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INTEGRATING PORTABLE ECG DEVICES WITH CLOUD SYSTEMS FOR CARDIAC ARRHYTHMIA DETECTION

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Abstract

This article presents a real-time, cloud-integrated cardiac monitoring system developed using a portable ECG device that communicates via HTTPS and REST API protocols. The raw ECG signals are transmitted in JSON format to a secure cloud server, where Symlet4 wavelet transform is employed to denoise the signals in real time. This process enables the accurate extraction of key cardiac features, including HRV, QRS complex, RR interval, QT interval, PR interval, ST segment, P wave, and T wave. These features are processed and stored for subsequent analysis. Arrhythmia classification is initially performed using rule-based clinical logic derived from these parameters, while a structured dataset is concurrently generated to support the development and training of machine learning models for future diagnostic applications. Additionally, HRV data is visualized in real time through a responsive frontend interface, facilitating remote cardiac health monitoring by healthcare professionals. The system was validated using ECG recordings from 98 patients of varying ages to assess performance, reliability, and scalability across diverse clinical and home care scenarios. This article highlights a novel implementation of wavelet-based ECG signal filtering integrated with cloud computing within a complete IoT-based healthcare architecture.

Keywords:

Portable ECG, Cloud-Based Monitoring, Symlet4 Wavelet, Arrhythmia Detection, Real-Time ECG, REST API, Wearable Health Device

1. INTRODUCTION

Cardiovascular diseases, particularly arrhythmias, are a leading cause of morbidity and mortality worldwide. Early detection and continuous monitoring of heart conditions are crucial for effective management and timely intervention. Traditional methods of cardiac monitoring often require patients to visit healthcare facilities, which can be inconvenient and impractical for long-term care. However, recent advancements in portable electrocardiogram (ECG) devices offer a promising solution for real-time monitoring of cardiac health in a more accessible and patient-friendly manner.

In [1], the authors developed a portable ECG device using the ESP32 microcontroller, the AD8232 analog front-end for ECG acquisition, and the MAX30100 sensor for SpO_2 measurement. The device transmits data to the Blynk IoT cloud platform, enabling remote, real-time monitoring of a patient's heart activity and blood oxygen level. The system is compact and wearable, making it suitable for daily use in home care settings.

Rama Reddy Rajanna et al. [2] focused on heart rate variability (HRV) as a key diagnostic feature. They implemented a low-power wireless sensor node comprising an AD8232 sensor, an MSP430 low-power microcontroller, and a CC3100 Wi-Fi booster module interfaced via SPI protocol. The system captures ECG signals, processes HRV data onboard, and transmits the results in real time to PubNub and visualizes it through the Freeboard.io dashboard, supporting applications in clinical and wearable health monitoring.

Kavita Waghmare and Shirish Kulkarni [3] proposed a design that integrates the ultra-low-power MSP432P401R microcontroller with ECG (via AD8232) and blood pressure sensors to collect data with high accuracy and low energy consumption. The sensor data is processed and visualized using Visual Studio on a computer and is also designed for cloud-based uploading through IoT infrastructure, making it particularly suitable for remote and rural healthcare environments.

The integration of portable ECG devices with cloud systems has revolutionized the way heart conditions, including arrhythmias, are monitored. Cloud-based solutions enable the remote collection, storage, and analysis of ECG data, allowing healthcare professionals to access patient information at any time, from anywhere. This continuous monitoring facilitates the early detection of arrhythmic events, providing healthcare providers with the tools necessary for accurate diagnosis and intervention [4]-[9].

In this research, we explore a cloud-based system designed for the transmission of ECG signals in real-time, leveraging HTTPS and REST API protocols for seamless communication between portable ECG devices and cloud platforms. The system securely stores ECG data in JSON format, where advanced algorithms analyze the data to detect potential arrhythmic patterns. The frontend interface of the system allows healthcare professionals to easily access and monitor patient data, further enhancing clinical decision-making and patient care. By combining portable ECG devices, cloud computing, and modern web technologies, this system offers a scalable, efficient, and cost-effective solution for remote arrhythmia monitoring, improving patient outcomes both in clinical settings and at home.

The novelty of this article lies in the real-time integration of a portable ECG device with a secure cloud system, where ECG signals are denoised using the Symlet4 wavelet transform directly on the server. Unlike prior systems that primarily focused on data acquisition or cloud transmission, this work enables real-time feature extraction (QRS-complex, RR-interval, QT, PR, ST, P-wave, T-wave, and HRV) and immediate arrhythmia classification based on medical rules. Furthermore, the extracted parameters are structured and saved as a labeled dataset for future machine learning model training. To the best of our knowledge, this is the first implementation to combine Symlet4-based ECG denoising, cloud-based rule-based arrhythmia detection, and automatic dataset generation within a unified IoT-to-ML healthcare pipeline.

2. DESIGNING A PORTABLE ECG DEVICE

We have designed a specialized portable device for transmitting and collecting ECG signals. This device incorporates an AD8232 ECG sensor, an ESP8266 Wi-Fi module, an A9G GSM/GPRS+GPS module, and a battery.

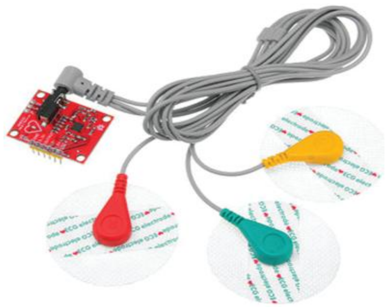

Fig.1. AD8232 ECG Sensor.

The AD8232 ECG sensor is designed to simplify the process of acquiring, amplifying, and filtering ECG signals. Its compact design and low power consumption make it an ideal choice for portable ECG devices, especially for battery-powered applications. The sensor includes essential components such as an operational amplifier and a signal conditioning stage to ensure clean and reliable ECG waveform output. One of the unique features of the AD8232 sensor is its ability to effectively eliminate noise caused by motion artifacts and electrical transmission lines. This ensures high-quality signal acquisition even in dynamic and fluctuating environments [10]-[13].

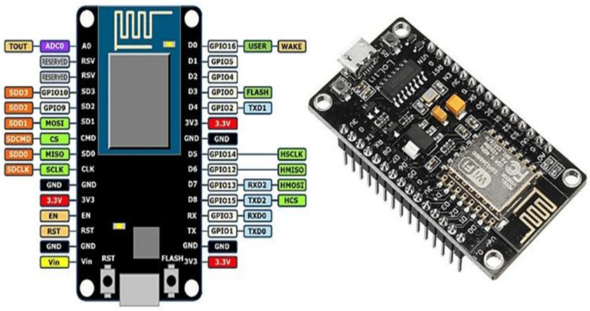

Fig.2. ESP8266 Wi-Fi Module

Fig.3. A9G GPS/GPRS+GSM Module

We used the ESP8266 module to send and collect ECG signals to a personal cloud computer via Wi-Fi. The ESP8266 is popular for its low cost and built-in Wi-Fi capabilities, making it ideal for Internet of Things (IoT) applications. Additionally, it has a pin for converting analog signals to digital, eliminating the need for extra devices [14]. In this system, the role of the ESP8266 microcontroller is to receive and transmit ECG signals. It converts the incoming analog signal from the AD8232 sensor into a digital form and sends the digital data to a cloud computer via Wi-Fi. The ESP8266 has 4 MB of memory. Another strong feature of this device is its compatibility with the Arduino IDE, which supports various popular operating systems such as Windows, Mac OS, and Linux [15].

The integration of GPS and GSM technologies into health monitoring devices has revolutionized their capabilities, particularly in applications such as remote health monitoring and emergency response systems. The A9G module, a compact GPS/GPRS+GSM solution, provides an excellent platform for developing a heart rate monitoring system [16]-[18]. This module allows real-time transmission of ECG data along with accurate location information, making it a valuable tool for healthcare applications. Incorporating the A9G into a heart rate monitor enables communication via GSM networks and the acquisition of location coordinates through GPS. When connected with AD8232 heart rate sensors, the system can not only measure heart rate but also send alerts and data to doctors in critical situations. This feature is especially useful for patients with cardiovascular diseases, athletes requiring performance monitoring, or individuals in remote areas who need immediate medical assistance [19]-[20].

Fig.4. Biocare ECG-300G ECG device battery

Table.1. Biocare ECG-300G ECG device battery specifications

Type	NI-MH
Capacity	2000 mAh
Volt	12 V
Virtue	Full Import Plug Wire, Import Terminals
Color	Blue

The Biocare ECG-300G battery is an excellent choice as a portable device designed to support continuous ECG signal acquisition, real-time processing, and display functions. This device enables operation over long distances, in emergency transport situations, or in areas with unreliable electrical infrastructure. When integrated into remote patient monitoring or IoT-supported heart activity monitoring systems, the high efficiency of the battery enhances the reliability and convenience of the system. In such conditions, ensuring an optimal power supply is crucial for continuous ECG data collection and transmission to medical service providers or monitoring systems [6].

The portable ECG device is developed using modern IoT technologies. This device allows for the acquisition of ECG signals from patients, real-time monitoring of the patient, and transmission of ECG data to cloud-based computing systems.

Fig.5. Appearance of the Designed Device

3. INTEGRATING PORTABLE ECG DEVICES WITH CLOUD SYSTEMS

Cloud computers are designed to receive, store, and analyze large volumes of data and are used across various fields. We have created the ecg.monitoring.uz webpage for sending and storing ECG signals, which is hosted on a local server computer. Our system, based on IoT and cloud technologies, helps doctors and medical professionals effectively monitor patients' heart conditions and collects critical data over the long term. Below is the architecture for data transmission and collection from the device.

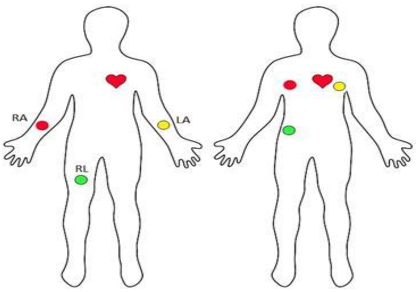

Fig.6. Placement of the AD8232 sensor on the patient's body.

This image shows the placement of the AD8232 sensor electrodes on the patient. These three electrodes form the primary system for acquiring the ECG signal.

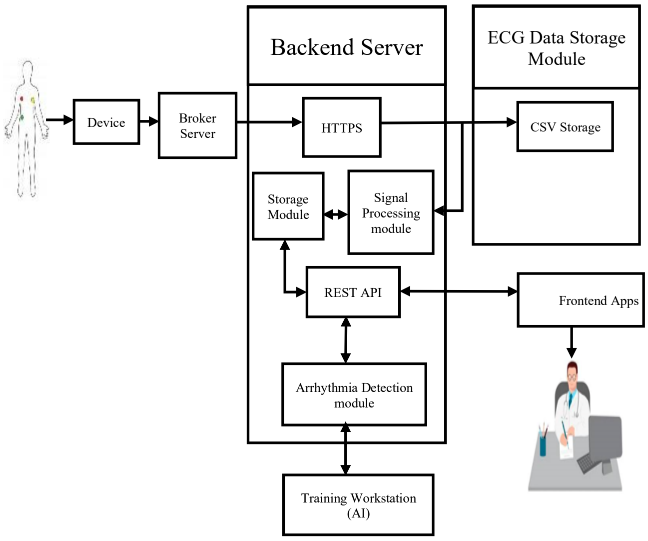

Fig.7. System Architecture Design

In this window, the list of patients and their corresponding ECG data are displayed. A separate device is installed for each patient, and this device is assigned to the patient. The collected ECG data is initially stored as raw signals. These raw data are filtered using wavelet transformations and used in diagnosing the patients. During the filtering process, essential features such as the QRS complex, ST segment, RR interval, and other heart rhythm indicators are identified, and this data helps doctors make accurate diagnoses. This system also enables real-time monitoring of the patient's condition and quick decision-making in medical care. to be classified. The API request is processed using the backend server program code which returns data to be displayed on the front end. The classification results are in the form of labels that are saved again to the database.

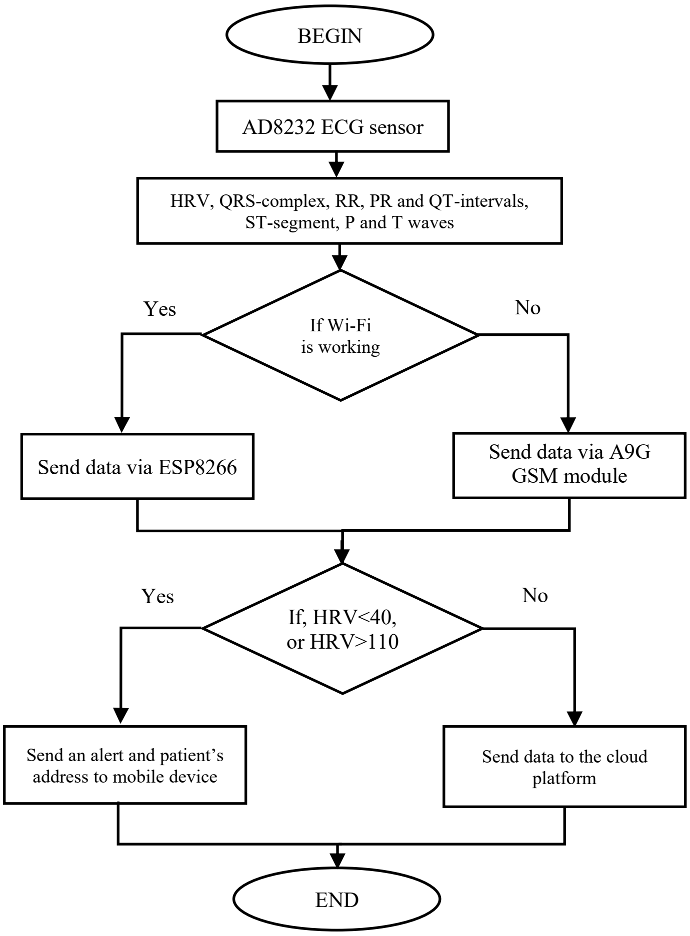

Fig.8. Algorithm of the proposed system.

In this algorithm, the AD8232 sensor collects various characteristics of ECG signals from the heart, such as heart rate (HR), QRS complex, ST segment, RR, PR, and QT intervals, and P and T waves. The ESP8266 module then converts the analog signal into a digital signal and transmits the data to the cloud computer. The transmitted data is stored and analyzed in the cloud and is subsequently used to assess the patient's diagnosis and health condition. This system enables real-time monitoring of the patient's heart activity and provides the opportunity for rapid medical assistance.

Fig.9. The appearance of the ecg-monitoring.uz website created for heart activity monitoring

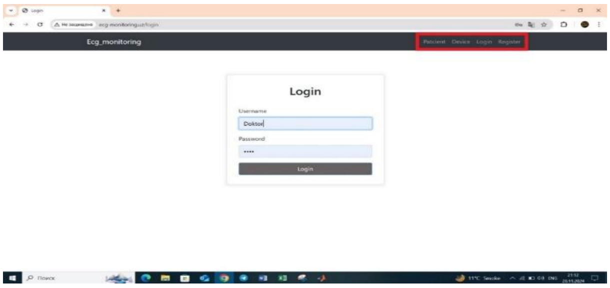

Fig.10. Login-password entry window for doctors to access the website

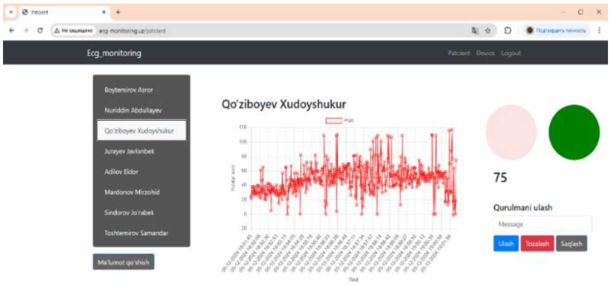

Fig.11. Real-time patient monitoring window for doctors

The doctor can monitor the patient's heart rate in real-time using this interface. The heart rate is displayed in both digital and graphical forms on the screen, while other characteristics are analyzed and collected on the backend of the website. If the patient's heart is functioning normally, a green LED light is displayed, indicating normalcy to the doctor. If the heart rate deviates from normal, a red LED light turns on, sending an alert to the doctor, signaling the need for immediate medical intervention. This system enables real-time monitoring of the patient's heart activity and provides the capability for rapid responses to emergencies.

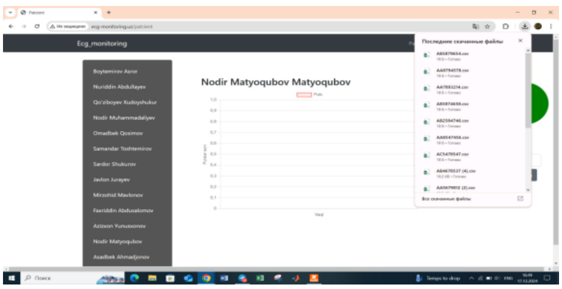

Fig.12. The process of downloading ECG data of patients

In this window, the list of patients and their corresponding ECG data are displayed. A separate device is installed for each patient, and this device is assigned to the patient. The collected ECG data is initially stored as raw signals. These raw data are filtered using wavelet transformations and used in diagnosing the patients. During the filtering process, essential features such as the QRS complex, ST segment, RR interval, and other heart rhythm indicators are identified, and this data helps doctors make accurate diagnoses. This system also enables real-time monitoring of the patient's condition and quick decision-making in medical care.

4. CLOUD-BASED DENOISING OF ECG SIGNALS USING SYMLET 4 WAVELET TRANSFORM

Wavelet analysis is widely used in identifying various features of ECG signals, filtering out noise, and preserving essential information. The main goal of compressing an ECG signal is to reduce its size while retaining its key characteristics. This process is effectively carried out using wavelet analysis, as it enables the decomposition of the signal in both time and frequency domains, allowing the removal of redundant or noisy components.

In the signal compression process, wavelet transform is first applied. The wavelet transform decomposes the signal into multiple levels. During this process, the signal is split into high- and low-frequency components. The high-frequency components typically contain noise or less important information, while the low-frequency components preserve the core features of the signal.

Mathematically, the wavelet transform is expressed as follows:

$$WT(f(t)) = \sum_{a,b} C_{a,b}\,\psi_{a,b}(t) \tag{1}$$

where, $\psi_{a,b}(t)$ - wavelets derived from the mother wavelet using scale and translation parameters. $C_{a,b}$ - wavelet coefficients obtained for each scale and position.

The main steps of signal compression are carried out as follows:

In wavelet transformation, the ECG signal is decomposed into multiple levels, producing both high- and low-frequency components. Typically, the low-frequency components preserve the core information of the signal, while the high-frequency components often contain redundant data or noise. During the compression process, high-frequency components are reduced or completely removed. Although these may include some signal details, they are usually unnecessary for preserving the main features of the ECG signal. Additionally, small wavelet coefficients—those representing minor variations or noise—are set to zero after the transformation. Since these small coefficients correspond to less significant parts of the signal, eliminating them does not substantially impact signal quality. For signal reconstruction, only the relevant portions of the low- and high-frequency components are retained, allowing the signal to be effectively restored.

The main advantages of wavelet filtering are as follows:

- Local analysis: Wavelets enable the analysis of signals in both time and frequency domains, allowing for precise identification and separation of noisy segments.
- Separation of large- and small-scale noise: Wavelet analysis makes it possible to isolate and remove noise from both large-scale and fine-scale components of the signal.
- One of the most commonly used methods in signal filtering is the thresholding technique**.** In this method, small coefficients of the signal are set to zero using a threshold value, while large coefficients are preserved.
- Soft thresholding: In this approach, all coefficients greater than the threshold are reduced in magnitude.
- Hard thresholding: Coefficients smaller than the threshold are set entirely to zero.

The thresholding method is highly effective for removing noise from signals while preserving the essential information. In the process of wavelet compression, the main goal is to reduce the size of the signal without losing its core characteristics. This is efficiently achieved by eliminating high-frequency components and reducing small wavelet coefficients to zero. In discrete wavelet transform, the signal is decomposed using an orthogonal wavelet basis. At each level of decomposition, the signal is divided into two components: low-frequency components that retain the main features of the signal, and high-frequency components that typically contain details or noise. Through this approach, the signal can be compressed while maintaining its significant parts:

Low-frequency component (c): retains the main part of the signal. High-frequency component (d): mainly contains the details of the signal or the noisy parts.

$$c_j[n] = \sum_k h[k] \cdot c_{j-1}[2n-k] \tag{2}$$

$$d_j[n] = \sum_k g[k] \cdot c_{j-1}[2n-k] \tag{3}$$

where, $c_j[n]$ is the low-frequency component, $d[n]$ is the high-frequency component, $h[k]$, $g[k]$ is the coefficients of the low-pass and high-pass filters, c_{j-1} is the signal at the previous decomposition level.

Wavelet decomposition is carried out over multiple levels. At each level, the signal is divided into high-frequency and low-frequency components. If J is the decomposition level, then the decomposition is expressed as follows:

$$S = c_j + d_j + d_{j-1} + \cdots + d_1 \tag{4}$$

where,

S is the original signal, c_j is the the lowest frequency component (main information), $d_j + d_{j-1} + \cdots + d_1$ is the high-frequency components (details) at each level

For signal compression, the coefficients obtained from the wavelet decomposition are analyzed, and the compression process is carried out in several stages. The high-frequency components (d_j) usually contain fine details or noisy parts of the signal. During the compression process, these components are reduced or completely removed.

$$\hat{d}_j = 0 \quad \text{for } j < \text{threshold} \tag{5}$$

where, $\hat{d}_j$ is the compressed form of the high-frequency component,

4.1 THRESHOLD

The selected threshold value for compression; this value is used to set small coefficients to zero. The thresholding method is widely used in calculating compression coefficients. This method reduces signal details by setting small wavelet coefficients to zero. There are two main types of thresholding:

4.1.1 Hard thresholding:

$$\hat{c}_j = \begin{cases} c_j, & \text{if} |c_j| \geq T \\ 0, & \text{if} |c_j| < T \end{cases} \tag{6}$$

In this method, all coefficients smaller than the threshold value are set to zero.

4.1.2 Soft thresholding:

$$\hat{c}_j = \begin{cases} \operatorname{sgn}(c_j) \cdot (|c_j| - T), & \text{if} |c_j| \geq T \\ 0, & \text{if} |c_j| < T \end{cases} \tag{7}$$

In this method, the values of coefficients greater than the threshold are reduced, but not set to zero. This approach allows the compression of redundant or less informative parts of the signal while preserving its essential components. After compression, the signal is reconstructed by combining the low-frequency component and the high-frequency components (if available). This reconstruction process is performed using the inverse wavelet transform:

$$\hat{S} = c_j + \hat{d}_j + \hat{d}_{j-1} + \cdots + \hat{d}_1 \tag{8}$$

where, $\hat{S}$ represents the compressed and reconstructed signal. The compression ratio is calculated as the ratio of the size of the original signal to the size of the compressed signal. Mathematically, it is expressed as follows:

$$\text{Compression Coefficient} = \frac{\text{Uncompressed signal size}}{\text{Compressed signal size}} \tag{9}$$

When analyzing the original signal through wavelet decomposition, all frequency components are preserved. The uncompressed signal size corresponds to the complete set of coefficients. This represents the algorithm for denoising water quality data.

The selection of the threshold value directly affects the quality of signal compression. A very high threshold value may lead to the removal of essential parts of the compressed signal, while a very low value may reduce the effectiveness of the compression. The following methods are commonly used to select the thresholding parameter. The universal threshold, proposed by Donoho, is suitable for denoising signals. It is calculated using the following formula:

$$T = \sigma\sqrt{2\log N} \tag{10}$$

where, σ is the noise variance, N is the length of the signal (number of coefficients).

This threshold value varies depending on the size of the signal and the amount of noise. The universal threshold provides effective compression and denoising of the signal. The VisuShrink method is similar to the universal threshold but is mainly used for compressing visual images. In VisuShrink, the threshold value is determined using the formula mentioned above.

The SureShrink method is used to select the thresholding parameter based on an optimal value. In this method, the threshold value is determined using Stein's Unbiased Risk Estimator (SURE). SureShrink provides good results in improving the quality of the compressed signal. This algorithm enables effective filtering of water quality data using compression coefficients.

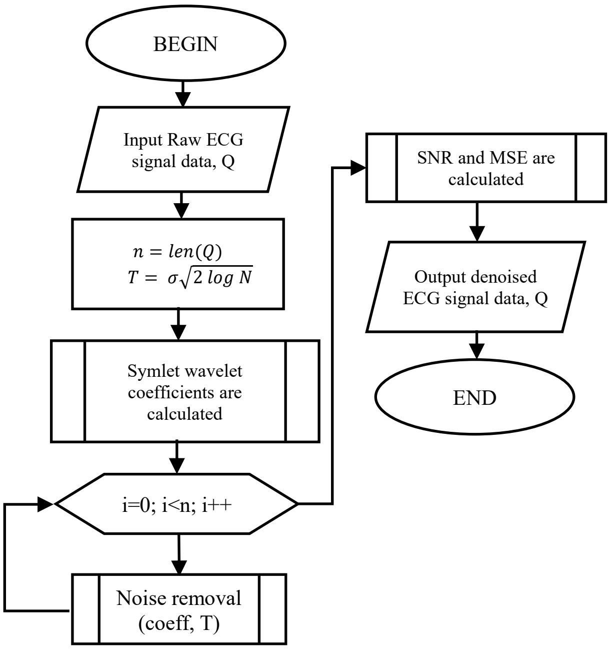

Fig.13. Noise removal algorithm using Sym4 wavelet.

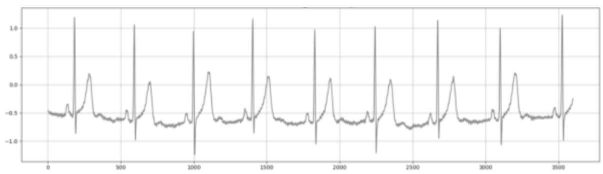

Fig.14. Raw ECG signal acquired from the AD8232 sensor.

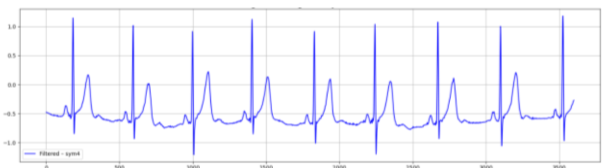

Fig.15. ECG signal graph denoised using the Symlet 4 wavelet.

5. ARRHYTHMIA CLASSIFICATION BASED ON EXTRACTED ECG PARAMETERS

Cardiac arrhythmia refers to an abnormal heart rhythm that can pose significant health risks if not detected and treated promptly. Early and accurate classification of arrhythmias is therefore critical in preventing potential complications such as stroke, heart failure, or sudden cardiac death. With the advancement of portable ECG technologies and cloud computing infrastructure, real-time detection and classification of arrhythmic events have become more feasible and scalable.

This section focuses on classifying arrhythmias based on the analysis of ECG parameters extracted after noise reduction using the Symlet 4 wavelet. The extracted features — including QRS-complex, RR-interval, QT-interval, PR-interval, ST-segment, P-wave, and T-wave — serve as key indicators of cardiac activity and are widely used in clinical diagnosis. By evaluating these features against known medical thresholds and diagnostic rules, arrhythmia types can be identified in real time.

In this work, rule-based medical logic is applied for initial classification, ensuring clinically interpretable outcomes. Additionally, the extracted parameters are stored in a structured dataset to support future machine learning–based classification systems. This dual approach enhances both the immediate decision-making process and long-term diagnostic development.

Table.2. Diagnostic Rules Based on ECG Parameters

ECG Criteria	Diagnostic Outcome
RR < 0.600 s	Sinus tachycardia
RR > 1.000 s	Sinus bradycardia
RR < 0.600 s and QRS > 0.120 s	Tachycardia
RR > 1.000 s and QRS > 0.120 s	Arrhythmia or heart block
Otherwise	Bradycardia
ST > 0.200 s	Myocardial infarction
ST < 0.100 s	Ischemia
PR > 0.200 s	Atrioventricular (AV) block
PR < 0.120 s	Pre-excitation syndrome (Wolff–Parkinson–White)
QT > 0.460 s	Long QT syndrome
QT < 0.360 s	Short QT syndrome
P > 0.110 s	Left atrial enlargement
P < 0.060 s	Right atrial enlargement
T < 0.030 mV	T-wave inversion (indicative of ischemia)
T > 0.60 mV	Hyperkalemia

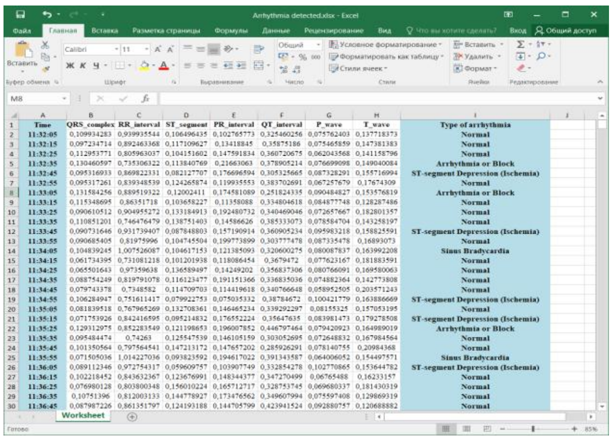

Fig.16. Result Obtained Based on the Algorithm for Detecting Cardiac Arrhythmia Diseases.

In the obtained results, the main features of the ECG signal and the corresponding heart rhythm analysis are presented. Each row contains values for the QRS complex, RR interval, ST segment, PR interval, QT interval, P wave, and T wave recorded over a specific time interval, reflecting key parameters of heart activity. The last column indicates the type of arrhythmia detected based on the ECG parameters. The label "Normal" represents a healthy heart rhythm. "Arrhythmia or Block" indicates an irregular heart rhythm or heart block. "ST-segment Depression (Ischemia)" suggests insufficient oxygen supply to the heart muscle. "Sinus Bradycardia" refers to a lower-than-normal heart rate, which may sometimes lead to dangerous conditions. These results enable the automation of the diagnosis process by applying machine learning and deep learning models

6. CONCLUSION

In the course of this research, a real-time, cloud-integrated cardiac monitoring system was successfully developed using a portable ECG device. The system architecture ensures secure communication through HTTPS and REST API protocols, with raw ECG data transmitted in JSON format to a cloud server. A key innovation lies in the application of the Symlet4 wavelet transform for server-side ECG denoising, enabling reliable extraction of clinically relevant parameters, including HRV, QRS complex, RR interval, QT interval, PR interval, ST segment, P wave, and T wave.

These extracted features formed the basis for rule-based arrhythmia classification and were simultaneously structured into a labeled dataset, intended for training machine learning models in future studies. Additionally, a responsive web-based interface was implemented to allow healthcare professionals to visualize HRV data in real time, supporting remote decision-making and continuous patient monitoring.

The system was validated using ECG data collected from 98 patients across various age groups, demonstrating its effectiveness, reliability, and adaptability in both clinical and home-based healthcare settings. This research provides a comprehensive IoT-based ECG monitoring pipeline that integrates wavelet filtering, real-time diagnostic logic, and dataset generation, thereby laying the groundwork for future AI-enhanced cardiac health applications.

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