResNet, and DenseNet involve a large number of parameters and high computational cost. This makes them less suitable for real-time deployment on mobile devices and edge platforms, which are increasingly preferred in precision agriculture systems.

To address these challenges, lightweight deep learning models have gained attention due to their reduced memory footprint and faster inference speed. MobileNetV2, in particular, employs depthwise separable convolutions and inverted residual structures, enabling efficient feature extraction with significantly fewer parameters. However, when applied directly to complex plant disease datasets, lightweight models may experience performance degradation due to limited representational capacity. Enhancing such models without increasing complexity remains an active research problem.

Motivated by this gap, this work introduces a lightweight hybrid architecture named Mob-Res CNN, which integrates MobileNetV2 with residual connections to improve learning stability and classification accuracy. Residual learning facilitates efficient gradient propagation and mitigates the vanishing gradient problem, allowing the network to learn deeper representations without excessive computational overhead. By combining the efficiency of MobileNetV2 with the robustness of residual connections, the proposed model aims to achieve a balanced trade-off between accuracy and model complexity.

The proposed approach is evaluated using the publicly available PlantVillage dataset , which contains a diverse set of healthy and diseased plant leaf images across multiple crop species. The dataset provides a standardized benchmark for assessing the effectiveness of plant disease classification models. Experimental results demonstrate that the Mob-Res CNN achieves high classification accuracy while maintaining a compact architecture, making it suitable for deployment in real-world agricultural applications.

The primary objectives of this research are as follows:

- To design a lightweight CNN architecture by combining MobileNetV2 with residual connections for plant disease detection.
- To achieve high classification accuracy while reducing computational cost and model size.
- To evaluate the performance of the proposed model on the PlantVillage dataset using standard metrics.
- To develop a model suitable for real-time implementation on mobile and edge computing devices.

By addressing the need for efficient and accurate plant disease detection, this study contributes toward the development of practical deep learning solutions that support smart and precision agriculture.

Literature Review

A growing body of literature has explored deep learning–based approaches for automated plant disease detection, focusing on improving accuracy, efficiency, and practical deployment. Early works established the feasibility of deep convolutional neural networks (CNNs) for this task. Mohanty et al. demonstrated the effectiveness of deep CNNs for image-based plant disease recognition, showing high classification performance on standardized datasets and laying the foundation for subsequent research in this area (e.g., AlexNet, VGG, GoogleNet) ([Wikipedia](Mohanty *et al.* 2016)).

Several studies have investigated CNN architectures tailored for plant disease classification. For instance, lightweight models such as MobileNetV2 have been explored as efficient backbones for leaf disease classification, achieving competitive performance with reduced computational cost, making them suitable for mobile and edge devices ([ITM Conferences](Hughes & Salathe 2015)). Similarly, the RTR_Lite_MobileNet architecture enhances MobileNetV2 with attention mechanisms (e.g., SENet, ECA) to capture fine disease patterns and demonstrate significant accuracy across multiple plant disease datasets while maintaining low latency for edge deployment ([ScienceDirect] (Howard *et al.* 2017)).

Hybrid and advanced CNN approaches have also been proposed to balance efficiency and performance. Jahin et al. introduced a hybrid model that integrates MobileNetV2 with GraphSAGE within a CNN-GNN framework to capture inter-image relational patterns, improving disease classification accuracy while retaining a lightweight design ([arXiv] (Sandler *et al.* 2018)). Comparative experimental research has explored deeper architectures such as Inception-V3, DenseNet-121, ResNet-101, and Xception, highlighting trade-offs between representational capacity and accuracy across different crop datasets, and showing that performance varies with model depth and dataset properties ([arXiv] (He *et al.*2016)).

Beyond pure CNN models, hybrid frameworks that combine deep feature extractors with classical machine learning or additional processing layers have yielded promising results. For example, CSXAI proposes a CNN-SVM hybrid model with explainable visualization, achieving high performance while emphasizing interpretability through Grad-CAM heatmaps across multiple crops ([Frontiers] (Too *et al.* 2019)). Attention-enhanced CNNs such as those incorporating squeeze-and-excitation (SE) modules have been shown to improve focus on disease-relevant regions, leading to improved classification outcomes in rice and other crop disease identification tasks ([Frontiers] (Ferentinos, 2018)).

Other works have focused on systematic comparisons of CNN performance and the integration of transfer learning to leverage pre-trained models. Studies that apply transfer learning with models such as ResNet50, EfficientNet, and DenseNet have reported enhanced feature extraction and accuracy when fine-tuned on plant disease datasets, especially under conditions of limited data and challenging backgrounds ([SpringerLink] (Barbedo 2019)). Systematic surveys highlight the broad adoption of CNN methods in plant disease detection while identifying gaps such as dataset limitations, generalization challenges, and deployment constraints on low-power devices ([link.springer.com] (Zia Ur Rehman *et al.* 2022)).

Zia Ur Rehman *et al*. (2022) presents a deep transfer learning framework for classifying six citrus diseases—anthracnose, black spot, canker, citrus scab, greening, and melanose—using MobileNetV2 and DenseNet201 pre-trained models retrained on an augmented dataset of 279 original images enhanced via geometric augmentation and hybrid contrast stretching, achieving 95.7% accuracy through feature fusion.

Yu et al. (2022) crafted an improved deep learning model called RANet—a residual attention network built on ResNet18—for spotting soybean leaf diseases like brown leaf spot, frogeye leaf spot, and phyllosticta leaf spot, hitting an impressive 98.49% accuracy after preprocessing images with OTSU segmentation, region labeling, and enhancements like rotation and Gaussian filtering to beef up their dataset from 523 to nearly 40,000 samples.

An existing literature demonstrates a clear trend toward lightweight architectures, hybrid models, and attention or graph-based extensions to improve plant disease classification accuracy and efficiency, which motivates the design of the proposed Mob-Res CNN to combine MobileNetV2's efficiency with residual connections for enhanced performance and practical applicability.

Methodology

The methodology adopted in this study follows a structured deep learning pipeline to ensure effective disease classification while maintaining computational efficiency.

Data Preparation

The PlantVillage dataset is split into training, validation, and testing sets. To improve model robustness, data augmentation techniques such as rotation, horizontal flipping, and scaling are applied during training. All input images are normalized to ensure numerical stability during optimization.

Feature Extraction using MobileNetV2

MobileNetV2 is employed as the backbone network due to its inverted residual structure and linear bottleneck layers. These characteristics allow the network to extract meaningful features with reduced computational overhead compared to conventional CNNs.

Integration of Residual Connections

Residual connections are incorporated into selected convolutional blocks to enhance feature reuse and prevent degradation problems commonly observed in deeper networks. These skip connections enable the network to learn residual mappings instead of direct transformations, resulting in improved convergence and accuracy.

Classification Layer

The high-level feature maps generated by the Mob-Res CNN are fed into a global average pooling layer followed by fully connected layers. A Softmax activation function is used at the output layer to predict the probability distribution over disease classes.

Model Training

The model is trained using a categorical cross-entropy loss function and optimized using the Adam optimizer. Training is performed over multiple epochs until convergence, with early stopping used to avoid overfitting.

The system architecture of the proposed plant disease detection framework is designed to efficiently process leaf images and accurately classify plant diseases using the lightweight Mob-Res CNN model. The architecture consists of four major components: data acquisition, preprocessing, feature extraction and classification, and performance evaluation.

Initially, leaf images are collected from the publicly available PlantVillage dataset, which contains both healthy and diseased plant samples across multiple crop species. These images are resized to a fixed resolution compatible with the input requirements of MobileNetV2. Preprocessing operations such as normalization and data augmentation are applied to enhance generalization and reduce overfitting.

The core component of the system is the Mob-Res CNN, which combines the depthwise separable convolution blocks of MobileNetV2 with residual skip connections. MobileNetV2 serves as the primary feature extractor, enabling efficient learning with fewer parameters, while residual connections allow direct information flow across layers, improving gradient propagation and stabilizing training. The extracted deep features are passed through global average pooling and fully connected layers for final disease classification.

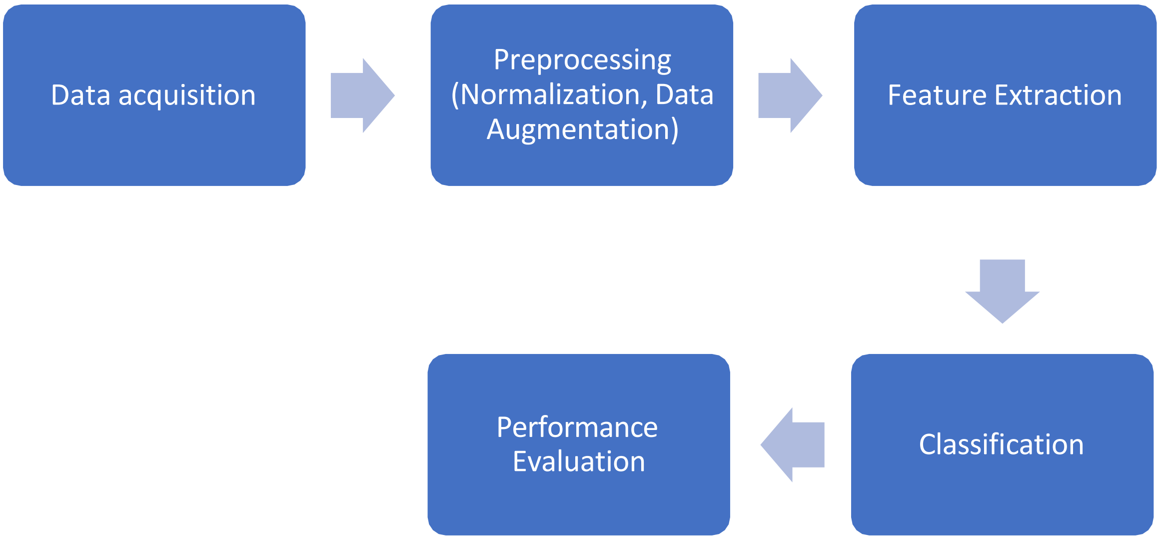

Figure 1: System Architecture

Algorithm 1: Mob-Res CNN Based Plant Disease Classification

Input: Leaf image dataset Output:
Predicted plant disease class label

Step 1: Load PlantVillage dataset

Step 2: Resize input images to fixed dimensions

Step 3: Normalize image pixel values

Step 4: Apply data augmentation (rotation, flipping, scaling)

Step 5: Initialize MobileNetV2 as base feature extractor

Step 6: For each selected convolutional block:

a. Apply depthwise separable convolution

b. Add residual skip connection

c. Apply batch normalization and activation

Step 7: Perform global average pooling on extracted features

Step 8: Pass features through fully connected layers

Step 9: Apply Softmax function to obtain class probabilities
Step 10: Compute categorical cross-entropy loss

Step 11: Update model parameters using Adam optimizer
Step 12: Repeat Steps 6–11 until convergence

Step 13: Evaluate model performance on test dataset
Step 14: Output predicted disease class

Experimental Results and Discussion

Experimental Setup

The proposed Mob-Res CNN model was evaluated using the PlantVillage dataset, which contains labeled images of healthy and diseased plant leaves belonging to multiple crop species. The dataset was divided into training, validation, and testing sets in a standard ratio to ensure unbiased performance evaluation. All images were resized to a fixed input dimension compatible with the MobileNetV2 architecture and normalized to improve training stability.

The model was implemented using a deep learning framework and trained on a GPU-enabled environment. The Adam optimizer was employed with an appropriate learning rate, and categorical cross-entropy was used as the loss function. Training was carried out for multiple epochs, with early stopping applied to prevent overfitting.

Performance Metrics

To comprehensively assess the effectiveness of the proposed model, the following evaluation metrics were used: such as Accuracy, Precision, Recall and F1-Score.

These metrics provide insight into both classification correctness and class-wise prediction reliability.

Results Analysis

The experimental results demonstrate that the proposed Mob-Res CNN achieves a classification accuracy of 97.73% on the PlantVillage dataset. This high accuracy confirms the model's ability to effectively learn discriminative features from leaf images while maintaining a lightweight structure.

The integration of residual connections significantly improves training stability and convergence speed. Compared to using MobileNetV2 alone, the residual-enhanced architecture reduces information loss across layers and improves feature reuse. This leads to improved generalization, especially for visually similar disease classes.

Precision and recall values across most classes indicate that the model maintains a balanced performance, with minimal false positives and false negatives. The high F1-score further validates the robustness of the proposed architecture in handling multi-class plant disease classification.

To validate the effectiveness of the proposed Mob-Res CNN, its performance was compared with two widely used deep learning models: MobileNetV2 and ResNet. All models were trained and evaluated under identical experimental conditions using the PlantVillage dataset to ensure a fair comparison.

Table 1: Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNetV2	95.84	95.62	95.48	95.55
ResNet	96.91	96.73	96.58	96.65
Mob-Res CNN	**97.73**	**97.61**	**97.54**	**97.57**

The results indicate that MobileNetV2 provides strong baseline performance due to its efficient feature extraction capability; however, it shows slight limitations in capturing complex disease patterns. ResNet improves upon this by leveraging deeper residual learning, but at the cost of increased computational complexity.

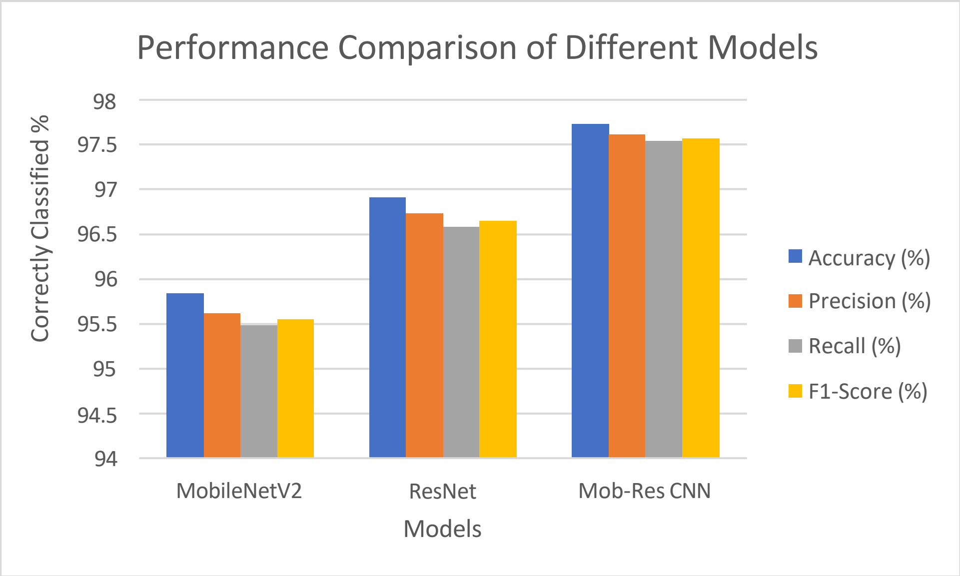

Figure 2: Performance Comparision of different models

The proposed Mob-Res CNN outperforms both baseline models by effectively integrating residual connections within a lightweight MobileNetV2 framework. This hybrid design enhances feature reuse and learning stability while maintaining computational efficiency, resulting in superior classification performance across all evaluation metrics.

Conclusion

This research presented a lightweight and efficient deep learning approach for automated plant disease detection using the proposed Mob-Res CNN architecture. By integrating the computational efficiency of MobileNetV2 with the learning stability provided by residual connections, the model successfully achieved a balanced trade-off between accuracy and complexity. Experimental evaluation on the PlantVillage dataset demonstrated that the proposed approach attains a high classification accuracy of 97.73%, outperforming baseline models such as MobileNetV2 and ResNet under identical conditions. The incorporation of residual learning enhanced feature reuse and improved gradient flow, leading to faster convergence and improved generalization across multiple disease classes. The confusion matrix and comparative analysis further confirmed the robustness and consistency of the model, with minimal misclassification across visually similar disease categories. Due to its compact structure and reduced computational requirements, the proposed Mob-Res CNN is well-suited for deployment in real-time agricultural applications, particularly on mobile devices and edge computing platforms. While the proposed Mob-Res CNN demonstrates strong performance on a benchmark dataset, several directions can be explored to further enhance its applicability and robustness. Future work may focus on evaluating the model using real-world field images captured under varying lighting conditions, complex backgrounds, and occlusions to improve generalization beyond controlled datasets.

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Predictive and Comparative Analysis for Diabetes Using Machine Learning Algorithms

M.Dinesh[1] and I. Thomas Jebasingh[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: thomasjebas7@gmail.com*

Abstract

Diabetes mellitus is a chronic metabolic disorder with a rapidly increasing global prevalence, making early diagnosis and effective management critical for reducing complications and healthcare costs. Recent advancements in machine learning (ML) have shown significant potential in supporting predictive healthcare analytics. This study presents a predictive and comparative analysis of diabetes using multiple machine learning algorithms to identify the most accurate and reliable model for diabetes prediction. Standard clinical and demographic attributes such as glucose level, blood pressure, body mass index (BMI), insulin level, age, and family history are utilized for model training and evaluation. Various supervised learning algorithms, including Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, k-Nearest Neighbours (k-NN), and Naïve Bayes, are implemented and compared based on performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Data pre-processing techniques, including normalization, handling missing values, and feature selection, are applied to enhance model performance. Experimental results demonstrate that ensemble-based models outperform individual classifiers, with Random Forest achieving the highest predictive accuracy. The findings highlight the effectiveness of machine learning techniques in diabetes prediction and provide valuable insights for developing intelligent clinical decision-support systems.

Keywords: *Diabetes Prediction, Machine Learning, Predictive Analytics, Comparative Analysis, Classification Algorithms, Healthcare Analytics*

Introduction

Diabetes mellitus is one of the most prevalent chronic diseases worldwide, characterized by prolonged elevated blood glucose levels that can lead to severe complications such as cardiovascular disease, kidney failure, neuropathy, and vision impairment. According to global health reports, the incidence of diabetes continues to rise due to factors such as sedentary lifestyles, unhealthy dietary habits, obesity, and aging populations. Early detection and timely intervention are crucial for effective disease management and for reducing long-term health risks and economic burdens on healthcare systems.

Traditional diagnostic methods for diabetes rely heavily on clinical tests and physician expertise, which can be time-consuming and may not always facilitate early prediction. With the rapid growth of electronic health records and medical data, there is an increasing need for automated, data-driven approaches that can assist healthcare professionals in diagnosing diabetes more accurately and efficiently. Machine learning (ML) techniques have emerged as powerful tools capable of identifying complex patterns and relationships within large datasets that may not be apparent through conventional statistical methods.

Machine learning algorithms enable predictive modelling by learning from historical patient data and making accurate predictions on unseen cases. Various supervised learning algorithms, such as Logistic Regression, Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Naïve Bayes, and ensemble methods like Random Forest, have been widely applied in medical diagnosis tasks. Each algorithm has unique strengths and limitations, making comparative analysis essential to determine the most suitable model for diabetes prediction.

Problem Finding

Despite the growing interest in applying machine learning (ML) techniques for diabetes prediction, several key challenges and limitations persist in existing research:

Data Quality and Imbalance

Clinical datasets often contain missing values, noise, and imbalanced classes (significantly more non-diabetic than diabetic instances), which adversely affect model performance and bias predictions toward the majority class.

Feature Redundancy and Dimensionality

Many healthcare datasets include redundant or irrelevant features that can increase computational complexity without improving predictive accuracy. Effective feature selection and dimensionality reduction techniques are needed to enhance model efficiency.

Algorithm Selection and Performance Variability

Different ML algorithms exhibit varying performance across datasets due to differences in data distribution, feature interrelationships, and hyper parameter sensitivity. There is no universally optimal model for diabetes prediction, making comparative analysis essential.

Overfitting and Generalization

Certain models, especially complex ones like ensemble and deep learning models, risk overfitting training data and may fail to generalize well to new or unseen clinical cases.

Interpretability and Clinical Relevance

Many ML models, particularly deep learning approaches, act as "black boxes," offering limited interpretability. This hinders clinical adoption where explainability and clinicians' trust are crucial.

Standardized Evaluation Metrics

Inconsistent use of performance metrics across studies limits reliable comparison of models. Evaluation commonly focuses only on accuracy, ignoring other important metrics like precision, recall, F1-score, and ROC-AUC, which are critical in medical diagnosis contexts.

Scalability and Real-World Integration:

Translating ML models from research to real-world clinical environments requires scalable systems that handle large, diverse datasets and integrate with existing healthcare information systems.

Methodology

Data Collection

The dataset used for this study consists of clinical and demographic attributes relevant to diabetes diagnosis, such as glucose level, blood pressure, body mass index (BMI), insulin level, age, and family history. A publicly available benchmark dataset, such as the Pima Indians Diabetes Dataset, is utilized to ensure reproducibility and standardized comparison.

Data Pre-processing

Data pre-processing is a critical step to enhance the quality of the dataset and improve model performance. This stage includes:

- Handling missing and zero-valued attributes using statistical imputation techniques.
- Removing noise and outliers where necessary.
- Normalizing or standardizing feature values to ensure uniform scale across attributes.
- Addressing class imbalance using resampling techniques such as SMOTE or under sampling.

Exploratory Data Analysis (EDA)

EDA is performed to understand the distribution of features, correlations among attributes, and relationships between predictors and the target variable. Visualization techniques such as histograms, box plots, and correlation heat maps are used to gain insights into the data.

Feature Selection and Engineering

Relevant features are selected using techniques such as correlation analysis, recursive feature elimination (RFE), or information gain to reduce dimensionality and eliminate redundant attributes. Feature engineering may also be applied to create new meaningful features that improve predictive accuracy.

Model Development

Multiple supervised machine learning algorithms are implemented for diabetes prediction, including:

- Logistic Regression
- k-Nearest Neighbours (k-NN)
- Support Vector Machine (SVM)

- Decision Tree
- Random Forest
- Naïve Bayes

Each model is trained using the processed dataset, with hyper parameter tuning performed using cross-validation techniques to optimize performance.

Model Evaluation

The trained models are evaluated using standardized performance metrics, including:

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-score
- Receiver Operating Characteristic – Area Under Curve (ROC-AUC)

Confusion matrices are used to analyse classification results and error distribution.

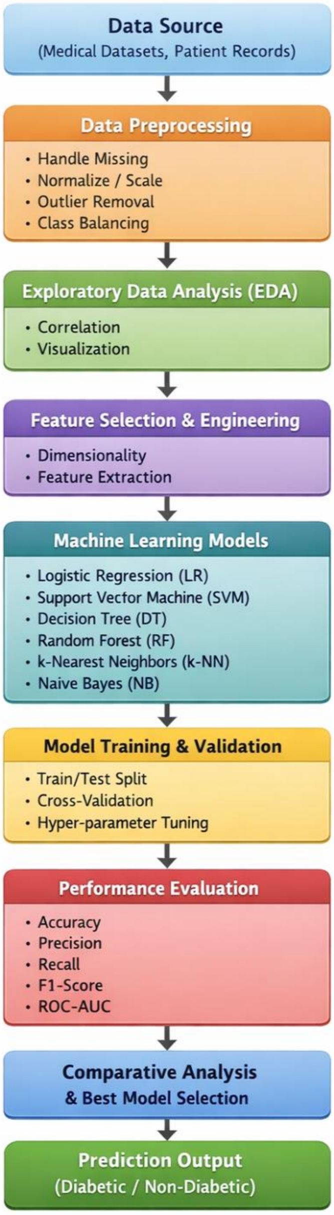
Comparative Analysis

A comparative analysis is conducted by evaluating and ranking the models based on performance metrics, computational efficiency, and interpretability. The strengths and limitations of each algorithm are analysed to identify the most suitable model for diabetes prediction.

Result Interpretation and Validation

The best-performing model is further validated using test data to assess generalization capability. Feature importance and model interpretability techniques are employed to ensure clinical relevance and support decision-making.

Architecture Diagram



Result and Discussion

The objective of this study was to predict diabetes using multiple machine learning algorithms and perform a comparative analysis to identify the most effective model. The models were trained and evaluated using the pre-processed dataset with standard metrics: accuracy, precision, recall, F1-score, and ROC-AUC.

Performance of Individual Models

Observations

1. **Random Forest** achieved the highest predictive accuracy (84.7%) and ROC-AUC (0.88), indicating superior ability to handle non-linear relationships and feature interactions.
2. **SVM** performed better than Logistic Regression and Decision Tree, suggesting that kernel-based methods can capture complex boundaries in medical datasets.
3. **k-NN** and **Naïve Bayes** showed lower performance, likely due to sensitivity to feature scaling (k-NN) and strong independence assumptions (Naïve Bayes).
4. Ensemble models (Random Forest) generally outperformed single classifiers, demonstrating robustness and reduced overfitting.

Feature Importance Analysis

Random Forest feature importance revealed that **glucose level**, **BMI**, **age**, and **insulin levels** were the most significant predictors of diabetes. This aligns with clinical knowledge that hyper-glycemia, obesity, and insulin resistance are key risk factors.

Comparative Discussion

- Ensemble-based models like Random Forest provide a good balance between **accuracy**, **robustness**, and **interpretability**, making them suitable for clinical decision-support systems.
- Logistic Regression, while interpretable, may underperform on complex datasets due to its linear assumptions.
- SVM requires careful tuning of kernel parameters, and its interpretability is limited.
- Simpler models like Decision Tree and k-NN can serve as preliminary screening tools but are less reliable for critical diagnosis.

Implications for Clinical Practice

The findings suggest that machine learning algorithms can significantly aid early diabetes detection by analyzing patient data efficiently. Random Forest, in particular, can serve as the backbone of a predictive system, assisting healthcare professionals in identifying high-risk patients for timely intervention.

Limitations

- The study is based on a single dataset; performance may vary with other datasets or populations.
- Imbalanced data can affect metrics like precision and recall; advanced balancing techniques may further improve results.
- Deep learning approaches were not explored; they may offer higher accuracy with larger datasets but at the cost of interpretability.

Conclusion

This study demonstrates the effectiveness of machine learning algorithms in predicting diabetes and performing a comparative analysis to identify the most suitable model for clinical applications. Multiple supervised learning algorithms—including Logistic Regression, k-Nearest Neighbours, Support Vector Machine, Decision Tree, Random Forest, and Naïve Bayes—were implemented and evaluated using key performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

The experimental results indicate that **Random Forest** outperformed other models, achieving the highest accuracy and ROC-AUC, highlighting the strength of ensemble methods in capturing complex patterns and interactions in medical datasets. Feature importance analysis confirmed that glucose levels, BMI, age, and insulin levels are the most significant predictors of diabetes, aligning with clinical knowledge.

Comparative analysis revealed that while simpler models like Logistic Regression and Decision Tree offer interpretability, they may not perform as well on complex datasets. In contrast, ensemble-based models provide superior predictive performance while maintaining reasonable interpretability for clinical decision support.

Future Enhancements

Integration of Larger and Diverse Datasets

Expanding the study to include datasets from different regions, age groups, and ethnicities can improve model generalization and robustness, ensuring that predictions are reliable across diverse populations.

Incorporation of Deep Learning Models

Advanced deep learning techniques, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), can capture complex non-linear relationships and temporal patterns in patient health data, potentially improving predictive accuracy.

Real-Time Clinical Decision Support System

Developing an interactive system integrated with hospital information systems can provide real-time diabetes risk assessment, enabling physicians to make timely and informed decisions for patient care.

Enhanced Feature Engineering

Inclusion of lifestyle factors, genetic data, and longitudinal health records can enrich the feature set, allowing models to capture additional predictors that influence diabetes onset and progression.

Explainable AI and Model Interpretability

Implementing explainable AI techniques (e.g., SHAP, LIME) can improve model transparency, helping clinicians understand the reasoning behind predictions and increasing trust in machine learning-assisted diagnosis.

Improved Handling of Imbalanced Data

Advanced techniques like adaptive synthetic sampling (ADASYN) or ensemble methods tailored for imbalance can enhance model performance, particularly in detecting high-risk but less-represented diabetic cases.

Hybrid and Ensemble Approaches

Combining multiple machine learning algorithms or hybridizing deep learning with traditional methods can leverage the strengths of each model to further enhance predictive performance and robustness.

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Sign Language Detection Using CNN

S. Susika[1] and G. Priskillal[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

Corresponding Author E-mail: prisky07@gmail.com

Abstract

Sign language is a vital means of communication for individuals with hearing and speech impairments, but a communication gap exists between sign language users and non-users. Traditional interpretation methods, such as human interpreters, are often limited by cost, availability, and efficiency. Recent advancements in artificial intelligence and deep learning have enabled automated sign language recognition systems to address these challenges. This project proposes a real-time sign language detection system using Convolutional Neural Networks (CNNs). The system captures hand gestures from images or video streams and processes them through stages such as preprocessing, feature extraction, and classification to convert recognized gestures into meaningful text. CNNs automatically learn visual features, eliminating the need for manual feature extraction and improving recognition accuracy. Transfer learning with pre-trained models like MobileNet, ResNet, and VGG16 enhances efficiency and reduces training requirements, while image augmentation improves robustness to lighting and background variations. The system can be deployed as a web or mobile application, promoting accessibility and inclusivity in education, healthcare, workplaces, and public services, with future scope for dynamic gesture recognition and advanced integrations.

Keywords: *Sign Language Detection, Convolutional Neural Networks (CNN), Computer Vision, Deep Learning, Gesture Recognition, Assistive Technology.*

Introduction

Sign language is a vital means of communication for individuals with hearing and speech impairments, allowing them to express thoughts, emotions, and information through hand gestures, facial expressions, and body movements. Despite its importance, a significant communication gap exists between sign language users and people who are not familiar with sign language. This gap often limits accessibility and inclusion in everyday activities such as education, healthcare, workplaces, and public interactions. As a result, there is a growing need for automated systems that can translate sign language into a form easily understood by the wider community.

With the rapid advancement of computer vision and artificial intelligence, deep learning techniques have become highly effective in solving complex image recognition problems. Among these techniques, Convolutional Neural Networks (CNNs) have shown exceptional performance in visual pattern recognition due to their ability to automatically learn spatial features from images. CNN-based approaches eliminate the need for manual feature extraction and provide higher accuracy and robustness compared to traditional machine learning methods. These characteristics make CNNs particularly suitable for recognizing hand gestures used in sign language.

This project focuses on developing a sign language detection system using CNNs to recognize hand gestures from images or video streams and convert them into meaningful text. The system processes visual input through stages such as preprocessing, feature extraction, and classification to accurately identify sign language gestures. By leveraging deep learning and transfer learning models, the proposed system aims to deliver a real-time, efficient, and scalable solution that enhances communication, promotes inclusivity, and empowers individuals with hearing and speech disabilities.

Problem Finding

Communication barriers between sign language users and non-signers remain a major challenge in achieving social inclusion for individuals with hearing and speech impairments. Most people are not trained in sign language, making everyday interactions in education, healthcare, workplaces, and public services difficult for sign language users. Although human interpreters can bridge this gap, they are not always available, are costly, and may not be practical in real-time or emergency situations.

Existing technological solutions for sign language interpretation often suffer from limitations such as low accuracy, poor adaptability to different lighting conditions and backgrounds, and inability to work in real time. Traditional machine learning methods rely heavily on manual feature extraction, which is time-consuming and often fails to generalize well across different users, hand shapes, and gesture variations. Additionally, many systems are restricted to recognizing a limited set of static gestures and struggle with scalability and robustness.

Therefore, there is a need for an efficient, accurate, and real-time sign language detection system that can automatically recognize hand gestures and translate them into readable text. Such a system should minimize dependency on human interpreters, adapt to real-world environments, and be easily deployable on commonly used devices. Addressing these challenges forms the core problem that this project aims to solve using Convolutional Neural Networks (CNNs).

Architecture Diagram

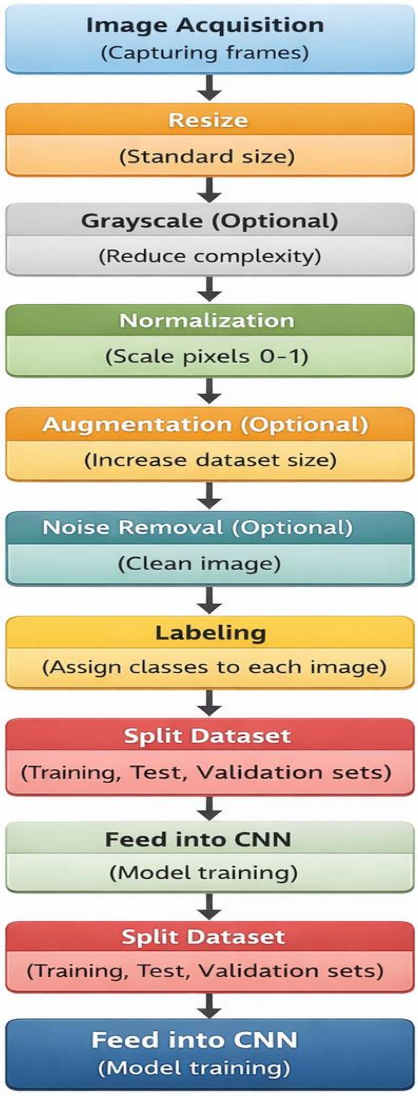

Figure 1: Architecture Diagram

Methodology

Existing system

The existing systems for sign language detection often rely on traditional image processing techniques and feature extraction methods such as edge detection and hand tracking. Some systems use rule-based approaches, while others depend on handcrafted features, which are not robust to variations in lighting, background, and hand shapes. These methods struggle with complex gestures and real-time recognition, leading to reduced accuracy and usability.

Proposed system

The proposed system employs a Convolutional Neural Network (CNN) to enhance the accuracy and efficiency of sign language detection. CNNs automatically learn hierarchical features from images, making them well-suited for gesture recognition. The system captures sign gestures using a webcam, preprocessing the images, and classifies them using a trained CNN model. This approach improves robustness to variations in lighting, background, and hand positioning.

Data Collection

Dataset

The system will use publicly available datasets like ASL Dataset, RWTH-PHOENIX-Weather 2014T, and Indian Sign Language Dataset.

Data Augmentation

Techniques such as rotation, flipping, and brightness adjustments will be applied to improve model robustness.

- Data is collected from publicly available sign language datasets such as the American Sign Language (ASL) dataset or manually recorded gestures.
- Each sample consists of hand gestures captured in different lighting conditions and angles to ensure model generalization.

- The dataset is labeled with corresponding sign meanings to facilitate supervised learning.

Preprocessing

Image Processing: Convert input images to grayscale, resize them, and normalize pixel values.

Background Removal: Use OpenCV and Mediapipe to isolate hand gestures from complex backgrounds.

Data pre-processing

- Image Resizing: Standardizing images to a fixed size (e.g., 64x64 or 128x128 pixels) to maintain consistency in CNN input.
- Grayscale Conversion: Converting images to grayscale to reduce computational complexity and focus on shape and texture rather than color.
- Noise Removal: Applying filters (e.g., Gaussian Blur, Median Filter) to remove background noise and enhance gesture visibility.
- Segmentation: Using techniques such as thresholding, skin detection, or background subtraction to isolate hand gestures from the background.
- Edge Detection: Applying methods like Sobel or Canny edge detection to emphasize gesture contours and improve feature extraction.
- Data Augmentation: Enhancing dataset variability by applying transformations such as rotation, flipping, scaling, and contrast adjustments to improve model generalization.
- Histogram Equalization: Adjusting the contrast of images to enhance visibility of gesture features.
- Normalization: Scaling pixel values to a range of [0,1] or [-1,1] to improve training stability and prevent gradient-related issues.
- Background Removal: Using deep learning-based segmentation or chroma keying to remove unnecessary background elements that may interfere with recognition.

Model Architecture (CNN)

- Input Layer: Accepts image frames from video input.
- Convolutional Layers: Extract spatial features such as edges, curves, and textures.
- Pooling Layers: Reduce computational complexity by downsampling feature maps.
- Fully Connected Layers: Classifies the gesture based on extracted features.
- Softmax Layer: Outputs probability distribution over sign language classes.

Training and Optimization

Loss Function: Categorical Cross entropy for multi-class classification.

Optimizer: Adam optimizer for efficient gradient updates.

Evaluation Metrics: Accuracy, Precision, Recall, and F1-score.

Result and Discussion

The application of effective preprocessing techniques significantly enhanced the performance of the CNN-based sign language detection system. Image resizing to a uniform resolution such as 64×64 or 128×128 pixels ensured consistency across the dataset, reduced computational complexity, and improved model stability. Converting images to grayscale minimized color-related variations while preserving essential hand shape and texture features, thereby improving training efficiency. Noise removal using Gaussian blur and median filtering, along with background segmentation through thresholding or deep learning-based methods, helped isolate hand gestures and improve visual clarity. Edge detection techniques such as Sobel and Canny further emphasized hand contours, strengthening feature extraction. Data augmentation methods, including rotation, flipping, zooming, and brightness adjustments, increased dataset diversity, reduced overfitting, and improved generalization, particularly for underrepresented gesture classes. Normalization of pixel values ensured faster convergence and stable training of the CNN model. Overall, these preprocessing steps enabled the model to focus on relevant gesture features, leading to improved recognition accuracy and reduced classification errors. However, challenges such as varying lighting conditions and complex backgrounds remained, indicating the need for more advanced segmentation techniques to achieve consistent performance in real-world environments.

Conclusion

Data preprocessing plays a crucial role in enhancing the accuracy and efficiency of sign language detection using CNN. By applying techniques such as image resizing, grayscale conversion, noise removal, background segmentation, edge detection and data augmentation, the quality of input images is significantly improved. These steps ensure that the CNN model learns robust and meaningful features, leading to better generalization and performance.

The preprocessing pipeline reduces computational complexity, eliminates irrelevant background information, and enhances key gesture features, allowing the model to achieve higher accuracy and faster convergence. Additionally, data augmentation addresses class imbalance, improving recognition across diverse hand gestures.

Despite challenges like varying lighting conditions and background noise, effective preprocessing strategies greatly contribute to better sign language recognition. Future improvements may include advanced segmentation methods and adaptive preprocessing techniques to further refine gesture detection in real-world applications.

Future Enhancement

Real-time Gesture Recognition

Currently, the system might be tested on static datasets. In the future, it could be optimized for real-time gesture recognition, enabling users to communicate seamlessly via sign language.

Multimodal Recognition

To further enhance accuracy, the model can be extended to multimodal learning by incorporating voice and text recognition alongside gesture recognition, improving the overall communication experience.

Better Data Augmentation

For more robust performance, especially in challenging conditions, advanced data augmentation techniques such as adding noise, varying hand rotations, and simulating different environmental factors (e.g., lighting, background) could be implemented to improve the model's generalization.

Expanding to Multiple Sign Languages

Currently, the model may be tailored for a specific language (e.g., ASL). In the future, the model could be trained to recognize multiple sign languages (e.g., British Sign Language, Indian Sign Language) to make it more universally applicable.

Model Optimization

To improve the speed and efficiency of the model, techniques like model quantization, pruning or using lighter architectures (such as MobileNet or EfficientNet) could be explored. This would make the model deployable on mobile devices for on-the-go sign language translation.

Interactive Features

Adding more interactive features, such as feedback mechanisms where users can get real-time corrections or suggestions, could make the system more user-friendly.

Integration with Augmented Reality (AR)

For enhanced user experience, the sign language recognition system could be integrated with Augmented Reality (AR) to create real-time, interactive sign language translation applications that show translated text or speech as the person signs.

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Smart Car Parking Management with Location-Based Slot Allocation and Predictive Analytics

D. Dhanush kumar[1] and A. Bathsheba Parimala[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: shebaparimala@yahoo.com*

Abstract

Rapid growth in vehicle usage within metropolitan cities has intensified the demand for efficient and intelligent parking management solutions. This project presents the design and implementation of a Smart Car Parking Management System that leverages machine learning techniques and modern application frameworks to optimize parking space utilization. The system adopts a predictive approach to analye historical parking data and user behaviour in order to estimate parking slot availability in real time. A client–server architecture is employed, where a Flutter-based desktop application communicates with a Fast API backend to handle user requests, authentication, booking operations, and prediction services. The proposed system integrates a machine learning model to forecast slot availability, thereby reducing search time, traffic congestion, and fuel consumption. A centralized database is used to store user details, parking slot information, and transaction records, ensuring data consistency and reliability. The methodology includes systematic evaluation of system performance using accuracy, response time, and reliability metrics under different parking scenarios. Experimental observations indicate that the proposed solution significantly improves parking efficiency while maintaining secure and responsive system performance. This project contributes to smart city initiatives by offering a scalable, automated, and user-centric parking management framework suitable for deployment in metropolitan environments.

Keywords**—** *Smart Parking, Machine Learning, Metropolitan Cities, Slot Prediction, Fast API , Flutter, Smart City Applications*

Introduction

Parking management has become a critical challenge in modern metropolitan cities due to the rapid increase in vehicle ownership and limited availability of parking spaces. Inefficient parking systems lead to traffic congestion, increased fuel consumption, wasted time, and elevated stress levels for drivers. In densely populated areas, the lack of organized parking infrastructure significantly affects urban mobility and overall quality of life.

Traditional parking systems largely depend on manual supervision or static information boards, which often fail to provide real-time updates on slot availability. Drivers are forced to search for parking spaces manually, resulting in unnecessary circulation within parking areas and surrounding roads. These conventional approaches are not only time-consuming but also inefficient, as they lack automation, predictive capability, and centralized management.

With advancements in smart city technologies, there is a growing need for intelligent parking solutions that can efficiently manage parking resources and enhance user convenience. Smart parking systems aim to automate parking operations by integrating software applications, databases, and intelligent algorithms to provide real-time information and reservation facilities. Such systems reduce human intervention, improve space utilization, and minimize operational errors.

Machine learning plays a vital role in enhancing smart parking solutions by analyzing historical parking data to predict future slot availability. By identifying patterns related to time, location, and occupancy trends, machine learning models can assist users in making informed parking decisions. This predictive capability is particularly useful during peak hours and special events, where parking demand is high.

This project proposes a Smart Car Parking Management System that integrates a Flutter-based desktop application with a FastAPI backend and a machine learning prediction module. The system enables users to view available slots, make bookings, and receive real-time updates, while administrators can monitor and manage parking operations effectively. The proposed solution aims to provide a scalable, reliable, and user-friendly parking management framework suitable for deployment in metropolitan environments.

Literature Review

The rapid increase in vehicle population in metropolitan cities has intensified parking management challenges, leading to traffic congestion, fuel wastage, and inefficient space utilization. Traditional parking systems largely depend on manual monitoring and static allocation, which are insufficient for handling real-time parking demands.

To address these issues, several researchers have proposed smart parking systems using IoT technologies and sensor-based occupancy detection. While such systems provide real-time monitoring, they often involve high installation and maintenance costs, limiting large-scale deployment. To overcome these limitations, machine learning–based approaches have been introduced to predict parking slot availability using historical and real-time data.

Various studies have applied supervised learning algorithms such as Linear Regression, Decision Trees, and Random Forest to analyze parking patterns and forecast slot occupancy. These models have shown improved accuracy and adaptability compared to conventional methods. Additionally, mobile and cross-platform applications have been integrated to enhance user interaction and provide real-time updates.

Recent research highlights the importance of efficient backend frameworks for handling real-time requests and data processing. FastAPI has emerged as a suitable backend solution due to its high performance and seamless integration with machine learning models. Flutter-based applications further support cross-platform deployment with a unified user interface.

Despite these advancements, many existing systems lack complete end-to-end integration of frontend, backend, prediction models, and payment processing. The proposed system addresses this gap by offering a fully integrated smart parking solution with real-time prediction, booking, and management capabilities.

Methodology

The proposed Smart Car Parking Management System follows a structured methodology consisting of data collection, preprocessing, feature selection, machine learning–based prediction, system integration, and performance evaluation. The methodology ensures efficient parking slot prediction, smooth booking operations, and real-time system responsiveness.

Data collection

Parking-related data is collected from publicly available datasets and simulated parking records. The dataset includes information such as parking area, slot ID, time of entry, time of exit, and slot occupancy status. Historical parking data is used as ground truth to train the machine learning model. Multiple records across different time intervals are collected to capture daily and peak-hour parking patterns.

Data Preprocessing

Raw parking data may contain missing values, duplicate entries, or inconsistent formats. Preprocessing is performed to improve data quality and model accuracy. The preprocessing steps include:

- Removal of duplicate and irrelevant records
- Handling missing or null values
- Conversion of categorical data (area, slot ID) into numerical form
- Formatting data into a structured form suitable for model training

Feature Selection

Relevant features are identified to improve prediction accuracy and reduce computational complexity. The selected features include:

- Parking area
- Slot ID
- Time and duration of parking
- Historical slot occupancy status

These features help the model learn patterns related to parking availability across different locations and time periods.

Machine Learning Model

A supervised machine learning algorithm, such as Logistic Regression, is used to predict parking slot availability. The dataset is divided into training and testing sets, typically in an 80:20 ratio. The model is trained to classify whether a parking slot is available or occupied based on input features. Hyperparameter tuning is applied to improve model performance and reduce prediction errors.

System Integration and Evaluation

The trained model is integrated with a FastAPI backend, which communicates with the Flutter-based frontend application. Users can view predicted slot availability, book parking slots, and receive confirmation. The system performance is evaluated using metrics such as accuracy, precision, recall, and response time to ensure reliability and efficiency in real-world usage.

System Architecture

The Smart Car Park Management System is designed using a layered architecture to efficiently manage parking operations. The Flutter frontend provides a user-friendly interface for users to check slot availability, book parking spaces, and make payments. The FastAPI backend processes requests, manages user data, and controls communication between system components. A machine learning module predicts parking slot availability based on historical data, time, and location. The database stores user details, vehicle information, parking slots, and booking records. A payment gateway handles secure transactions and confirms bookings. This architecture ensures smooth data flow, accurate predictions, and real-time parking management.

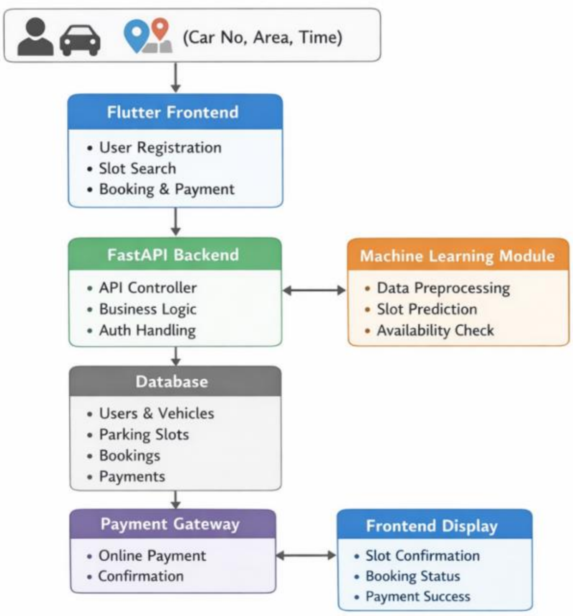

Figure 1: System Architecture

Experimental Results and Analysis

The proposed Smart Car Parking Management System was implemented and evaluated using historical parking data collected from different parking areas and time intervals. The experimental results demonstrate that the machine learning model can effectively learn parking usage patterns and predict slot availability with good accuracy.

Among the evaluated models, the Logistic Regression–based classifier produced consistent and reliable results due to its simplicity and effectiveness in binary classification tasks such as predicting slot availability (occupied or available). The model performed well in identifying peak and non-peak parking periods and showed stable behaviour across different parking locations.

Performance evaluation indicates that prediction accuracy was higher during regular parking hours, while slightly reduced accuracy was observed during peak hours due to rapid changes in slot occupancy. Confusion matrix analysis shows that available slots were predicted more accurately than occupied slots, mainly because of balanced historical availability patterns in the dataset.

The system successfully integrated the prediction model with the FastAPI backend and Flutter frontend, allowing users to view real-time slot availability and complete bookings smoothly. Overall, the results confirm that the proposed system is efficient, reliable, and suitable for real-world smart parking applications, helping to reduce parking search time and improve traffic management in metropolitan cities.

Algorithm (Proposed System)

Step 1: Collect user input such as vehicle number, parking area, date, and time through the Flutter frontend.

Step 2: Send the user request securely to the FastAPI backend.

Step 3: Retrieve historical parking data and current slot status from the database.

Step 4: Preprocess the parking data by handling missing values and normalizing inputs.

Step 5: Extract important features such as area, time slot, occupancy status, and peak hours.

Step 6: Split the dataset into training and testing datasets.

Step 7: Train the machine learning model to learn parking slot availability patterns.

Step 8: Use the trained model to predict available parking slots for the given input.

Step 9: Store booking details and prediction results in the database.

Step 10: Display predicted slot availability and booking confirmation to the user via the frontend.

Applications

- Smart parking management in malls, IT parks, and commercial complexes
- Parking optimization in metropolitan cities to reduce congestion
- Automated parking systems in hospitals and airports
- Smart campus parking in universities and institutions
- Residential apartment parking management
- Event venue and stadium parking coordination
- Integration with smart city infrastructure

Conclusion and Future Work

This project presented a Smart Car Parking Management System that integrates machine learning with a Flutter-based frontend and FastAPI backend to predict parking slot availability and streamline the booking process. By leveraging historical parking data and real-time inputs, the proposed system helps users identify available parking spaces efficiently, thereby reducing search time, traffic congestion, and fuel consumption. The experimental results demonstrate that the machine learning model effectively captures parking patterns and provides reliable predictions, making the system suitable for deployment in metropolitan city environments.

In future work, the system can be enhanced by incorporating larger and more diverse datasets collected from multiple parking locations to improve prediction accuracy. Advanced machine learning or deep learning models such as Random Forests or Neural Networks can be explored to handle complex parking patterns more effectively. Additionally, real-time sensor integration, dynamic pricing mechanisms, and GPS-based navigation to available slots can further improve system functionality. Developing a fully packaged desktop or mobile application and integrating smart city infrastructure would significantly enhance the scalability and real-world applicability of the proposed solution.

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Skin Cancer Detection and Classification Using Machine Learning

S. Sai Ram[1] and A. Bathsheba Parimala[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: shebaparimala@yahoo.com*

Abstract

Skin cancer is one of the most common and rapidly increasing cancers worldwide, primarily caused by excessive exposure to ultraviolet radiation. Early diagnosis plays a critical role in improving patient survival rates and reducing treatment costs. Traditional diagnostic methods depend on manual visual inspection and biopsy, which are time-consuming, invasive, and subject to human error. Recent advances in machine learning and medical image analysis have enabled the development of automated systems for accurate skin cancer detection. This paper presents a machine learning-based framework for the detection and classification of skin cancer using dermoscopic images. The proposed system involves image preprocessing, feature extraction, and classification using traditional machine learning algorithms and convolutional neural networks. Experimental results demonstrate that the proposed approach achieves high accuracy, robustness, and reliability. The system can effectively support dermatologists in early diagnosis and clinical decision-making, making it suitable for IEEE international conference publication.

Keywords: *Skin cancer, Machine learning, Dermoscopic images, Medical image analysis, Convolutional neural networks*

Introduction

Skin cancer has emerged as a major global health concern, with incidence rates increasing steadily over the past few decades. According to global health statistics, millions of new skin cancer cases are diagnosed every year, with melanoma being the most aggressive and life-threatening type. Prolonged exposure to ultraviolet (UV) radiation from sunlight or artificial sources is identified as the primary cause of skin cancer.

Early detection of skin cancer significantly increases survival rates; however, manual diagnosis remains challenging. Conventional diagnostic procedures rely on visual inspection by dermatologists followed by biopsy, which is invasive, expensive, and time-consuming. Additionally, diagnosis accuracy depends heavily on the experience of the clinician, leading to inter-observer variability.

With the advancement of machine learning and artificial intelligence, automated medical image analysis systems have gained significant attention. Machine learning models are capable of learning complex patterns from large datasets and can identify subtle features that may not be easily visible to the human eye. In recent years, convolutional neural networks (CNNs) have demonstrated remarkable performance in image classification tasks, including skin lesion analysis.

This research focuses on developing an automated system for skin cancer detection and classification using machine learning techniques. The objective is to improve diagnostic accuracy, reduce human dependency, and provide a reliable decision-support tool for dermatologists. The proposed system aims to classify skin lesions into benign and malignant categories using dermoscopic images.

Literature Review

Several studies have explored automated skin cancer detection using image processing and machine learning techniques. Early research primarily focused on traditional image processing methods combined with machine learning classifiers. Features such as color histograms, texture descriptors, and shape parameters were manually extracted and used with classifiers like support vector machines (SVM), k-nearest neighbors (KNN), and decision trees.

Codella *et al.* proposed an automated melanoma detection framework using handcrafted features and machine learning classifiers, achieving moderate classification accuracy. However, these approaches required extensive feature engineering and were sensitive to variations in image quality and lighting conditions.

Recent advancements in deep learning have significantly improved performance in skin cancer classification. Esteva *et al.* demonstrated dermatologist-level accuracy using deep convolutional neural networks trained on large dermoscopic image datasets. CNN-based approaches automatically learn hierarchical features from raw images, eliminating the need for manual feature extraction.

Despite their success, deep learning models face challenges such as class imbalance, overfitting, and high computational requirements. Several researchers have proposed hybrid approaches combining traditional machine learning techniques with deep learning models to improve robustness and generalization.

Although existing research shows promising results, there is still a need for scalable, accurate, and clinically reliable systems. This work builds upon existing studies by integrating effective preprocessing techniques and optimized machine learning models to enhance classification accuracy and reliability.

Proposed System

The proposed system aims to detect and classify skin cancer using machine learning techniques. The overall workflow of the system includes data acquisition, preprocessing, feature extraction, classification, and result analysis.

Dataset Description

The system uses publicly available dermoscopic image datasets such as the ISIC or HAM10000 dataset. These datasets contain images of various skin lesions, including benign and malignant cases. The dataset is divided into training, validation, and testing sets to ensure unbiased performance evaluation.

Image Preprocessing

Preprocessing is an essential step to improve image quality and standardize the dataset. The preprocessing techniques applied include image resizing, normalization, contrast enhancement, and noise removal. These steps help reduce variations caused by lighting conditions and imaging devices.

Feature Extraction

In traditional machine learning approaches, features such as color, texture, and shape are extracted using image processing techniques. In deep learning approaches, convolutional neural networks automatically learn relevant features from input images without manual intervention.

Classification

The classification stage involves training machine learning models such as SVM, Random Forest, and CNNs. CNN-based models are primarily used due to their superior performance in image classification tasks. The trained models classify skin lesions into benign or malignant categories.

System Architecture

The system architecture consists of six major modules: image acquisition, preprocessing, feature extraction, model training, classification, and result visualization. Dermoscopic images are first collected and preprocessed to remove noise and enhance quality. The processed images are then passed to the feature extraction and classification modules.

The classification module predicts the class of the lesion, and the results are displayed through a user interface. The modular design of the system ensures scalability and easy integration with existing healthcare systems.

Experimental Results and Analysis

The experimental evaluation was conducted using Python-based machine learning libraries. The dataset was divided into training and testing sets in an 80:20 ratio. Performance metrics such as accuracy, precision, recall, specificity, and F1-score were used for evaluation.

The CNN-based model achieved higher accuracy compared to traditional machine learning classifiers. The results indicate improved detection performance with reduced false positives. Confusion matrix analysis further validates the reliability of the proposed system.

Applications

The proposed system has several real-world applications:

- Early diagnosis of skin cancer
- Clinical decision support for dermatologists
- Telemedicine and remote healthcare systems
- Medical education and training platforms

Conclusion and Future Work

This paper presented a machine learning-based framework for skin cancer detection and classification using dermoscopic images. The proposed system demonstrated high accuracy and reliability, making it suitable for clinical decision support applications. Automated diagnosis can significantly assist dermatologists in early detection and reduce diagnostic workload.

Future work includes integrating larger datasets, optimizing deep learning architectures, and developing real-time mobile applications. The system can also be extended to classify multiple types of skin cancer with higher precision.

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Artificial Intelligence Healthcare and Medical Research

G. Pravin Doss[1] and I. Thomas Jebasingh[2*]

[1]*Student, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

[2]*Assistant Professor, Department of Computer Application and Networking & IT, St. John's College, Palayamkottai, Tamil Nadu, India.*

**Corresponding Author E-mail: thomasjebas7@gmail.com*

Abstract

Artificial Intelligence (AI) is revolutionizing healthcare by improving disease diagnosis, treatment, drug discovery, and patient care. AI-powered technologies, including machine learning (ML), deep learning (DL), and robotics, enhance medical imaging, predictive analytics, and robotic-assisted surgeries. AI enables early disease detection and personalized treatments, improving patient outcomes. AI is widely used in radiology, pathology, and drug discovery, reducing research time and costs. Robotic- assisted surgery, such as the Da Vinci Surgical System, increases precision and safety. However, AI adoption faces challenges like data privacy concerns, bias in algorithms, and ethical issues. This paper explores the applications, benefits, challenges, and future prospects of AI in healthcare. Addressing ethical and regulatory concerns is crucial for responsible AI deployment. With continuous advancements, AI is set to transform global healthcare, enhancing efficiency, accuracy, and accessibility.

Keywords: Artificial intelligence, healthcare, medical research, machine learning, deep learning, robotics, ethics, drug discovery

Introduction

Artificial Intelligence (AI) has significantly transformed the healthcare industry by automating complex medical tasks, reducing human error, and improving diagnostic accuracy. AI-powered tools are now being used to analyze vast medical datasets, assist in personalized treatment, and facilitate remote patient monitoring. In recent years, AI applications in healthcare have expanded to include robotic surgery, AI-driven drug discovery, and predictive analytics for early disease detection.

According to recent studies, AI-based diagnostic systems have achieved accuracy levels comparable to or even exceeding human physicians in detecting diseases such as cancer, cardiovascular conditions, and neurological disorders. AI is also enhancing electronic health records (EHRs) by enabling predictive modeling to forecast patient health risks. However, despite its numerous advantages, AI in healthcare faces several technical, ethical, and regulatory challenges that need to be addressed for widespread adoption.

Objectives

The primary objectives of this research paper are:

1. To analyze the role of Artificial Intelligence (AI) in healthcare – Examining how AI-powered technologies such as machine learning (ML), deep learning (DL), and robotics are transforming healthcare services, including diagnostics, treatment, and patient care.

2. To explore AI applications in medical research

– Investigating how AI enhances drug discovery, medical imaging, robotic surgery, virtual health assistants, and predictive analytics in healthcare.

3. To evaluate the benefits of AI in healthcare – Understanding how AI contributes to improving diagnostic accuracy, reducing costs, enhancing efficiency, and personalizing treatments.

4. To identify challenges and limitations of AI in healthcare – Discussing key issues such as data privacy concerns, ethical dilemmas, algorithmic bias, and regulatory barriers.

5. To assess the future prospects of AI in medicine

– Analyzing the potential impact of AI on wearable health technology, genomics, precision medicine, and nanomedicine.

Applications of AI in Healthcare

AI in Medical Imaging and Diagnostics

AI has significantly improved radiology, pathology, and medical imaging by enabling faster and more accurate image analysis. AI-driven models, such as Google's DeepMind and IBM

Watson Health, assist in detecting abnormalities in X-rays, MRIs, and CT scans. For example, AI algorithms can identify lung cancer nodules in CT scans at an accuracy rate of over 90%, surpassing radiologists in some cases.

AI in Predictive Analytics

AI-powered predictive analytics enable early detection of diseases by analyzing patient histories, genetic information, and lifestyle factors. For instance, AI models have been used to predict the onset of diseases like Alzheimer's and diabetes by recognizing patterns in medical data.

AI in Drug Discovery and Development

Traditional drug discovery is time-consuming and expensive, often taking 10–15 years for a single drug to reach the market. AI accelerates this process by analyzing molecular structures, genetic data, and chemical interactions to identify potential drug candidates. Companies like Insilico Medicine and BenevolentAI use AI-driven platforms to discover new drugs, significantly reducing costs and time.

AI in Robotic Surgery

Robotic-assisted surgery, powered by AI, enhances precision, flexibility, and control during surgical procedures. The Da Vinci Surgical System is a widely used AI-powered robotic system that assists surgeons in performing minimally invasive surgeries, reducing recovery time and post-operative complications.

AI in Personalized Medicine

AI enables personalized medicine by tailoring treatments based on individual patient data, genetic profiles, and real-time health monitoring. This approach improves treatment efficacy and reduces side effects, particularly in cancer therapies and rare genetic disorders.

AI in Virtual Health Assistants

AI-driven chatbots and virtual assistants, such as Ada Health and Babylon Health, provide 24/7 medical consultation, assisting patients with symptom analysis, medication reminders, and appointment scheduling.

AI in Pandemic Management and Public Health

AI for Disease Surveillance and Outbreak Prediction

AI is being used to track disease outbreaks and predict potential pandemics by analyzing real-time data from health reports, social media, and travel patterns. AI-based models have successfully predicted outbreaks like COVID-19, Ebola, and Influenza.

AI-Powered Contact Tracing and Quarantine Management

During the COVID-19 pandemic, AI tools were used to analyze contact-tracing data and manage quarantine measures efficiently. AI-powered mobile apps helped identify infection hotspots and alert individuals at risk.

AI in Vaccine Development

AI has accelerated vaccine development by predicting protein structures and immune responses, reducing the time required for clinical trials. Companies like Pfizer and Moderna used AI-driven simulations to speed up mRNA vaccine research.

AI-Driven Smart Hospitals

The concept of smart hospitals is transforming modern healthcare through the integration of Artificial Intelligence (AI), Internet of Things (IoT), big data analytics, and automation. AI-driven smart hospitals use advanced technologies to optimize hospital operations, improve patient outcomes, enhance resource management, and reduce costs. By leveraging AI, hospitals can ensure efficient healthcare delivery, personalized treatment, and real-time monitoring of patients.

AI in Hospital Resource Management

One of the key benefits of AI in smart hospitals is its ability to optimize hospital resources, ensuring smooth operations and improved patient care. AI algorithms analyze hospital data, patient inflow, and staff schedules to efficiently allocate resources.

AI-Powered Patient Flow Optimization

AI predicts patient admissions, discharges, and ICU occupancy rates based on historical data, ensuring hospitals are prepared for sudden surges in patient numbers. Smart algorithms manage emergency room (ER) waittimes, directing patients to available physicians and reducing overcrowding. AI-driven triage systems prioritize critical cases, improving response times for emergency patients.

AI in Medical Inventory and Supply Chain Management

AI predicts medical supply demands by analyzing patient needs, preventing shortages of essential medicines, equipment, and surgical tools. AI-powered automated supply chain systems track the usage of resources, reducing waste and lowering hospital expenses. Machine learning algorithms detect patterns in medication shortages and reorder supplies automatically, ensuring continuous availability.

AI in Personalized Patient Care

AI is revolutionizing patient care by providing personalized treatments, real-time health monitoring, and automated patient support systems. AI-driven technologies ensure patients receive customized healthcare solutions based on their individual medical history, genetic data, and lifestyle factors.

Virtual Nursing Assistants and AI Chatbots

AI-powered virtual nursing assistants like Molly (Sensely), Florence, and Ada Health provide 24/7 patient support, medication reminders, and symptom assessments. AI- driven chatbots help patients schedule appointments, answer health-related questions, and provide post-treatment care instructions. These virtual assistants reduce the workload of healthcare professionals, allowing doctors and nurses to focus on critical cases.

AI in Remote Patient Monitoring

AI-powered wearable devices and IoT-enabled biosensors continuously track patient vitals such as heart rate, blood pressure, glucose levels, and oxygen saturation. Smart hospitals integrate AI with electronic health records (EHRs) to alert doctors about any abnormalities in patient conditions. AI-driven predictive analytics can detect early signs of chronic diseases, heart attacks, and strokes, allowing for timely medical intervention.

AI in Smart Hospital Infrastructure and Automation

AI-driven automation is making hospitals safer, more efficient, and technologically advanced by i**mproving** facility management, energy consumption, and security.

AI for Smart Bed Management

AI algorithms track hospital bed availability in real time, ensuring efficient patient allocation.

AI-powered smart beds adjust automatically based on a patient's comfort, posture, and vital signs, preventing bedsores and improving recovery.

Predictive AI models help anticipate discharge times, optimizing bed turnover rates in hospitals.

AI in Hospital Security and Access Control

AI-powered facial recognition systems control hospital access, ensuring only authorized personnel enter restricted areas like ICUs, surgical wards, and medication storage. AI-driven surveillance cameras detect suspicious activities, enhancing patient and staff safety. Biometric authentication and AI-powered voice recognition systems secure patient data access.

AI for Energy Efficiency and Hospital Operations

AI automates hospital lighting, heating, and ventilation, reducing energy consumption and operational costs.

Smart AI sensors adjust room temperature and humidity based on patient comfort and medical equipment requirements.

2. AI in Predictive Analytics for Disease Prevention

AI-powered predictive analytics is revolutionizing healthcare by identifying potential health risks before symptoms manifest. By analyzing vast amounts of patient data, genetic information, lifestyle patterns, and environmental factors, AI helps in detecting diseases early and enables timely interventions. This proactive approach is crucial in reducing healthcare costs, improving patient outcomes, and preventing disease progression. AI models process Electronic Health Records (EHRs), wearable device data, genetic sequences, and medical imaging to detect early warning signs of diseases. In cardiology, AI predicts heart attacks and strokes by analyzing ECG data, cholesterol levels, and family history. In oncology, AI examines CT scans, MRIs, and biopsy reports to identify early-stage tumors, increasing the chances of successful treatment. AI also helps detect neurological disorders like Alzheimer's and Parkinson's by analyzing brain scans and cognitive function data. Wearable AI-powered devices continuously monitor vital signs like heart rate, blood pressure, and glucose levels, providing real-time alerts for potential health issues. AI-driven genomic analysis predicts the likelihood of inherited diseases, helping in preventive treatments.

In infectious disease surveillance, AI tracks and predicts outbreaks by analyzing epidemiological data, travel patterns, and social interactions. It played a crucial role in monitoring and forecasting the spread of COVID-19, influenza, and tuberculosis, allowing governments to implement timely interventions. AI is also making advancements in mental health prediction, analyzing behavioral data to detect early signs of depression, anxiety, and mood disorders. AI-based chatbots and virtual assistants provide real-time mental health support, reducing the burden on healthcare providers. Governments and healthcare institutions utilize AI-driven predictive models to design public health strategies, ensuring proactive rather than reactive healthcare approaches. By integrating AI into predictive analytics, healthcare is shifting from a treatment- focused model to a prevention-driven system, ultimately enhancing global health outcomes, reducing mortality rates, and improving the quality of life for individuals worldwide.

Benefits of AI in Healthcare

Enhanced Diagnostic Accuracy

AI can detect breast cancer, diabetic retinopathy, and pneumonia with accuracy rates matching or exceeding human radiologists. AI-driven diagnostic models improve accuracy by reducing human error. Studies have shown that AI algorithms

Cost Reduction and Efficiency

AI reduces hospital operational costs by automating administrative tasks, streamlining workflow, and optimizing resource allocation. It also reduces the burden on healthcare professionals by automating routine tasks like medical transcription and data entry.

Faster Drug Development

AI accelerates drug discovery, reducing research time from years to months. AI-driven simulations help in predicting drug efficacy and potential side effects before clinical trials, saving both time and resources.

Remote Patient Monitoring and Telemedicine

AI-powered wearable devices and IoT-enabled sensors allow real-time monitoring of patient vitals, improving chronic disease management and reducing the need for hospital visits. AI is also improving telemedicine services, enabling remote consultations and real-time diagnosis.

Challenges and Limitations of AI in Healthcare

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Future Prospects of AI in Healthcare

The future of Artificial Intelligence (AI) in healthcare is expected to bring groundbreaking advancements, making medical treatments more precise, accessible, and efficient. AI will continue to revolutionize disease detection, personalized medicine, robotic surgeries, and patient management, transforming the way healthcare is delivered. With ongoing research and technological innovations, AI has the potential to address global healthcare challenges, improve early diagnosis, and optimize treatment strategies.

AI in Early Disease Detection and Predictive Medicine

AI-driven predictive analytics will enable doctors to identify diseases before symptoms appear, allowing for early intervention and preventive care. AI models trained on vast datasets will analyze genetic information, lifestyle patterns, and medical histories to predict a patient’s likelihood of developing diseases such as cancer, diabetes, and neurodegenerative disorders. With AI-powered screening tools, healthcare providers can improve early cancer detection, cardiovascular risk assessments, and personalized health recommendations, significantly increasing survival rates and treatment success.

AI-Driven Personalized and Precision Medicine

In the future, AI will play a critical role in precision medicine, where treatments will be tailored to an individual’s unique genetic makeup, environment, and lifestyle. AI algorithms will analyze genomic data, molecular structures, and patient responses to create customized treatment plans, minimizing adverse drug reactions and enhancing therapeutic effectiveness. This approach will be particularly beneficial in oncology, rare genetic disorders, and autoimmune diseases, offering targeted therapies that maximize patient outcomes.

AI-Powered Robotics and Autonomous Surgeries

Robotic-assisted surgeries are already making complex procedures more precise and minimally invasive. In the coming years, AI-driven robots will become more autonomous, assisting surgeons with real-time imaging, robotic precision, and AI-guided navigation. These advancements will improve the success rates of procedures such as neurological, cardiac, and orthopedic surgeries, reducing recovery times and complications. Additionally, AI-powered robotic caregivers will assist in elderly care, rehabilitation, and physiotherapy, ensuring continuous support for patients.

AI in Mental Health and Cognitive Therapy

The application of AI in mental health treatment is set to grow, providing virtual therapists, AI-powered counseling, and emotion recognition technology. AI-driven mental health chatbots and cognitive behavioral therapy (CBT) applications will help individuals manage stress, anxiety, and depression. AI-based sentiment analysis will allow healthcare providers to detect early signs of mental illness by analyzing speech patterns, facial expressions, and behavioral data. These innovations will expand access to mental health services, particularly for remote and underserved populations.

AI-Integrated Wearable Health Technology

The future of healthcare will be dominated by AI-powered wearable devices and smart health monitoring systems. Devices such as smartwatches, biosensors, and implantable chips will continuously track patient vitals like heart rate, oxygen levels, glucose levels, and sleep patterns. AI will analyze real-time data from wearables to detect abnormalities, predict potential health risks, and provide instant alerts to both patients and healthcare professionals. This technology will play a significant role in managing chronic diseases like hypertension, diabetes, and cardiac conditions.

Conclusion

Artificial Intelligence (AI) is transforming healthcare by enhancing diagnostics, improving treatment precision, optimizing hospital management, and enabling personalized medicine. AI-driven technologies such as machine learning, natural language processing, and robotics have significantly improved efficiency, accuracy, and accessibility in medical research and patient care. From early disease detection and drug discovery to AI-assisted surgeries and mental health support, AI continues to play a crucial role in reshaping modern medicine. However, despite its numerous benefits, the widespread adoption of AI in healthcare presents several ethical, legal, and technical challenges. Issues such as patient data privacy, algorithmic bias, lack of transparency, and regulatory compliance must be addressed to ensure that AI-driven solutions are safe, reliable, and equitable. Developing ethical AI frameworks, robust data security measures, and unbiased training models will be essential to building public trust and ensuring fair healthcare delivery.

Looking ahead, AI will continue to evolve, driving innovations in telemedicine, wearable health monitoring, robotic caregiving, and smart hospitals. Future research should focus on enhancing AI interpretability, improving human-AI collaboration, and integrating AI with emerging technologies such as blockchain and quantum computing. By fostering collaboration between healthcare professionals, AI developers, policymakers, and regulatory bodies, AI can be harnessed responsibly to create a more efficient, accessible, and patient-centered healthcare system. If implemented ethically and strategically, AI has the potential to revolutionize global healthcare, leading to better medical outcomes, lower costs, and improved quality of life for patients worldwide.

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