

# AI-Based Portable Cardiogram System for Real-Time ECG Monitoring

Aman Singh<sup>1</sup>, Devansh Indoliyan<sup>2</sup>, Arpit Sharma<sup>3</sup>,  
Dipendra Singh Kulra<sup>4</sup>, and Abhishek Singh Rawat<sup>5</sup>

<sup>1,2,3,4,5</sup> B.Tech Computer Science & Engineering,

Tula's Institute of Technology, Dehradun, India

<sup>1</sup> [aman.202204085@tulas.edu.in](mailto:aman.202204085@tulas.edu.in), <sup>2</sup> [devansh.202204099@tulas.edu.in](mailto:devansh.202204099@tulas.edu.in), <sup>3</sup> [arpit.202204094@tulas.edu.in](mailto:arpit.202204094@tulas.edu.in)

<sup>4</sup> [dipendra.202204040@tulas.edu.in](mailto:dipendra.202204040@tulas.edu.in), <sup>5</sup> [abhisheksinghrawat@tulas.edu.in](mailto:abhisheksinghrawat@tulas.edu.in)

**Abstract:** Cardiovascular diseases remain one of the leading causes of mortality worldwide, creating a strong need for continuous, low-cost, and accessible cardiac monitoring systems. Traditional electrocardiogram systems are generally bulky, expensive, and mostly limited to hospital environments. This paper presents an AI-powered portable ECG monitoring system designed for real-time cardiac signal acquisition, storage, analysis, and report generation. The proposed system uses an ESP32 microcontroller for signal acquisition and wireless transmission, a Node.js backend for API-based communication, and a MySQL database for storing patient records and ECG reports. The system extracts important cardiac parameters such as heart rate, RR interval, and heart rate variability. An artificial intelligence module is proposed for automated arrhythmia detection and abnormal pattern classification. A web-based dashboard enables visualization of ECG data and patient report management. The proposed system provides a scalable, portable, and cost-effective solution for telemedicine, remote patient monitoring, and preventive cardiac healthcare.

**Keywords:** Terms—ECG monitoring, ESP32, Node.js, MySQL, Artificial Intelligence, Arrhythmia Detection, Telemedicine, IoT Healthcare

## I. INTRODUCTION

Cardiovascular diseases are among the most serious health challenges worldwide. Early diagnosis and continuous monitoring of cardiac activity are essential for preventing severe heart-related complications. Electrocardiography is a widely used non-invasive technique that records the electrical activity of the heart and helps in identifying abnormalities such as arrhythmia, myocardial ischemia, and conduction disorders.

Conventional ECG machines are accurate but are usually large, costly, and dependent on hospital infrastructure. These limitations make them unsuitable for continuous home-based monitoring, rural healthcare, and emergency situations where real-time cardiac information is required.

Recent developments in embedded systems, Internet of Things, wireless communication, and artificial intelligence have created new opportunities for portable healthcare monitoring devices. Microcontrollers such as ESP32 provide low-cost processing, wireless communication, and low power consumption. By combining ESP32 with backend technologies such as Node.js and MySQL, ECG data can be collected, stored, analyzed, and accessed remotely through a web-based dashboard.

This paper proposes an AI-powered portable ECG monitoring system that can acquire ECG signals, calculate cardiac parameters, store patient reports, and support automated abnormality detection. The system is designed to be affordable, scalable, and suitable for telemedicine and preventive healthcare.

Recent advancements in digital healthcare have accelerated the adoption of Internet of Things (IoT) technologies in medical applications. IoT-enabled healthcare devices provide continuous monitoring, real-time data collection, and remote access to patient information. These capabilities are particularly valuable for cardiovascular disease



management, where continuous observation can significantly improve patient outcomes. Portable ECG systems integrated with wireless communication technologies enable patients to monitor their cardiac health outside traditional hospital environments.

Furthermore, artificial intelligence has emerged as a powerful tool for medical signal analysis. Machine learning algorithms can identify hidden patterns in ECG signals that may not be immediately apparent through manual observation. By combining IoT technology with AI-driven analytics, healthcare providers can improve diagnostic accuracy, reduce response times, and enhance preventive healthcare services.

## II. RELATED WORK

Several researchers have worked on portable ECG monitoring systems using embedded platforms such as Arduino, Raspberry Pi, ARM processors, and ESP32. Early ECG monitoring systems were mostly hospital-based and required wired connections. Although these systems provided accurate results, they lacked portability and were not suitable for long-term monitoring.

Wireless ECG systems improved portability by using Blue-tooth, Wi-Fi, and Bluetooth Low Energy communication. BLE-based systems are useful for low-power wearable devices, while Wi-Fi-based systems are suitable for cloud-connected healthcare platforms. However, many existing systems face problems such as signal noise, motion artifacts, limited storage, and lack of intelligent analysis.

Signal processing methods such as filtering, R-peak detection, and heart rate variability analysis are commonly used for ECG interpretation. The Pan-Tompkins algorithm is one of the most widely used methods for QRS complex detection. In recent years, machine learning and deep learning techniques such as support vector machines, convolutional neural networks, and recurrent neural networks have been used for arrhythmia classification and automated ECG diagnosis.

Despite these advancements, there is still a need for a low-cost, portable, and easy-to-use ECG monitoring system that integrates hardware, backend storage, web dashboard, and AI-based analysis in a single platform.

Commercial wearable devices such as smartwatches and fitness bands have demonstrated the feasibility of continuous cardiac monitoring in everyday life. Devices including Apple Watch and Fitbit have incorporated ECG recording capabilities, enabling users to detect irregular heart rhythms and seek medical attention when necessary. Although these devices improve accessibility, they are often proprietary and provide limited customization for research purposes. Recent studies have also explored deep learning techniques for ECG classification. Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures have shown promising performance in detecting arrhythmias and other cardiac abnormalities. These approaches achieve high classification accuracy when trained on large annotated datasets such as the MIT-BIH Arrhythmia Database.

## III. PROPOSED SYSTEM ARCHITECTURE

The proposed AI-powered portable ECG monitoring system is designed using a layered architecture that integrates hardware components, wireless communication technologies, backend services, database management, artificial intelligence, and a web-based dashboard. The architecture aims to provide real-time ECG acquisition, reliable data transmission, intelligent cardiac analysis, and efficient report generation. The modular design ensures scalability, maintainability, and future integration of advanced healthcare features.

The ECG sensor captures the electrical activity of the heart and sends the signal to the ESP32 microcontroller. The ESP32 processes the signal and transmits the data to the backend server. The Node.js backend receives ECG data through REST APIs and stores patient reports in a MySQL database. The AI module analyzes cardiac parameters and supports abnormality detection. Finally, the web dashboard displays ECG reports to users and healthcare professionals. The complete system consists of seven major layers: Data Acquisition Layer, Embedded Processing Layer, Communication Layer, Backend Layer, Database Layer, AI Analytics Layer, and Application Layer. Each layer performs a specific function and collectively contributes to the overall operation of the system.



**SYSTEM ARCHITECTURE**  
AI-Powered Portable ECG Monitoring System

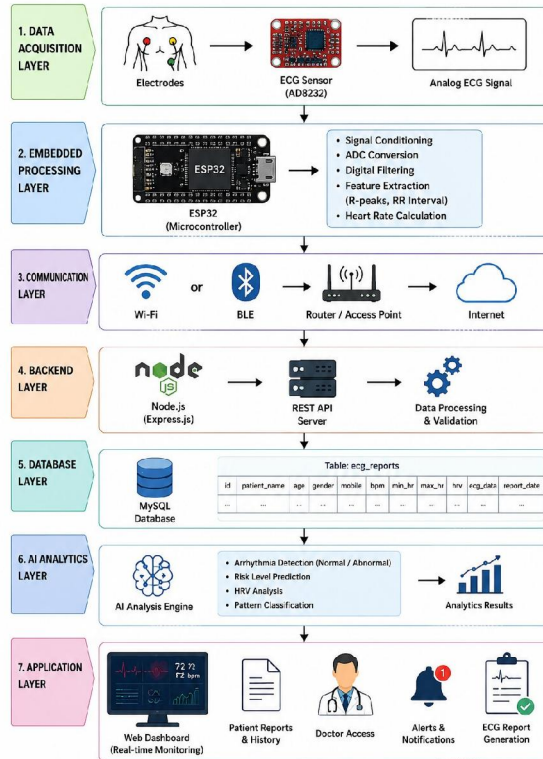


Fig. 1. Proposed system architecture of the portable ECG monitoring system.

**A. Hardware Layer**

The Hardware Layer forms the foundation of the proposed portable ECG monitoring system and is responsible for acquiring physiological signals from the patient. This layer consists of ECG electrodes, an AD8232 ECG sensor module, an ESP32-C6 microcontroller, and a power supply unit. The ECG electrodes are attached to the patient's body to capture the electrical activity generated by the heart during each cardiac cycle.

The acquired bioelectrical signals are extremely weak and susceptible to various types of noise such as muscle activity, motion artifacts, and electromagnetic interference. To address these challenges, the AD8232 sensor module performs signal amplification and preliminary filtering before forwarding the signal to the microcontroller. The ESP32-C6 receives the analog ECG waveform and converts it into digital data using its built-in Analog-to-Digital Converter (ADC).

The microcontroller performs initial processing operations and prepares the ECG samples for wireless transmission. Due to its low power consumption, integrated wireless capabilities, and high computational performance, the ESP32-C6 is well suited for portable healthcare applications. The hardware architecture is compact, lightweight, and cost-effective, making it suitable for continuous cardiac monitoring in both clinical and home environments.



### **B. Backend Layer**

The Backend Layer serves as the central processing and communication unit of the proposed system. It is developed using Node.js and Express.js, which provide a scalable and efficient environment for handling incoming ECG data and user requests. The backend acts as an intermediary between the hardware device, database, and web application.

When ECG data is transmitted from the ESP32 device, the backend receives the information through RESTful API endpoints. The received data is validated, processed, and organized before being stored in the database. The backend is also responsible for handling report generation, patient record management, authentication mechanisms, and data retrieval operations.

One of the major advantages of using Node.js is its event-driven architecture, which enables efficient handling of multiple requests simultaneously. This capability is important in healthcare applications where multiple ECG reports may be processed concurrently. Furthermore, the backend provides a secure and structured framework for communication between different layers of the system, ensuring reliability and scalability for future enhancements.

### **C. Database Layer**

The Database Layer is responsible for storing, organizing, and managing patient information and ECG reports. A MySQL database is used due to its reliability, scalability, and compatibility with modern web technologies. The database serves as a centralized repository where all patient-related information is securely maintained.

The primary table used in the system is the `ecg_reports` table, which stores details such as patient name, age, gender, mobile number, heart rate, minimum heart rate, maximum heart rate, HRV values, ECG waveform data, and report timestamps. This structured storage mechanism enables efficient retrieval and analysis of patient records whenever required.

The database architecture supports long-term storage of ECG reports, allowing healthcare professionals to monitor historical trends and compare cardiac parameters over time. In addition, centralized storage facilitates future integration with cloud computing platforms and remote healthcare services. The database plays a critical role in ensuring data consistency, accessibility, and efficient report management within the proposed system.

### **D. Application Layer**

The Application Layer provides the user interface through which patients and healthcare professionals interact with the system. This layer is implemented as a web-based dashboard that displays ECG waveforms, patient information, calculated cardiac parameters, and generated reports in an organized and user-friendly format.

The dashboard enables real-time visualization of ECG signals received from the backend server. Users can view important cardiac metrics such as heart rate, RR interval, and heart rate variability. Additionally, the application provides access to previously generated reports, allowing doctors to review historical patient data and monitor long-term cardiac health trends.

The application layer is designed with simplicity and accessibility in mind, ensuring that users can operate the system without requiring extensive technical knowledge. Features such as report downloads, patient history management, and graphical ECG visualization improve the overall user experience. Furthermore, the web-based architecture allows access from multiple devices, making the system suitable for telemedicine, remote healthcare monitoring, and preventive cardiac care applications.

## **IV. METHODOLOGY**

The methodology of the proposed system includes ECG acquisition, preprocessing, feature extraction, database storage, AI-based analysis, and report generation.



### A. ECG Signal Acquisition

ECG signal acquisition is the first stage of the proposed monitoring system. Surface electrodes are attached to the patient's body to detect the electrical impulses generated by the heart during each cardiac cycle. These bioelectrical signals are extremely weak and require proper amplification and conditioning before they can be processed digitally.

The AD8232 ECG sensor module is employed to acquire and amplify the ECG signal. The sensor is specifically designed for wearable and portable biomedical applications and provides high-quality ECG waveforms while minimizing noise. The conditioned analog signal is then transmitted to the ESP32-C6 microcontroller for digitization and further processing. Accurate signal acquisition is essential because the quality of the recorded ECG directly affects feature extraction, heart rate calculation, and subsequent diagnostic analysis.

### B. Signal Preprocessing

Raw ECG recordings often contain unwanted noise and artifacts caused by muscle movement, electrode displacement, baseline drift, and electromagnetic interference from surrounding electronic devices. These disturbances can significantly reduce signal quality and affect the accuracy of cardiac parameter estimation.

To improve signal quality, preprocessing techniques are applied before feature extraction. Filtering operations such as low-pass filtering, high-pass filtering, and notch filtering are

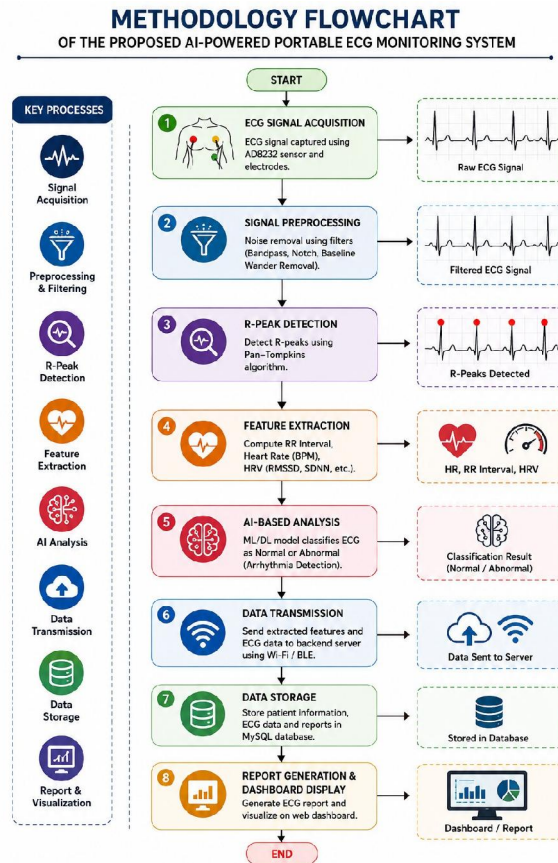


Fig. 2. Methodology flowchart of the proposed ECG monitoring system.

used to remove baseline wander and powerline interference. The preprocessing stage enhances the visibility of important ECG components including the P-wave, QRS complex, and T-wave. As a result, subsequent analysis becomes more reliable and computationally efficient.



### **C. R-Peak Detection**

R-peak detection is one of the most important stages in ECG signal analysis because it forms the basis for calculating various cardiac parameters. The R-wave represents ventricular depolarization and is generally the most prominent feature within an ECG waveform.

In the proposed system, R-peaks are identified using threshold-based peak detection methods. The algorithm scans incoming ECG samples and locates significant peaks corresponding to ventricular activity. Once the R-peaks are identified, the time interval between consecutive peaks is calculated. These intervals, commonly referred to as RR intervals, are further utilized for heart rate estimation and heart rate variability analysis.

### **D. Heart Rate Calculation**

Heart rate is calculated using the RR interval, which is the time difference between two consecutive R-peaks detected in

$$HR = \frac{60}{RR \text{ Interval}} \quad (1)$$

The ECG waveform.

where HR represents the heart rate in beats per minute (BPM) and RR interval is measured in seconds.

Heart rate is one of the most important physiological parameters used to evaluate cardiovascular health. It indicates the number of heartbeats occurring within one minute and provides valuable information regarding the functioning of the heart. For healthy adults, the normal resting heart rate generally ranges between 60 and 100 beats per minute, although variations may occur depending on age, physical activity, and overall health condition.

In the proposed system, the RR interval is obtained from the detected R-peaks of the ECG waveform. Once the RR interval is calculated, the corresponding heart rate is determined using Equation (1). A shorter RR interval indicates a higher heart rate, whereas a longer RR interval corresponds to a lower heart rate. The calculated BPM value is displayed on the web dashboard and stored in the database for future analysis and report generation.

Continuous heart rate monitoring allows healthcare professionals to observe cardiac trends over time and identify abnormal conditions such as tachycardia and bradycardia. Therefore, accurate heart rate estimation plays a crucial role in the overall effectiveness of the proposed ECG monitoring system..

### **E. Heart Rate Variability**

Heart Rate Variability (HRV) represents the variation in time intervals between successive heartbeats. HRV is considered an important physiological marker that reflects the balance between the sympathetic and parasympathetic nervous systems. Higher HRV values generally indicate better cardiovascular adaptability and autonomic regulation, whereas lower HRV values may suggest stress, fatigue, or potential cardiac abnormalities.

In the proposed system, HRV metrics are computed using RR interval measurements obtained from the ECG signal. These values provide additional insights into cardiac health beyond conventional heart rate monitoring. HRV analysis can assist healthcare professionals in identifying early signs of cardiovascular dysfunction and monitoring long-term patient health conditions.

### **F. AI-Based Arrhythmia Detection**

Artificial Intelligence plays a significant role in modern healthcare systems by enabling automated interpretation of biomedical signals. In ECG analysis, AI algorithms can identify hidden patterns and abnormalities that may not be immediately visible through manual inspection.



The proposed system incorporates an extendable AI frame-work capable of supporting machine learning and deep learn-ing models for arrhythmia detection. Features such as heart rate, RR intervals, HRV values, and waveform morphology can be used as inputs to classification models. Future im-plementations may utilize Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures trained on publicly available datasets such as the MIT-BIH Arrhythmia Database. These models can assist healthcare professionals in detecting abnormal cardiac rhythms with improved accuracy and efficiency.

### V. DATABASE DESIGN

The proposed ECG monitoring system utilizes a MySQL database to store patient information, ECG parameters, and generated reports. A database management system is essential for maintaining data consistency, enabling efficient retrieval of records, and supporting long-term monitoring of patient health conditions. The use of a relational database ensures that large volumes of ECG data can be organized and managed effectively.

The primary table used in the system is the `ecg_reports` table, which stores information such as patient name, age, gender, mobile number, heart rate, minimum heart rate, maximum heart rate, heart rate variability values, ECG waveform data, and report generation timestamps. Each record is uniquely identified through a primary key, ensuring reliable storage and retrieval operations.

The database architecture supports historical analysis of ECG reports, allowing healthcare professionals to compare current and previous cardiac measurements. This capability is particularly useful for monitoring chronic cardiovascular conditions and evaluating patient progress over time. Further-more, the database can be extended to support cloud-based storage solutions, enabling remote access to medical records from different locations. The database layer therefore plays a crucial role in ensuring data integrity, scalability, and efficient management of healthcare information.

TABLE I: DATABASE SCHEMA OF ECG REPORTS TABLE

Field Name	Data Type	Description
id	INT	Unique report ID
patient name	VARCHAR(100)	Patient name
age	INT	Patient age
gender	VARCHAR(20)	Gender of patient
mobile	VARCHAR(20)	Mobile number
bpm	INT	Heart rate value
min hr	INT	Minimum heart rate
max hr-	INT	Maximum heart rate
hrv	FLOAT	Heart rate variability
ecg data	LONGTEXT	Recorded ECG samples
report date	DATETIME	Report generation time

### VII. EXPERIMENTAL SETUP

The experimental setup was developed to evaluate the performance and reliability of the proposed portable ECG monitoring system. The hardware configuration consists of an AD8232 ECG sensor module connected to an ESP32-C6 microcontroller. Surface electrodes were attached to the subject to acquire ECG signals and transmit the recorded data to the processing unit.



The software architecture was developed using Node.js and Express.js for backend processing and API communication. A MySQL database was used to store patient information and ECG reports. The web-based dashboard was implemented to provide real-time visualization of ECG signals and display calculated cardiac parameters such as heart rate and heart rate variability.

Several test sessions were conducted to verify the functionality of the system. ECG signals were acquired under resting conditions and transmitted wirelessly to the backend server. The received data was processed, stored in the database, and displayed on the dashboard. The experimental setup successfully demonstrated end-to-end communication between the hardware, backend, database, and application layers.

The system was also evaluated in terms of response time, wireless communication reliability, report generation capability, and overall usability. The results indicate that the proposed architecture is capable of supporting real-time ECG monitoring applications in both clinical and remote healthcare environments.

TABLE II: EXPERIMENTAL CONFIGURATION

Component	Specification
Microcontroller	ESP32-C6
ECG Sensor	AD8232
Communication	Wi-Fi / BLE
Backend Framework	Node.js + Express.js
Database	MySQL
Frontend	React.js
Operating System	Windows 11
Browser	Google Chrome
Power Source	USB/Battery

### VIII. RESULTS AND DISCUSSION

The proposed ECG monitoring system was successfully implemented and tested using the developed hardware and software infrastructure. During experimentation, the ECG sensor was able to capture clear cardiac waveforms containing identifiable P-waves, QRS complexes, and T-waves. The acquired data was transmitted successfully from the ESP32-C6 microcontroller to the backend server through wireless communication.

The backend system processed incoming ECG data and stored patient records within the MySQL database without significant delay. The developed dashboard displayed ECG reports, patient information, and calculated cardiac parameters in real time. The report generation functionality operated correctly and allowed users to access previously recorded ECG sessions through the database.

The results demonstrate that the proposed architecture provides reliable communication between all system components. The integration of hardware acquisition, backend processing, database management, and dashboard visualization creates a complete end-to-end ECG monitoring platform. The modular architecture also allows future integration of artificial intelligence algorithms for automated arrhythmia detection and predictive healthcare analytics. One of the major advantages of the proposed system is its low implementation cost compared to conventional hospital-based ECG equipment. The portable design improves accessibility and makes continuous monitoring possible in home-care environments. Additionally, centralized data storage enables healthcare professionals to review historical patient information and monitor long-term cardiac trends.

Despite these advantages, certain limitations remain. The current implementation utilizes a single-lead ECG configuration, which does not provide the same diagnostic detail as a standard clinical 12-lead ECG system. Motion artifacts and electrode displacement may also affect signal quality under certain conditions. Future enhancements can address these limitations through advanced filtering techniques, improved hardware design, and multi-lead ECG integration.



TABLE III  
SYSTEM PERFORMANCE EVALUATION

Metric	Observed Result
ECG Acquisition	Successful
Data Transmission	Successful
Database Storage	Successful
Report Generation	Successful
Dashboard Display	Successful
Real-Time Monitoring	Supported

### IX. CONCLUSION AND FUTURE WORK

The implementation of the proposed system highlights the potential of integrating Internet of Things technologies with healthcare monitoring applications. By combining embedded hardware, wireless communication, database management, and intelligent analytics within a unified platform, the system provides a practical solution for continuous cardiac monitoring. The architecture can be deployed in hospitals, clinics, remote healthcare centers, and home-care environments, thereby improving accessibility to cardiac healthcare services.

Future work will focus on expanding the functionality of the system through the integration of advanced machine learning and deep learning models. Automated arrhythmia detection, risk prediction, and personalized health recommendations can significantly enhance diagnostic capabilities. Additional physiological sensors such as SpO<sub>2</sub>, blood pressure, respiratory rate, and body temperature sensors may also be incorporated to develop a comprehensive health monitoring platform.

Further research will investigate cloud-based healthcare architectures, mobile application integration, and real-time alert systems capable of notifying healthcare professionals during emergency situations. Multi-lead ECG acquisition and large-scale clinical validation studies will also be explored to improve diagnostic accuracy and support practical deployment in real-world healthcare environments.

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