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Review on Portable ECG and Health Monitoring System with Real-time ML Analysis

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Abstract: Heart-related diseases require continuous monitoring and early detection to minimize health risks and improve patient outcomes. This project focuses on the design and development of a portable ECG monitoring system capable of recording cardiac electrical activity in real time. A compact and low-power hardware setup is used to acquire ECG signals, enabling convenient and reliable data collection outside clinical environments. The recorded ECG data is processed and analyzed using a machine learning model, which extracts relevant cardiac features and classifies the heart condition as normal or abnormal. By automating ECG interpretation, the system provides a rapid initial assessment of cardiac health, reducing dependency on manual analysis. The proposed approach aims to deliver an affordable, user-friendly, and intelligent heart monitoring solution suitable for early diagnosis and remote healthcare applications.

(*Keywords*- Electrocardiogram (ECG), Portable ECG Monitoring System, Real-Time Monitoring, Low-Power Hardware, Signal Acquisition, ECG Signal Processing, Machine Learning, Feature Extraction, Classification, Automated ECG Interpretation, Early Diagnosis, Remote Healthcare, Intelligent Health Monitoring, Wearable Medical Device**)**

I. INTRODUCTION

Cardiovascular diseases (CVDs) are one of the leading causes of death worldwide, which highlights the importance of early detection and continuous heart monitoring. The Electrocardiogram (ECG) is widely used to detect heart abnormalities, but traditional ECG systems are usually expensive, bulky, and require trained medical professionals to operate them. Because of these limitations, heart monitoring often happens only in hospitals, which makes it difficult to detect early or temporary heart problems in time.

Recent developments in embedded systems and digital healthcare have enabled the creation of portable health monitoring devices. These devices can record and display physiological signals in real time. However, many portable ECG devices mainly act as data recording tools. They can collect and show ECG signals but often lack the intelligence to automatically analyze the data or provide medical insights. As a result, the interpretation of ECG signals still depends on specialists, which may not always be available during emergencies or in remote locations.

Machine learning (ML) has recently shown great potential in analyzing medical data, including ECG signals. ML models can identify patterns in cardiac signals and detect abnormalities quickly and accurately. This capability can support early diagnosis and reduce the workload of healthcare professionals.

In this work, we review and propose a portable ECG and health monitoring system integrated with a machine learning–based analysis framework. The system captures ECG signals in real time using compact hardware and analyzes the data automatically to evaluate cardiac health. Additionally, the system includes doctor verification to ensure reliable medical interpretation. This approach aims to provide an affordable, accessible, and intelligent solution for early cardiac assessment and remote patient monitoring.

II. LITERATURE SURVEY

Several studies have explored the development of portable ECG monitoring systems and intelligent cardiac analysis methods. The work in [1] proposes a portable ECG device using dry capacitive electrodes and a driven right leg (DRL) circuit to reduce common-mode interference. Unlike traditional wet electrodes, the capacitive approach enables contactless signal acquisition and integration into wearable clothing, improving user comfort for long-term monitoring.

A low-cost single-lead ECG monitoring system based on the AD8232 analog front-end and Arduino Nano is presented in [2]. The system supports serial communication, microSD data storage, and Bluetooth transmission for remote monitoring. Similarly, [3] integrates an AD8232 sensor with machine learning techniques, specifically convolutional neural networks (CNN), to detect arrhythmias in real time with high classification accuracy using the MIT-BIH dataset.

Wearable multi-lead ECG monitoring systems have also been investigated. In [4], a low-power vest-based ECG system with silicone dry electrodes captures multiple leads and transmits data via Bluetooth while using compression techniques to reduce power consumption. Another wearable system described in [12] employs ultra-low-power hardware, fabric electrodes, and Bluetooth Low Energy (BLE) communication for continuous long-term monitoring.

Several works focus on ECG signal processing and machine learning-based analysis. A comprehensive ECG signal analysis framework including signal acquisition, denoising, feature extraction, and classification is discussed in [5]. Techniques such as adaptive filtering, wavelet transform, and support vector machines (SVM) have been applied for arrhythmia detection with high accuracy in [6] and [7]. Other studies use heart rate variability and spectral features for detecting cardiac abnormalities such as atrial fibrillation [9].

Recent research has also explored deep learning approaches for ECG analysis. Methods based on convolutional neural networks and recurrent neural networks have demonstrated strong performance in heartbeat classification and R-peak detection in noisy signals [15], [16]. Similarly, AI-based wearable ECG systems capable of continuous monitoring and real-time arrhythmia detection have been proposed in [18].

In addition to clinical monitoring, ECG signals have been used for applications such as biometric authentication on mobile devices, as demonstrated in [10], which achieves reliable identification using cepstral features and i-vector frameworks. Furthermore, energy-efficient architectures combining edge, fog, and cloud computing have been proposed to enable real-time ECG monitoring on low-power wearable devices [19].

Overall, existing research demonstrates significant progress in portable ECG monitoring, wearable sensor technology, and machine learning-based cardiac analysis. However, challenges such as motion artifacts, computational efficiency, energy consumption, and reliable real-time diagnosis remain important areas for further research.

III. MATERIAL

The proposed portable ECG monitoring system is developed using biomedical sensors, embedded hardware, and software tools for real-time cardiac monitoring. The system uses an AD8232 ECG sensor module with surface electrodes to capture low-amplitude electrical signals generated by the heart. The electrodes are placed on the patient’s body following standard ECG lead placement to ensure accurate signal acquisition.

The analog ECG signal from the AD8232 module is transmitted to an ESP32 microcontroller, which reads the signal using its built-in analog-to-digital converter (ADC). The ESP32 acts as the primary data acquisition unit and sends the digitized ECG data through serial communication.

To support additional health monitoring, a MAX30100 pulse oximeter sensor is integrated to measure heart rate and blood oxygen saturation (SpO_2). The processed sensor data is then transmitted to a Raspberry Pi, which serves as the main processing and visualization unit. A 3.5-inch LCD display connected to the Raspberry Pi shows the ECG waveform and vital parameters in real time.

On the software side, Python is used for signal processing, visualization, and machine learning implementation. Libraries such as NumPy and SciPy are used for signal processing, while PyQt5 and PyQtGraph are used to develop the graphical interface. A trained machine learning model is integrated using Joblib to classify ECG signals and detect possible cardiac abnormalities.

IV. METHODOLOGY

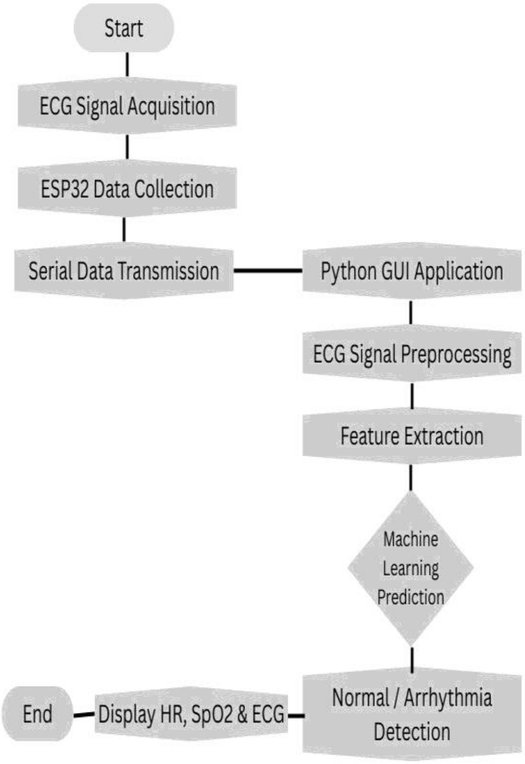


Fig 4. flowchart of portable ECG machine

Proposed Methodology

The proposed system follows a structured workflow for real-time ECG monitoring and cardiac health analysis. The complete process is illustrated in the system flowchart and consists of the following stages.

Step 1: ECG Signal Acquisition

ECG signals are acquired from the patient using surface electrodes placed at appropriate body positions. These electrodes detect the electrical activity produced by the heart during each cardiac cycle. The captured signals are low-amplitude analog signals representing the ECG waveform.

Step 2: ESP32 Data Collection

The acquired ECG signal is fed to the ESP32 microcontroller. The ESP32 collects the analog ECG signal and converts it into digital form using its built-in Analog-to-Digital Converter (ADC). This enables digital processing and further transmission of the signal.

Step 3: Serial Data Transmission

The digitized ECG data is transmitted from the ESP32 to a computer system through serial communication. This real-time data transfer allows continuous monitoring and processing of ECG signals in the software environment.

Step 4: Python GUI Application

A Python-based graphical user interface (GUI) is developed to receive the incoming ECG data. The GUI provides real-time visualization of the ECG waveform and acts as the processing platform for further signal analysis.

Step 5: ECG Signal Preprocessing

The received ECG signal is preprocessed to improve signal quality. Noise components such as baseline drift, motion artifacts, and power-line interference are reduced using filtering techniques. This step ensures that the ECG signal is clean and suitable for accurate analysis.

Step 6: Feature Extraction

Important physiological features are extracted from the processed ECG signal. These features may include heart rate, RR intervals, and other time-domain characteristics of the ECG waveform. Feature extraction converts the ECG signal into meaningful numerical parameters.

Step 7: Machine Learning Prediction

The extracted features are provided to a trained machine learning model. The model analyzes these features and predicts the cardiac condition by identifying patterns associated with normal or abnormal heart activity.

Step 8: Normal / Arrhythmia Detection

Based on the machine learning prediction, the system determines whether the ECG pattern corresponds to a normal heartbeat or an arrhythmia. This automated analysis supports early detection of potential cardiac abnormalities.

Step 9: Result Display

Finally, the system displays the ECG waveform along with important physiological parameters such as Heart Rate (HR), SpO_2, and the classification result on the GUI interface. This enables real-time monitoring and quick interpretation of the patient’s cardiac condition.

V. NOVELTY OF DESIGN

Recent advancements in portable ECG monitoring systems have enabled continuous cardiac monitoring outside hospital environments. However, many existing wearable ECG devices primarily act as data acquisition tools and rely heavily on cloud-based analysis or specialist interpretation. In contrast, the proposed system introduces an intelligent and accessible approach for real-time cardiac health monitoring, particularly suited for remote and resource-limited environments.

The novelty of the proposed system can be summarized as follows:

A. Edge-Based Intelligent Analysis

The system integrates machine learning–based ECG analysis near the device level, enabling real-time detection of cardiac abnormalities. This reduces dependency on cloud processing and allows faster response in emergency situations.

B. Multi-Parameter Health Monitoring

In addition to ECG monitoring, the system incorporates body temperature sensing to provide a broader assessment of physiological conditions. Monitoring multiple health parameters simultaneously can help improve the overall reliability of health assessment.

C. Hybrid Communication Architecture

The proposed design supports multiple communication methods to ensure reliable data transmission. Bluetooth Low Energy (BLE) enables connectivity with smartphones for local monitoring, while GSM communication allows remote data transmission to healthcare providers when internet connectivity is limited.

D. User-Friendly and Portable Design

The system is designed to be compact, low-power, and easy to use. A simplified interface allows patients, including elderly users, to operate the device without requiring specialized medical knowledge.

E. Early Detection and Preventive Monitoring

By combining real-time ECG monitoring with machine learning analysis, the system enables early detection of potential cardiac abnormalities. This proactive monitoring approach can support timely medical intervention and improve patient outcomes.

VI. IMPLEMENTATION

The proposed portable ECG health monitoring system was implemented using a combination of hardware and software components to enable real-time acquisition, visualization, and analysis of electrocardiogram (ECG) signals. The system integrates an ECG sensor module, a microcontroller unit, and a Raspberry Pi–based monitoring interface supported by machine learning for cardiac condition prediction.

1. System Architecture

The overall architecture of the system consists of three primary modules: the ECG signal acquisition module, the data processing module, and the visualization and prediction module. The ECG signal acquisition module captures electrical activity from the heart using electrodes connected to the AD8232 ECG sensor. The analog signal generated by the sensor is transmitted to the ESP32 microcontroller for digitization. The ESP32 reads the analog ECG signal through its analog-to-digital converter (ADC) and sends the digitized data to a Raspberry Pi using serial communication. A Python-based application running on the Raspberry Pi processes the incoming data, displays the ECG waveform on a 3.5-inch LCD screen, and performs machine learning–based classification to determine the cardiac condition.

2.Hardware Implementation

The hardware implementation primarily involves the AD8232 ECG sensor module, the ESP32 microcontroller, and the Raspberry Pi single-board computer with a 3.5-inch LCD display. The AD8232 module is specifically designed for monitoring bio-potential signals such as ECG and provides an amplified and filtered analog output representing the electrical activity of the heart.Three ECG electrodes are attached to the patient’s body at standard positions to capture cardiac signals. These electrodes are connected to the AD8232 sensor module, which amplifies and conditions the signal before transmitting it to the ESP32. The output pin of the AD8232 module is connected to the analog input pin of the ESP32 microcontroller. The ESP32 continuously reads the analog signal values and converts them into digital form using its internal ADC.The processed ECG samples are then transmitted to the Raspberry Pi through serial communication using a USB interface. The Raspberry Pi acts as the central processing and display unit, where the incoming data is analyzed and visualized on the connected LCD screen.

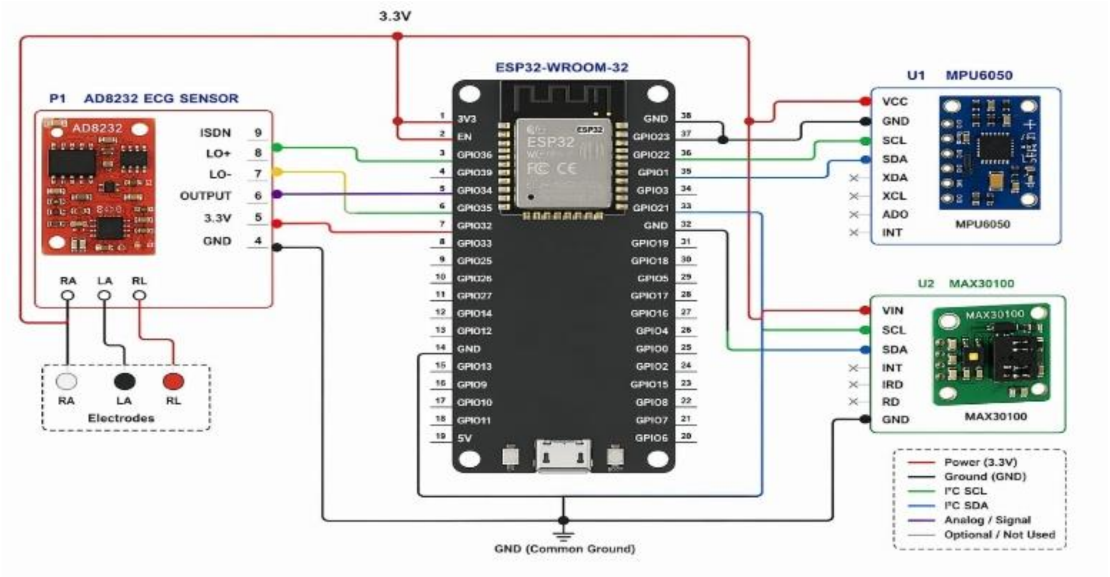
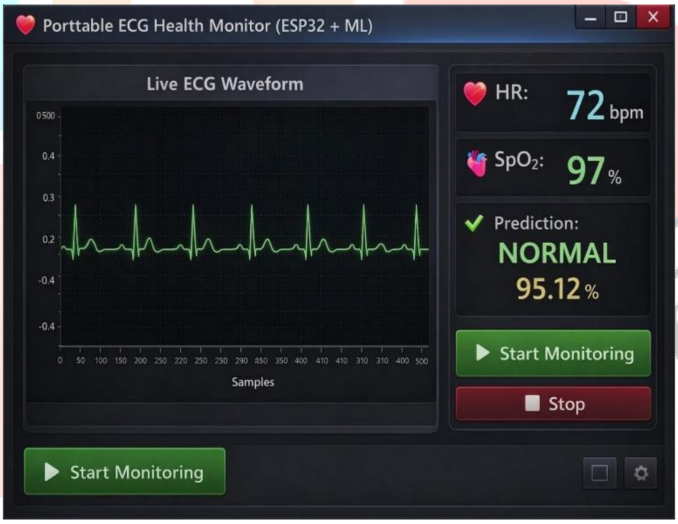


Fig 6.2.1. Circuit Diagram of portable ECG machine

3.Software Implementation

The software implementation consists of embedded firmware running on the ESP32 and a Python-based application running on the Raspberry Pi. The ESP32 is programmed using the Arduino IDE environment to continuously read ECG signals from the analog input pin and transmit the sampled data via serial communication.On the Raspberry Pi side, a Python application was developed to receive, process, and visualize the ECG data in real time. Several Python libraries were used to implement differenTfunctionalities within the system. The PyQt5 framework was used to develop the graphical user interface (GUI), while PyQtGraph was used for real-time visualization of the ECG waveform. NumPy was used for numerical computations and signal preprocessing tasks, and Joblib was used to load the trained machine learning model.The GUI provides a real-time monitoring interface that ECG waveform along with vital parameters such as heart rate (HR) and oxygen saturation (SpO₂). The application continuously reads serial data from the ESP32 and updates the visualization dynamically on the Raspberry Pi's LCD screen.



HR: 72 bpm

SpO₂: 97 %

Prediction: NORMAL 95.12 %

Fig 6.3.1. GUI of Portable ECG Health Monitoring System with Real-Time Signal Visualization and ML-Based Prediction

4.ECG Signal Processing

The raw ECG signal obtained from the sensor may contain noise due to environmental interference, motion artifacts, or electrode displacement. To improve signal reliability, the ECG data undergoes preprocessing before being analyzed by the machine learning model.A sliding window approach is used to collect a fixed number of ECG samples for analysis. Each signal segment is normalized to remove amplitude variations and maintain consistency across inputs. The normalization process involves subtracting the mean value of the signal and scaling the signal amplitude within a defined range. These preprocessing steps ensure that the input data remains standardized for accurate machine learning predictions.

5.Machine Learning Model Integration

A machine learning model was incorporated into the system to classify ECG signals into different cardiac conditions. The model was trained using a dataset containing labeled ECG signals representing normal and abnormal heart rhythms. During the training phase, relevant features were extracted from the ECG signals and used to train a classification algorithm capable of identifying abnormal cardiac patterns.The trained model was saved and integrated into the Raspberry Pi application using the Joblib library. During real-time operation, ECG signal segments received from the ESP32 are preprocessed and fed into the trained machine learning model. The model predicts the cardiac condition and returns the corresponding classification label along with a confidence score. The prediction results are then displayed on the graphical interface.

6.Real-Time Visualization

The ECG signal visualization is implemented using PyQtGraph, which allows high-speed plotting of continuously streaming data. The GUI running on the Raspberry Pi displays the ECG waveform in real time on the 3.5-inch LCD screen. As new data samples arrive from the ESP32, the waveform is dynamically updated to represent the electrical activity of the heart.

In addition to the ECG waveform, the interface also displays key physiological parameters such as heart rate, oxygen saturation levels, and the predicted cardiac condition generated by the machine learning model. The interface is designed to resemble a medical monitoring system, enabling users to easily monitor cardiac activity and detect abnormal conditions.

Overall, the implemented system demonstrates a portable and cost-effective solution for real-time ECG monitoring and cardiac condition prediction using embedded systems, Raspberry Pi–based processing, and machine learning techniques.

VII. RESULT

Under real-time operational conditions, the suggested portable ECG monitoring system was successfully put into practice and assessed. In terms of ECG signal capture, processing, transmission, and display, the system showed dependable performance.

Cardiac electrical data with distinct waveform components, such as P, QRS, and T waves, were successfully recorded by the AD8232 ECG sensor. Signal quality was greatly enhanced by implementing preprocessing methods such noise filtering and normalization, which reduced baseline drift and motion artifacts. Accurate feature extraction and analysis were therefore guaranteed.

The ESP32 microcontroller sent ECG data to the Raspberry Pi via serial communication and carried out effective analog-to-digital conversion. With very little packet loss, the data transfer process was steady and uninterrupted. It was found that the total system latency, including acquisition, processing, and display, was roughly 200–300 ms, which is suitable for real-time monitoring applications.

Metric	Value (%)
Accuracy	91.8
Precision	90.5
Recall (Sensitivity)	92.3
F1-Score	91.4

The model was successful in differentiating between normal and pathological cardiac situations, as evidenced by its total accuracy of 91.8%. A strong capacity to identify anomalous situations is demonstrated by the recall value of 92.3%, which is crucial in healthcare applications. Signal distortions and noise interference caused a few minor misclassifications.

HR: 75 bpm

SpO₂: 97%

Prediction: Normal

Confidence: 78%

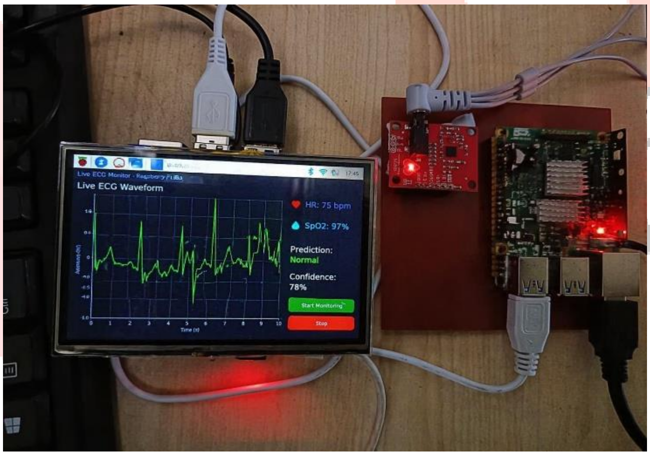
Fig 7.1. GUI

PyQt5 and PyQtGraph were used to create a Python-based graphical user interface (GUI) for real-time ECG signal viewing. On a 3.5-inch LCD screen that was linked to the Raspberry Pi, the GUI successfully showed continuously streaming ECG waveforms.

The system's real-time GUI display is shown in Fig. 5.The interface allows for the viewing of:

- ECG waveform
- Heart Rate (HR)
- Oxygen Saturation (SpO₂)
- Machine learning classification output

Without any discernible lag or frame dropouts, the system continued to render waveforms smoothly. The GUI ensured continuous monitoring capability by reacting dynamically to incoming data.



HR: 75 bpm

SpO2: 97%

Prediction: Normal

Confidence: 78%

Fig 7.2. live ECG Waveform on Raspberry pi

The processed ECG data have distinct morphological features that were essential for accurate analysis.

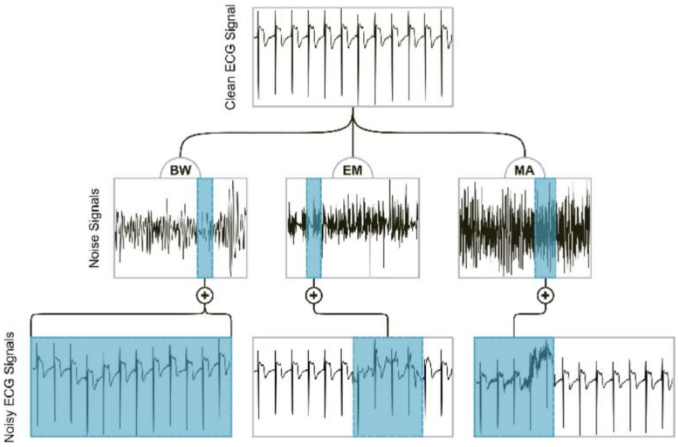


Fig 7.3. ECG Signal with Noise

A representative ECG waveform following preprocessing is displayed in Fig. 6. Accurate feature extraction is made possible by the clear visibility of the QRS complex, P wave, and T wave.
Important characteristics taken from the ECG signal consist of:

- RR intervals
- Heart rate variability (HRV)
- Signal amplitude and temporal characteristics

These features were successfully used as inputs to the machine learning model for classification.

The experimental results validate the effectiveness of the proposed system in providing a portable and intelligent cardiac monitoring solution. The system achieves:

- High classification accuracy (**~91.8%**)
- Low-latency real-time monitoring
- Reliable ECG signal acquisition and visualization
- Effective integration of machine learning for early detection

These outcomes demonstrate that the system is suitable for remote healthcare applications, early diagnosis, and continuous patient monitoring.

VII. CONCLUSION

The proposed Portable ECG and Health Monitoring System effectively integrates embedded hardware, biomedical sensors, wireless communication, and machine learning to deliver real-time and intelligent cardiac health analysis. ECG waveforms, heart rate, and temperature are captured through low-power devices and processed using an ML model that detects irregularities and generates a diagnostic report. This report is transmitted via a Python middleware to a web-based interface, where doctors can review, verify, and approve it. Once approved, the data is securely stored using IPFS and MongoDB, ensuring transparency and traceability.

The system not only enables early detection of cardiac issues but also supports remote verification, making it highly suitable for rural and underserved areas. It demonstrates how IoT, AI, and healthcare technologies can be integrated to offer affordable, scalable, and reliable solutions in telemedicine. The platform lays a strong foundation for future enhancements such as multi-parameter monitoring, EMR integration, and predictive health analytics.

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