RESEARCH PAPER

Smart Healthcare System for Cardiovascular Disease Monitoring Using ECG Data and Stacking Classifier

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ABSTRACT

Cardiovascular diseases (CVDs) rank among the primary causes of global mortality, underscoring the necessity for ongoing and real-time monitoring to facilitate early detection and prompt intervention. This study introduces an IoT-enabled smart healthcare system aimed at monitoring cardiovascular diseases through ECG data and machine learning classification techniques. The system employs wearable ECG sensors to gather real-time cardiac signals, which are subsequently transmitted to a cloud-based platform for sophisticated processing and analysis. Data collection is followed by pre-processing and feature selection to improve classification accuracy. Various machine-learning models, such as Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naïve Bayes, Random Forest, Gradient Boosting, and AdaBoost, are employed for the classification of ECG signals. An ensemble learning approach is utilized to enhance diagnostic accuracy by integrating multiple classifiers. The final trained model is integrated into an IoT-based healthcare framework, facilitating remote monitoring and real-time notifications for abnormal cardiac events. Experimental results demonstrate that the proposed system achieves enhanced classification performance. The stacking classifier demonstrated the highest accuracy at 97% among the evaluated models, surpassing conventional machine learning approaches. The dataset was partitioned into 80% for training (11,641 samples) and 20% for testing (2,911 samples), facilitating an optimal balance for model evaluation.

Keywords: Machine Learning (ML), Internet of Things (IoT), cardiovascular disease (CVD), Stacking Classifier

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1. Introduction

Cardiovascular diseases (CVDs) continue to be a major contributor to global mortality, representing a substantial share of annual deaths [1]. Identifying cardiovascular conditions at an early stage and maintaining ongoing observation are essential for enhancing patient outcomes and alleviating the strain on healthcare systems [2]. Many times requiring several trips to healthcare facilities, traditional diagnostic techniques provide difficulties for people living in rural or disadvantaged areas [3]. The current difference in accessibility emphasizes the need of creative ideas using modern technology to provide remote and real-time cardiovascular health monitoring.

Electrocardiography (ECG) serves as a dependable method for identifying cardiovascular irregularities through the examination of the heart's electrical activity [4]. Recent advancements in wearable technology have led to the development of compact ECG sensors, facilitating continuous monitoring of heart activity beyond clinical environments [5]. The combination of these sensors with Internet of Things (IoT) platforms facilitates smooth data transmission, immediate analysis, and remote healthcare consultations, directing attention toward personalized and preventive care [6].

This study presents a smart healthcare system utilizing IoT technology for the remote monitoring of cardiovascular diseases. ECG sensors generate real-time data that is transmitted securely to a cloud-based platform via the lightweight Message Queuing Telemetry Transport (MQTT) protocol. MQTT is suitable for this application due to its efficient data transfer, minimal bandwidth consumption, and ability to function in resource-constrained environments [7]. This architecture helps healthcare staff to remotely monitor and assess patient ECG data in real time, therefore supporting quick medical advice.

By analyzing the data, the gadget can spot changes in the ST slope and other abnormalities in the ECG patterns, which can be a sign of serious heart issues [8]. Delays in diagnosis and treatment can be minimized when abnormalities are detected since the patient is alerted to seek medical consultation quickly. This approach not only enhances current health monitoring but also maximizes healthcare resources since it helps doctors to properly prioritize individuals at more risk. Finding anomalies could lead the patient to be advised for a quick medical appointment, therefore reducing diagnosis and treatment delays. This strategy simplifies healthcare resources and enhances continuous health surveillance, therefore helping doctors to properly rank patients with more risk.

This work aims to create an efficient and scalable cardiovascular disease detecting and monitoring system. With phase, 1 IoT will assist with irregular pulse rate detection. Should the pulse rate be below or over the threshold, it will indicate ecg and from ecg, st slope will be ideated either the patient is at risk or not. Our work employs ECG sensors, IoT technology, and a stacking classifier to improve cardiovascular treatment in distant and resource-limited areas. Early detection and action should improve patient outcomes.

2. Related Work

The incorporation of Internet of Things (IoT) technologies into healthcare systems has resulted in a significant transformation in the monitoring and control of cardiovascular diseases (CVDs). Internet of Things-enabled systems have demonstrated a great deal of promise in a number of areas, including real-time health data, enhanced remote patient care, and a reduction in the workload of healthcare facilities. This review of the literature on ECG-based cardiovascular disease monitoring systems explores current findings with an eye toward the Internet of Things (IoT), the MQTT protocol, and remote health diagnostics. As a result of the fact that electrocardiography (ECG) provides complete insights into the rhythm of the heart and the electrical activity of the heart, it has become the foundation for both the diagnosis and monitoring of cardiovascular illnesses. According to the findings of a number of studies, abnormal rhythms or strange wave patterns on an electrocardiogram (ECG) are excellent indicators of cardiovascular diseases (CVDs) [9]. Because they are able to continuously monitor the activity of the heart, wearable electrocardiogram monitors have gained widespread recognition for their ability to assist in the early detection of illnesses such as arrhythmias and ischemia episodes [10]. The Internet of Things has made it possible to perform remote monitoring and real-time data processing, which is especially helpful for chronic diseases such as cardiovascular diseases (CVDs). In order to facilitate the collection, transmission, and evaluation of health data, Internet of Things (IoT) systems are constructed from interconnected sensors, communication protocols, and cloud-based platforms. Rahman [11] demonstrated that Internet of Things (IoT)-enabled electrocardiogram (ECG) monitoring systems vastly reduce the amount of time it takes to diagnose cardiac events, hence improving patient outcomes. These solutions are suitable for environments with limited resources since they offer scalability as well as accessibility when implemented. MQTT, which stands for Message Queuing Telemetry Transport, is a protocol that is widely used in Internet of Things devices. Its lightweight and efficient design makes it particularly suitable for networks with low bandwidth. The advantages of MQTT in healthcare Internet of Things systems are demonstrated by study conducted by Lee and Park [12], which highlights the low bandwidth utilization and reliable data transfer capabilities of MQTT. Through the use of its publish-subscribed methodology, MQTT ensures the speedy and secure transmission of electrocardiogram (ECG) data between devices and servers, hence enabling medical professionals to perform remote diagnosis operations. In the fight against cardiovascular diseases (CVDs), remote monitoring devices have emerged as indispensable tools, particularly for patients who live in rural or economically disadvantaged areas. IoT-based electrocardiogram (ECG) monitoring devices provide physicians with real-time access to patient data, which enables them to provide prompt therapies, as stated in research conducted by Singh [13]. Cloud platforms that are integrated with machine learning algorithms improve these systems by evaluating electrocardiogram (ECG) data by identifying early signs of cardiovascular disease (CVD). In-person consultations are becoming less necessary as a result of these changes, which brings about improvements in patient convenience and the delivery of healthcare. The Internet of Things (IoT) and cloud computing, according to Albahri [14], are able to store and analyze massive volumes of electrocardiogram (ECG) data, providing medical professionals with useful information that enables them to make a diagnosis more quickly. Gupta [15] demonstrated how Internet of Things (IoT)-integrated real-time electrocardiogram (ECG) monitoring devices could potentially notify patients about potential cardiac crises, hence reducing the number of fatalities. In addition, Zhang [16] investigated the extent to which wearable electrocardiogram (ECG) devices were able to bridge the gap in healthcare that existed in rural areas and discovered that they were rather successful. According to the findings of the study, these tools provide patients with real-time notifications and enable virtual consultations with specialists, which ultimately leads to an improvement in the delivery of healthcare in places that are economically disadvantaged. The heart rate, the heart rhythm, the P wave, the PR segment, the Q wave, the QRS waveform, the ST segment deviation, and the T wave are all aspects of an electrocardiogram that each contribute to the diagnosis of a separate cardiovascular illness. Among these, early myocardial infarction (MI) identification depends critically on ST segment deviation and T wave abnormalities [17]. Commonly monitored by smart devices, heart rate and rhythm irregularities help to identify arrhythmias like atrial fibrillation (AF) and ventricular tachycardia (VT [18]).

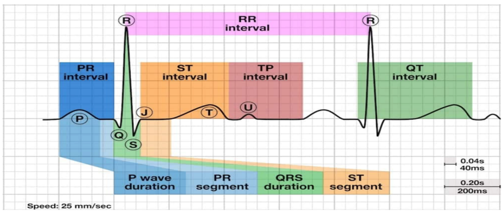

Fig 1. Graphical presentation of PR-interval in electrocardiogram [30].

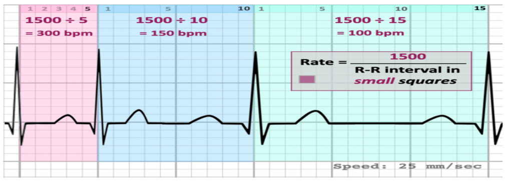

Fig. 2. Small square method to calculate rate [31].

Designed to compute heart rate using R wave intervals, ECG paper Heart rate is calculated using the usual ECG paper speed of 25 mm/sec using methods like 1500 divided by the number of tiny squares between two R waves [20]. The maximal heart rate (MHR) is obtained by subtracting a person's age from 220 [21]. Automated ECG interpretation may sometimes inaccurately assess heart rate due to waveform anomalies [22]. Arrhythmia refers to irregular cardiac rhythms, which can be classified into bradyarrhythmia (characterized by slow, irregular rhythms) and tachyarrhythmia (characterized by rapid, irregular rhythms). A consistent P wave in normal electrocardiograms precedes each QRS complex. The absence of P waves and the presence of abnormal QRS complexes indicate arrhythmias such as atrial fibrillation or supraventricular tachycardia (SVT) [23]. Bradyarrhythmias are identified through the interaction between P waves and QRS complexes, with anomalies indicating varying degrees of atrioventricular (AV) block [24]. As a sign of atrial depolarization, the P wave should be smooth and have a length of less than 0.12 seconds. If the P wave is taller than 2.5 mm, it may indicate right atrial enlargement, whereas a broad P wave indicates left atrial enlargement.Internet of Things (IoT) applications in electrocardiogram (ECG) monitoring systems for cardiovascular disorders are on the rise, according to research. Improved accessibility, easier remote diagnostics, and earlier detection of cardiovascular disease (CVD) are all possible outcomes of these technological developments. If a stacking classifier is applied, the expected accuracy could be improved. According to reference 26, a narrow QRS complex (<120 msec) signifies ventricular depolarization, while a large QRS complex can suggest bundle branch blockages or ventricular hypertrophy. The first negative QRS complex deflection is Q waves. A pathological Q wave (width > 0.04 sec, depth > 2 mm) indicates prior myocardial infarction [17]. While ST depression (>0.5 mm) indicates myocardial ischemia, ST segment elevation (>1 mm) is a main sign of myocardial infarction [27]. Detecting acute coronary syndromes and other cardiac anomalies depends on these criteria [28]. While inverted T waves could suggest myocardial ischemia, tall, peaked T waves are linked with hyperkalemia [29].Ranging from 120 to 200 msec, the PR interval can indicate conduction anomalies including first-degree AV block or pre-excitation syndromes such Wolff-Parkinson-White (WPW) syndrome [20]. Research implies a rising use for IoT in ECG-based systems for the monitoring of cardiac diseases. These innovations have demonstrated significant potential for boosting accessibility, facilitating remote diagnostics, and enabling early diagnosis of cardiovascular disorders. The anticipated accuracy may be enhanced through the utilization of a stacking classifier.

3. Proposed Methodology

To address the identified gaps, we propose a novel IoT-enabled system for real-time cardiovascular disease detection and remote monitoring using ECG sensors. This system leverages advanced IoT technologies, the MQTT protocol, and machine learning-based analytics to provide a comprehensive and scalable solution. The proposed methodology consists of the following components:

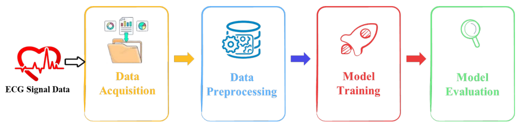

Fig.3. Proposed CVDPT Architecture

3.1 Data Acquisition

The first stage in creating a smart healthcare system for cardiovascular disease observing powered by the Internet of Things is acquiring high-quality ECG data. The ECG signals used in this study are from publicly available PTB Diagnostic ECG Database datasets. These datasets—comprising recordings of both normal and abnormal heart activity—help shape an effective classification algorithm. The PTB Diagnostic ECG Database is a high-quality dataset mainly for the diagnosis of myocardial infarction (heart attack) and other cardiac illnesses. Often used in machine learning and clinical research, the dataset was compiled by the Physikalisch-Technische Bundesanstalt (PTB) in Germany.

Dataset Details:

- **Source:** PhysioNet (https://physionet.org/content/ptbdb)
- **Number of Subjects:** 294 patients (aged 17 to 87 years)
- **Number of Records:** 549 ECG recordings
- **Sampling Frequency:** 1,000 Hz
- **Number of Leads:** 12-lead ECG system
- **Annotations:** Includes metadata such as patient age, gender, and diagnosis (e.g., myocardial infarction, heart failure, conduction disturbances, etc.)

3.2 Data Pre-processing

Data loading: Each row of the feature matrices generated from the actual ECG signals represents an individual ECG recording.

Addressing Missing Values: To safeguard data integrity, the datasets are examined for any missing or corrupted values, which are then either imputed or eliminated.

Duplicate Removal: To minimize model bias and guarantee accurate predictions, redundant records are found and removed.

Feature Selection: The obtained ECG signal attributes are represented by the feature vectors, which are separated from the ECG recordings along with their accompanying labels.

Normalization of Data: To normalize the feature values inside a specific band, usually 0 to 1, min-max scaling is utilized. The efficiency and reliability of machine learning models are enhanced by this procedure.

3.3 Model Development and Training

Subsequent to data pre-processing, multiple machine learning models were developed and trained to classify cardiovascular illness utilizing ECG data. The utilized classifiers comprise Logistic Regression: A statistical model that assesses the probability of cardiovascular disease incidence by examining linear patterns in ECG signals. Naïve Bayes: A probabilistic classification method that presumes feature independence, resulting in significantly inferior performance due to this limitation. K-Nearest Neighbors (KNN): A distance-based method that classifies ECG data by juxtaposing it with the nearest labeled cases. Support Vector Machine (SVM): A kernel-based learning approach that identifies ideal hyperplanes to distinguish between normal and pathological ECG patterns. Gradient Boosting (GB): An ensemble learning method that improves prediction accuracy through the iterative enhancement of weak classifiers. Stacking Classifier: A composite ensemble model that integrates Random Forest (RF), K-Nearest Neighbors (KNN), and Gradient Boosting (GB) as foundational learners, with Random Forest functioning as the meta-learner. This architecture exhibited extraordinary performance, with an outstanding accuracy of 97%, exceeding all individual models. The models were trained and verified with ECG datasets, highlighting the effectiveness of sophisticated ensemble methods in classifying cardiovascular diseases. The stacking method, specifically, demonstrated the benefits of utilizing many classifiers to improve overall diagnostic precision.

3.4 Model Evaluation and Performance Metrics

After being trained, common classification metrics were used to test each model's accuracy in detecting cardiovascular diseases. Parts of the review process were:

Accuracy Score: This score shows how many successfully classified ECG signals there were. On the PTBDB dataset, the stacking classifier had an amazing 97% accuracy rate.

Confusion Matrix: Provides a breakdown of actual versus predicted classifications, including:

True Positives (TP): 752
True Negatives (TN): 2065
False Positives (FP): 37
False Negatives (FN): 57

Table 1: Confusion Matrix of proposed CVDPT

	Predicted Positive	**Predicted Negative**
Actual Positive	**TP = 752**	**FN = 57**
Actual Negative	**FP = 37**	**TN = 2065**

Classification Report: The accuracy, recall, and F1-score all came in at a perfect 96%, showing that the model is strong even when datasets aren't balanced.
These measurements show that the stacking classifier is very good at watching cardiovascular disease in real time using ECGs. It is more accurate and reliable than other models.

4. Results and Discussion

The proposed IoT-enabled smart healthcare system for cardiovascular disease monitoring utilizes ECG data and machine learning classifiers to ensure accurate and timely detection of cardiac abnormalities. The experimental evaluation included multiple classifiers, comparing their performance based on accuracy, precision, recall, and F1-score.

Table 2: Performance Comparison

Classifier	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.8313	0.8000	0.7600	0.7800
Naive_Bayes	0.6173	0.6500	0.6800	0.6100
KNN	0.9603	0.9500	0.9600	0.9600
SVM	0.9322	0.9200	0.9100	0.9100
Gradient Boosting	0.9502	0.9400	0.9300	0.9400
AdaBoost	0.8610	0.8300	0.8100	0.8200
Stacking Classifier	**0.9700**	**0.9600**	**0.9600**	**0.9600**

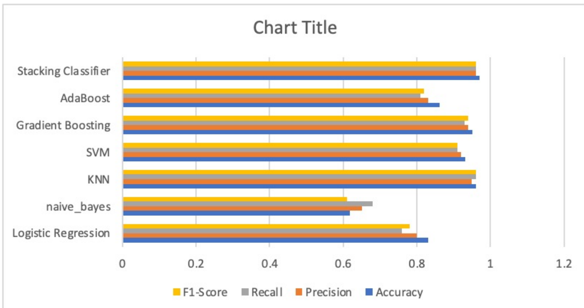

Fig.4 Performance evaluation comparison

Of the assessed models, Stacking classifier had the best accuracy of 97%, hence being the most dependable classifier for ECG-based cardiovascular illness identification. The model showed excellent classification performance across all criteria, hence verifying its strength in processing ECG signals. Strong classification capabilities were shown by K-Nearest Neighbors (KNN) (96.03%), Gradient Boosting

(95.02%), and Support Vector Machine (SVM) (93.22%), following RF, thereby confirming their appropriateness for ECG signal analysis. While Naïve Bayes (61.73%) exhibited the lowest accuracy, suggesting its constraints in ECG-based classification, Logistic Regression (83.13%) performed moderately.

The IoT-based system's integration guarantees real-time data collecting and processing. The ECG sensor records heart signals, which the MQTT protocol sends for quick communication with processing and storage units situated in the cloud. The cloud-based machine learning-based categorization models enable automatic diagnosis and alarm generation in case of unusual heart activity.

The findings show that, especially Random Forest, ensemble-learning techniques beat conventional classifiers in ECG signal classification. RF's excellent accuracy and dependability make it the best option for real-time deployment in IoT-based healthcare applications. Future developments could concentrate on maximizing hybrid models and deep learning architectures to increase prediction accuracy and scalability for large-scale ECG monitoring.

5. Conclusion

Designed to track cardiovascular diseases by means of ECG data analysis and machine learning classification methods, this paper offers an IoT-enabled smart healthcare system. Real-time cardiac monitoring and diagnosis are made possible by wearable ECG sensors, cloud computing, and advanced classification methods. Machine learning models, specifically the stacking classifier, exhibited enhanced performance relative to conventional methods, attaining a classification accuracy of 97%. The confusion matrix showed low false positives and negatives, confirming the system's reliability. ECG monitoring using IoT and machine learning can improve early identification and proactive intervention for cardiovascular diseases, according to the study. The system is reliable and practical for healthcare due to its high accuracy, recall, and F1-score. Remote monitoring allows ongoing patient evaluation, reducing the need for hospital visits and improving medical treatment, especially in remote and poor areas. Future studies may use deep learning, dataset expansion, and physiological parameters like blood pressure and oxygen saturation to measure cardiovascular risk more thoroughly. Wearable technologies and cloud computing will scale and streamline healthcare systems, making them crucial for cardiovascular disease management.

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