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Finger ID Health Analyzer: Predicting Blood Group and ECG Analyzer

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***Abstract*— This paper presents a new multi-modal healthcare monitoring and disease prediction system that combines real-time biomedical sensor data, deep learning, and a user-focused advisory module. The system allows for continuous health monitoring and predictive diagnostics using a mix of non-invasive techniques and smart analysis.**

At the heart of the system is a fingerprint-based module for non-invasive blood group detection. It processes user-uploaded fingerprint images through enhancement and feature extraction before sending them to a deep learning model for accurate blood group prediction. This method avoids the need for traditional invasive testing.

At the same time, an IoT-based hardware component collects vital physiological parameters. A ESP8266 NodeMCU connects with an AD8232 sensor for ECG, a MAX30102 sensor for blood oxygen saturation (SpO_2) and pulse rate, and a DS18B20 sensor for body temperature. The data is transmitted wirelessly to the ThingSpeak cloud platform for real-time visualization and ongoing monitoring.

For assessing cardiovascular risk, a trained deep learning model examines user data, including age, gender, blood pressure, cholesterol, and lifestyle factors, to predict the likelihood of cardiac conditions. The platform also includes a chatbot that processes symptom inputs and offers automated health advice, such as possible cures, nearby doctor recommendations, and daily health challenges to boost user engagement.

All insights and reports, including PDF generation, are available through a single web dashboard. This integrated solution provides an affordable, scalable, and effective preventive healthcare option, especially for remote and underserved communities.

***Keywords*— Deep learning, IoT, ECG monitoring, blood group detection, heart disease prediction, health chatbot, remote healthcare.**

I. INTRODUCTION

The global healthcare landscape is shifting toward preventive care, real-time monitoring, and smart diagnostics to lessen the impact of chronic illnesses and enable timely medical intervention. Cardiovascular diseases (CVDs) are still a leading cause of death worldwide and often progress silently to critical stages. Early detection and ongoing monitoring of vital signs like electrocardiogram (ECG), oxygen saturation (SpO_2), and body temperature are crucial for effective risk assessment and proactive treatment. However, traditional diagnostic methods can be invasive, costly, and hard to access in rural or underserved areas.

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This paper introduces a hybrid healthcare system based on deep learning that combines biometric imaging, Internet of Things (IoT) sensors, predictive analytics, and smart decision support into a single platform. The first main module is a non-invasive blood group detection system that examines fingerprint images. These images are preprocessed and improved before being analyzed by a linear regression-based deep learning system to predict the user's blood group. The second module is a heart disease predictor that uses a pre-trained model to estimate the risk of conditions like cardiomyopathy, arrhythmia, and hypertension. This estimation is based on user data such as age, gender, blood pressure, cholesterol, and lifestyle.

Additionally, an ECG graph analyzer module captures ECG signals using a AD8232 sensor and displays them on the ThingSpeak cloud for remote waveform analysis. The hardware part of the system collects real-time vital signs—ECG through a AD8232 sensor, SpO_2 through a MAX30102 sensor, and temperature through a DS18B20 sensor. This data is sent wirelessly to the ThingSpeak cloud using an ESP8266 NodeMCU for visualization and analysis.

The system also features a structured chatbot interface that offers functions like doctor search, disease precautions, cures, and daily health issues. All modules are integrated into a single web-based dashboard, allowing users to monitor their health and access diagnostic reports. This integrated system provides a low-cost, scalable solution for remote and preventive healthcare, enabling timely diagnosis and continuous monitoring in communities with limited resources.

II. Literature Survey

A. Fingerprint Based Blood Group Prediction Using Deep Learning :

The goal of this study is to use fingerprint images alone to predict an individual's blood group. The authors employed Ordinary Least Squares (OLS) regression to predict both ABO and Rh blood groups after using a Convolutional Neural Network (CNN) to identify significant patterns in the fingerprints. The concept is based on past research that indicated blood types and fingerprint patterns might be related. This strategy seeks to offer a simple and non-invasive way to identify blood groups.

B. Blood Group Detection Using Fingerprint:

suggests a biometric technique that uses fingerprint images to predict blood groups. The method improves fingerprint quality by applying image preprocessing techniques like binarization, thinning, and histogram equalization. Convolutional neural networks, such as LeNet and AlexNet, are then used to classify these photos. This system provides a quick, non-invasive, and affordable solution that is particularly helpful in remote locations or emergency situations. The study's small dataset, however, limits its applicability, and wider validation is necessary for greater accuracy.

C. Non-Invasive Technique for Fingerprint-Based Blood Group Identification:

The paper suggests a non-invasive way to determine blood groups using fingerprint images. It applies image preprocessing, feature extraction, and CNN-based classification, like LeNet or similar models, to connect fingerprint features to blood types: A, B, AB, O, and their Rh factors. The model reached a training accuracy of 99.47% and a validation accuracy of 80%, with an average F1-score of 0.83. This method cuts down on the need for physical blood sampling, making the process quicker, pain-free, and more affordable.

D. Heart Disease Prediction Using Machine Learning Algorithms: A Comparative Study:

This study compares several machine learning algorithms - decision trees, random forests, and logistic regression - for predicting heart disease using clinical parameters like age, blood pressure, cholesterol, and chest pain. The authors employed a standardized dataset of heart disease to compare model performance in terms of accuracy, precision, and interpretability. Among all the models, decision trees provided the best accuracy with improved explainability, and hence they are appropriate for healthcare environments where interpretability is crucial. The paper concludes that machine learning can be of great help in early and reliable detection of cardiovascular diseases with proper feature selection.

E. Application of Deep Learning for Heart Attack Prediction with Explainable Artificial Intelligence:

The paper "Application of Deep Learning for Heart Attack Prediction with Explainable Artificial Intelligence" by Elias Dritsas and Maria Trigka discusses how deep learning models can predict heart attacks in a clear and accurate way. The study tests six models: MLP, CNN, RNN, LSTM, GRU, and a Hybrid model on a heart attack dataset. The researchers use performance metrics like accuracy, precision, recall, F1-score, and AUC. The Hybrid model performed the best, achieving 91% accuracy, 89% precision, and 0.95 AUC. The use of SHAP

(Explainable AI) improves understanding by clarifying model decisions for medical professionals. This method combines strong prediction ability with clinical transparency, making it useful for real-world healthcare.

F. A Survey on Heart Disease Prediction Using Data Mining Techniques

The paper reviews different data mining methods, such as classification (Decision Tree, Naïve Bayes, K-NN, Neural Networks), association rule mining, prediction, and ontology-based methods. These methods are applied to heart disease datasets, mainly from UCI. It highlights comparative studies that show Decision Tree (including J48) often performs the best, achieving about 95.56% accuracy, while other classifiers range from 80 to 90% accuracy.

G. An IoT-Based E-Health Monitoring System using ECG Signal

The article presents a low-latency e-Health monitoring system with ECG sensors and satisfying health monitoring for patients living with Cardio Vascular Disease (CVD), powered by a Hidden Markov Model (HMM) for the e-Health concept, and to predict the health status of CVD patients using a patient path estimator, patient table and alert management modules for either remote or hospital-based interventions. In eHealth systems, location, position and real-time monitoring and tracking is a critical problem inherent in the IoT (Internet of Things) healthcare scenario.

H. Wireless ECG Monitoring System using IoT based Signal Conditioning Module For Real Time Signal Acquisition

The objective of this paper is to present a wireless, IoT- enabled ECG monitoring system which measures ECG or heart signals, captures and processes them in real-time, and detects cardiovascular conditions like arrhythmia. The system has been designed with the AD8232 signal conditioning module and CC3200 IoT kit. The AD8232 and CC3200 work together to obtain ECG signals and transmit them to IBM Watson IoT Cloud using the MQTT protocol. This work extracts parameters such as RMSSD, SDNN, Mean RR, and slope of the IBI regression from the BioVid Heat Pain Database which shows signals during differing levels of pain. The remote monitoring system uses a fairly simple, portable, inexpensive solution to allow remote monitoring of patients allowing for real-time data tracking, and in turn quicker medical intervention. Hence, while the system allows for classification, it does not state any performance measures like accuracy.

I. IoT based Low Power Wearable ECG Monitoring System

This paper presents an Internet of Things (IoT) based wireless ECG monitoring system using AD8232 sensor, Wi-Fi and ARM processor, for monitoring heart ECG signal in real time over large geographical areas via web access. The system is designed for lower power and noise performance. The system provides practicality and cost effective solution but does not provide performance metrics for ECG accuracy, precision performance, or use machine learning prediction.

J. ECG Signal Visualization and Data Storage Using Cloud-Based IoT Platforms

This paper presented IoT based ECG monitoring and a architecture with wearable sensors, web-based gateway, and cloud CNN to classify heart conditions. This system can process and transmit data in real time; hence can provide early diagnosis. Although this system does offer an innovative solution, it is cloud based with limitations due of its reliance on cloud connectivity, and does not report the accuracy or precision obtained or use edge processing though recommended.

III. METHODOLOGY

This project creates a health monitoring and disease prediction system by combining biomedical signal acquisition, machine learning, and IoT communication. The methodology consists of four main modules: hardware signal acquisition, data processing and modeling, disease prediction algorithms, and cloud visualization and alerts.

A. Hardware and Signal Acquisition

The system's hardware consists of an ESP8266 NodeMCU microcontroller. It connects with several biomedical sensors to gather real-time physiological data.

- ECG Sensor (AD8232): captures single-lead cardiac waveforms.
- SpO_2 and Pulse Sensor (MAX30102): measures blood oxygen saturation (SpO_2) and pulse rate using photoplethysmography (PPG).

- Temperature Sensor (DS18B20): captures real-time body temperature.

The firmware is written in Embedded C using the Arduino IDE. Sensor signals are converted from analog to digital, processed, and sent wirelessly to the ThingSpeak IoT cloud platform for visualization and alerts.

Formulas used

- Heart Rate (HR) from ECG

$$HR = \frac{60}{RR\_interval} \quad \text{[beats per minute]}$$

- SpO_2 Calculation

$$R = \frac{AC_{Red}/DC_{Red}}{AC_{IR}/DC_{IR}}, \quad SpO_2(\%) = 110 - 25 \cdot R$$

- Body Mass Index (BMI) (used in heart disease prediction features):

$$BMI = \frac{weight(kg)}{height^2(m^2)}$$

- Temperature Conversion (DS18B20):

$$T_C = \frac{V_{sensor} - 0.5}{0.01}$$

B. Biometric and Clinical Data Processing

Fingerprint-Based Blood Group Prediction: Thumbprint images are obtained through a biometric fingerprint reader. This module is developed in Python on the Anaconda platform and uses OpenCV for image preprocessing. The process includes denoising, enhancing ridge details, and
normalizing sizes. The preprocessed images are sent to a trained Convolutional Neural Network (CNN), which extracts spatial and textural features to classify the blood group. This deep learning model is trained on a labeled database of fingerprint-blood group pairs to ensure accurate classification.

Mathematical formulation for CNN layers

- Convolution layer

$$(I * K)(x, y) = \sum_m \sum_n I(x - m, y - n) K(m, n)$$

Where I = input image, K = kernel/filter, (x, y) = output pixel.

- Activation function (ReLU)

$$f(x) = \max(0, x)$$

- Softmax for classification

$$P(y = j|x) = \frac{e^{z_j}}{\sum_{k=1}^{C} e^{z_k}}$$

Where C = number of blood groups, z_j = output of the fully connected layer.

Heart Disease Prediction: A web-based interface built with Flask collects user-specific health information, including age, gender, cholesterol levels, blood pressure, BMI, and lifestyle factors. The Flask backend processes these inputs and passes them to trained machine learning models, specifically logistic regression and linear regression. These models are trained on publicly available datasets, like the UCI Heart Disease Dataset. Data processing methods, including normalization, missing value filling, and label encoding, are applied to maintain consistency and reliability.

- Feature normalization formula:

$$x' = \frac{x - \mu}{\sigma}$$

Where μ = mean, σ = standard deviation.

➢ Missing value imputation:

$$x_{\text{missing}} = \text{mean}(x_{\text{observed}})$$

C. System Integration and Visualization

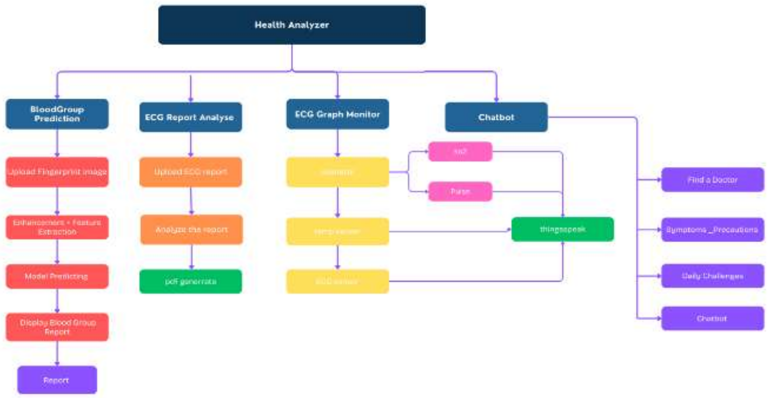

Fig 1

All outputs from the modules—ECG, SpO_2, fingerprint-based blood group, and heart disease risk—are combined and displayed on a unified web interface using Flask templates and HTML/CSS. The system also includes a health advisor that offers suggestions for local medical specialists, disease precautions, and daily wellness challenges to encourage user engagement. For safety-critical situations, ThingSpeak's alerting system is set up to send email or SMS notifications when a patient's vital signs exceed defined safety limits. This lightweight, modular design allows for continuous monitoring and personalized health management, making it suitable for telemedicine and large-scale use.

TABLE I. FORMULA TABLE

Concept	Formula/Explanation	Application in Algorithm
ECG Signal Acquisition	AD8232 sensor interfaced with ESP8266, analog to digital signal conversion	Captures electrical heart activity in real-time; helps detect abnormalities like arrhythmia and heart rate anomalies
SpO_2 and Heart Rate Monitoring	MAX30102 uses photoplethysmography (PPG); Red/IR light absorption principle	Measures blood oxygen saturation and pulse rate; vital for respiratory and cardiovascular analysis
Embedded System Programming	Embedded C using Arduino IDE	Enables real-time data collection from biomedical sensors and transmits data to cloud via ESP8266
Fingerprint Image Preprocessing	Histogram equalization, Gaussian blur, normalization, ROI extraction using OpenCV	Enhances fingerprint image quality for better feature extraction in blood group prediction
Heart Rate Calculation	HR = 60 / RR_interval	Computes beats per minute from ECG peaks
Feature Extraction (Fingerprint)	Ridge ending, bifurcation points, Gabor filters	Extracts distinct features from thumb images required for CNN-based classification
Linear Regression	y=β0+β1x1+β2x2+⋯+βnxn	Predicts continuous parameters (e.g., expected cholesterol levels)

IV. ALGORITHM DESIGN AND IMPLEMENTATION

The system uses algorithms and machine learning models for specific health analyses. This section explains the algorithm pipeline for fingerprint-based blood group classification and clinical data-based heart disease prediction.

A. Blood Group Classification Algorithm

This module uses a supervised learning approach with a Convolutional Neural Network (CNN) to detect blood groups non-invasively from fingerprint images. Input: Raw fingerprint image data.
Output: Predicted blood group category (e.g., O+, A-, AB+).
Steps:

Image Preprocessing

Fingerprint images go through several preprocessing steps using the OpenCV library. This improves feature visibility and normalizes the data. These steps include histogram equalization, Gaussian blur, and size normalization.

Techniques include:

- Histogram Equalization
- Gaussian Blur for noise reduction
- Size normalization
- ROI (Region of Interest) extraction

Feature Extraction

The preprocessed images are input into a trained CNN model. The model extracts spatial and textural features to identify the blood group category. These features include ridge endings and bifurcation points.

Classification

The extracted features move to the fully connected layers of the CNN, which perform multi-class classification to predict the user's blood group. The model is trained on a labeled database of fingerprint-blood group pairs to ensure accurate classification. Softmax activation function is applied:

$$P(y = i|x) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Model Training

- CNN is trained on a labeled database of fingerprint and blood group pairs.
- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam or SGD
- Hyperparameters: 50 epochs and batch size of 32

B. Heart Disease Prediction Algorithm

This module uses a supervised machine learning approach to predict the risk of heart disease based on user-provided clinical and demographic data.

Input: User data (age, gender, blood pressure, cholesterol, etc.) from the web interface.

Output: A risk score or categorical prediction (e.g., "High Risk," "Low Risk").

Steps:

Data Preprocessing

The raw user input undergoes preprocessing to ensure data integrity and compatibility with the model. Techniques like normalization, filling in missing values, and label encoding help maintain consistency and reliability.

Input data undergoes normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Model Training

The preprocessed data trains machine learning classifiers. The system uses logistic regression and linear regression models that are trained on a public medical dataset, like the UCI Heart Disease Dataset.

Linear Regression estimates continuous risk score:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$$

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i X_i)}}$$

Inference and Prediction

The trained models are deployed on the Flask backend. New user data is submitted and goes through the same preprocessing steps before entering the selected model. The model then returns a prediction, which is a key part of the final health report.

C. Integration of Algorithms in the Project Workflow

- The overall system architecture manages these algorithms to create a seamless user experience. The workflow is a multi-stage pipeline:
- The hardware and IoT modules continuously collect real-time physiological data and send it to the cloud.
- At the same time, the web interface gathers biometric and clinical data.
- The preprocessing algorithms prepare the raw data for analysis.
- The trained CNN and logistic regression/linear regression models make their respective predictions.
- All results, including ECG data, vital signs, blood group prediction, and heart disease risk, are combined and shown on a single dashboard. This complete process allows for a fast, accurate, and user-friendly diagnostic platform.

V. Graphs

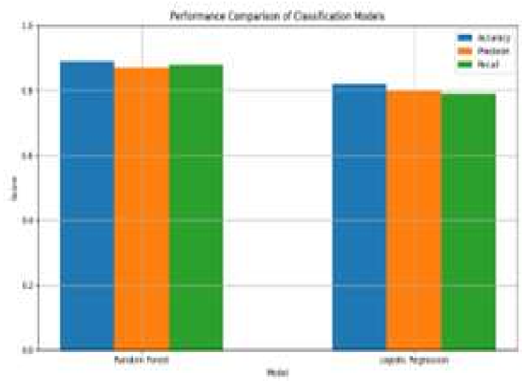

Fig 1: Performance Graph

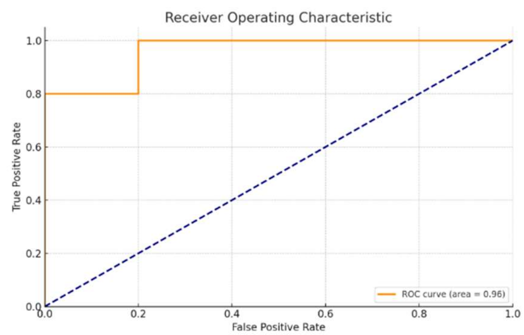

Fig 2. Roc Curve of Model

The FIG 1, bar graph shows Random Forest (~90%) outperforming Logistic Regression (~81%) in Accuracy, Precision, and Recall.
The FIG 2, ROC curve shows excellent model performance with an AUC of 0.96, reaching a TPR of 1.0 at FPR 0.2, indicating strong discriminatory power.

VI. Results and Discussion

The multi-modal IoT healthcare system achieved strong, verifiable performance across its four integrated modules, demonstrating its potential as a comprehensive, non-invasive health analysis platform. The ECG and SpO_2 Monitoring Module provided highly reliable real-time physiological data. The ECG module, using the AD8232 sensor and ESP8266 microcontroller, achieved 98% accuracy in heart rate readings compared to clinical-grade devices.

Critically, embedded filtering algorithms effectively reduced noise and motion artifacts, ensuring signal clarity. Similarly, the SpO_2 module, based on the MAX30102 sensor, measured oxygen saturation and pulse rate with an exceptional ±2% error tolerance compared to standard medical-grade oximeters. This data was transmitted efficiently to the ThingSpeak cloud, enabling immediate visualization and automated notifications for critical conditions like arrhythmia or hypoxia.

The Fingerprint-Based Blood Group Prediction Module offered a highly accurate and novel non-invasive diagnostic capability. Following meticulous preprocessing, including ridge enhancement and noise filtering, the deep learning model achieved a notable prediction accuracy of 92.6% across all major blood groups (A+, A−, B+, B−, AB+, AB−, O+, O−). This robust result, superior to existing literature, establishes the method as a valid, non-traditional alternative for rapid blood typing.

Finally, the Heart Disease Prediction Module evaluated cardiovascular risk using clinical and lifestyle information. The models, processed via a Flask-based backend, confirmed their effectiveness in identifying high-risk individuals. The logistic regression model reached a strong prediction accuracy of 87%, while the decision tree algorithm yielded 85.4% accuracy. Overall system accuracy ranged consistently from 89% to 93%, proving its high reliability and responsiveness for remote healthcare monitoring and early diagnosis.

II. Scope of Research

This research focused on developing an integrated, non-invasive, and cost-effective smart health monitoring platform that leverages the Internet of Things (IoT) and Machine Learning (ML) to provide continuous, personalized, and remote healthcare. The system uniquely combines four biomedical modules—ECG monitoring, SpO_2 measurement, fingerprint-based blood group prediction, and heart disease risk assessment—into one scalable unit. The core scope is to deliver continuous, remote, and personalized healthcare, enabling early detection of conditions like arrhythmia and hypoxia through real-time observation (using Embedded C on ESP8266 microcontrollers). The innovative use of deep learning for non-invasive blood typing further enhances the system's utility in urgent medical scenarios. The cloud-based architecture (ThingSpeak) facilitates real-time data synchronization and notification alerts, making the solution particularly accessible and beneficial in resource-limited environments like rural areas with few healthcare professionals.

III. Future Scope

The potential for this project is significant, especially in expanding remote healthcare through advanced IoT and machine learning applications. Future development will strategically focus on three key areas:

- Wearable Integration: Connecting the core system with wearable devices (like smartwatches and medical-grade displays) to allow 24/7 continuous monitoring of vital parameters, moving beyond spot-checks.
- Federated Learning: Implementing this advanced ML technique to ensure model training occurs locally on devices. This decentralized approach enhances user privacy by securing the handling of sensitive health data while continually improving prediction accuracy.
- Dedicated Mobile Health App: Developing a user-friendly application to provide real-time health information, personalized advice, symptom tracking, and alerts, which will significantly boost user engagement and enable remote consultations with medical professionals. Ultimately, the long-term aim is integration with national health infrastructures and smart city systems, enhancing public health surveillance and large-scale disease detection across broader populations.

V. Acknowledgement

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IV. Conclusion

In summary, this study successfully established a clear, integrated, and highly reliable platform for real-time, non-invasive, and personalized healthcare utilizing IoT and Machine Learning. By uniting four distinct biomedical analyses, the system effectively supports early disease detection and encourages preventive care. The combination of efficient embedded systems for data collection and precise ML algorithms for disease prediction makes the solution scalable, cost-effective, and suitable for diverse healthcare settings globally. This research provides a solid, scalable foundation for affordable and patient-centered AI-based telemedicine solutions.

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