PulsePatch: A Wearable ECG Patch for Real-Time Arrhythmia Detection and Remote Cardiac Monitoring

Devasena S K
Dept. of Computer Science & Engineering
Saintgits College of Engineering
Kerala, India
Email: devasenask8@gmail.com

Diya Elizabeth Sibi
Dept. of Computer Science & Engineering
Saintgits College of Engineering
Kerala, India
Email: diaelza04@gmail.com

Diya Nair
Dept. of Computer Science & Engineering
Saintgits College of Engineering
Kerala, India
Email: ndiya1303@gmail.com

Gayathri Sreekumar
Dept. of Computer Science & Engineering
Saintgits College of Engineering
Kerala, India
Email: gayathriiii013@gmail.com

Er. Lini Ickappan
Dept. of Computer Science & Engineering
Saintgits College of Engineering
Kerala, India
Email: lini.ickappan@saintgits.org

***Abstract*—Cardiovascular diseases are a leading cause of global mortality, with cardiac arrhythmias often acting as early indicators of life-threatening conditions. Continuous electrocardiogram (ECG) monitoring enables early diagnosis, yet existing solutions such as Holter monitors remain bulky, costly, and unsuitable for long-term daily use. This paper presents *PulsePatch*, a compact wearable ECG patch designed for continuous real-time cardiac monitoring and on-device arrhythmia detection. The system integrates an AD8232 ECG sensor with an ESP32 microcontroller to acquire and preprocess ECG signals using noise filtering, baseline correction, and R-peak detection techniques. A lightweight arrhythmia detection approach identifies conditions such as atrial fibrillation, bradycardia, and tachycardia. Processed data and alerts are transmitted wirelessly to a mobile application for visualization and remote monitoring. Experimental validation using real ECG signals demonstrates reliable waveform acquisition and system feasibility. PulsePatch provides a low-cost, portable, and scalable solution for continuous cardiac care and early arrhythmia detection.**

Keywords— Wearable ECG; Arrhythmia Detection; Biomedical Signal Processing; Embedded Systems; Real-Time Monitoring

I. Introduction

Cardiovascular diseases (CVDs) account for millions of deaths annually and pose a major public health challenge worldwide. In India, the prevalence of heart-related disorders is increasing rapidly, affecting not only elderly populations but also younger individuals due to lifestyle changes and stress-related factors. Among these conditions, cardiac arrhythmias—abnormal heart rhythms—often precede severe complications such as stroke, heart failure, and sudden cardiac arrest.

Electrocardiography (ECG) remains the gold standard for monitoring cardiac electrical activity. However, conventional ECG systems are largely confined to clinical environments and short-duration monitoring. Holter monitors, while portable, are often uncomfortable, expensive, and designed primarily for offline analysis. Consequently, intermittent arrhythmias occurring outside clinical settings frequently go undetected.

Recent advances in wearable electronics and embedded systems have enabled compact health-monitoring devices capable of continuous data acquisition. Nevertheless, challenges remain in ensuring signal quality, real-time processing, low power consumption, and user comfort. This paper introduces *PulsePatch*, a wearable ECG patch that addresses these challenges by combining efficient hardware design, embedded signal processing, and wireless connectivity for real-time arrhythmia detection and remote monitoring.

The proposed system emphasizes an end-to-end engineering approach, integrating signal acquisition, on-device preprocessing, wireless data transmission, and web-based visualization into a unified platform. Unlike conventional solutions that rely on proprietary hardware or mobile applications, PulsePatch leverages low-cost embedded components and a browser-based interface to enable platform-independent access. The system is designed to support both real-time monitoring and offline analysis, making it suitable for continuous, remote, and scalable cardiac rhythm assessment in non-clinical environments.

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II. Related Work

Wearable electrocardiogram (ECG) monitoring systems have gained significant attention due to their potential for continuous cardiac health monitoring outside clinical environments. Numerous studies have explored lightweight signal processing and machine learning techniques to enable real-time arrhythmia detection on wearable devices.

Recent advances in deep learning have significantly improved automated ECG analysis. Convolutional neural networks (CNNs) have shown strong capability in extracting morphological features such as P-waves, QRS complexes, and T-waves directly from ECG signals [11]–[13]. These approaches have demonstrated high diagnostic accuracy and have been successfully applied to large-scale arrhythmia classification tasks.

Recurrent neural networks (RNNs) and their variants have also been widely used for modeling temporal dependencies in ECG signals. Yildirim [15] proposed a bidirectional LSTM-based architecture for ECG classification that captures sequential heartbeat patterns effectively. Similarly, Hou et al. [8] introduced an LSTM-based autoencoder model for ECG arrhythmia classification, demonstrating improved feature representation for abnormal rhythm detection. Hybrid CNN–RNN architectures have also been explored to combine spatial feature extraction with temporal modeling capabilities [14], [20].

Several studies have focused on improving the efficiency of ECG classification models for deployment in wearable and embedded devices. Jeon et al. [7] proposed a lightweight deep learning model for fast ECG beat classification optimized for real-time applications. Similarly, Busia et al. [1] introduced a tiny transformer-based architecture designed for low-power arrhythmia classification on embedded systems. Zishan et al. [3] further investigated arrhythmia classification using dense neural networks implemented on low-cost microcontrollers.

In addition to algorithmic developments, research has also focused on wearable ECG monitoring platforms for continuous cardiac health tracking. Kim et al. [5] proposed a wearable ECG monitoring system capable of real-time cardiovascular disease detection. Similarly, Baca and Palomino Valdivia [**?**] investigated deep learning-based arrhythmia detection using smartwatch ECG recordings. Other studies have explored atrial fibrillation detection using multimodal physiological signals such as ECG and PPG [4], [6], [17].

Traditional ECG signal processing techniques also remain important in automated cardiac analysis. Classical methods such as QRS detection algorithms [19] and feature extraction based on signal envelopes [9] are often used in preprocessing stages to improve the robustness of arrhythmia detection systems. Additionally, publicly available datasets such as the MIT-BIH Arrhythmia Database have played a critical role in advancing ECG research and benchmarking classification models [18].

Despite these advancements, many existing deep learning models require substantial computational resources and often rely on GPU acceleration or cloud-based processing. This limitation makes their deployment challenging in resource-constrained wearable devices. Therefore, developing lightweight deep learning architectures capable of achieving high classification accuracy while maintaining low computational complexity remains an important research direction.

III. System Overview

PulsePatch is designed as an end-to-end wearable cardiac monitoring system comprising three primary components:

- A wearable ECG patch for continuous signal acquisition
- An embedded processing and communication unit for data acquisition and wireless transmission
- A web-based application for visualization and alerts

The ECG patch continuously captures cardiac signals through skin-mounted electrodes. These signals are transmitted wirelessly to the software platform, where signal processing and arrhythmia detection are performed. The processed outputs are then visualized through the user interface, enabling real-time monitoring, historical review, and timely alerts.

IV. Hardware Design

The hardware architecture of PulsePatch is designed to ensure reliable ECG acquisition, low power operation, and portability.

A. ECG Sensor Module

The AD8232 ECG sensor module serves as the analog front end for cardiac signal acquisition. It amplifies the low-amplitude electrical signals generated by the heart and applies analog filtering to reduce motion artifacts and high-frequency noise. The conditioned analog output is provided to the microcontroller for digitization.

B. Microcontroller Unit

The system uses an ESP32 microcontroller for ECG data acquisition and wireless transmission. The analog ECG signal is sampled using the ESP32's 12-bit ADC and streamed in real time via Bluetooth Serial communication. Leads-off detection is implemented using dedicated GPIO pins to ensure proper electrode connection during operation. The ESP32 was selected due to its integrated Bluetooth capability, low power modes, and sufficient computational resources for real-time signal handling.

C. Power Management

The device is powered by a rechargeable Li-Po battery. A TP4056-based charging module provides safe and regulated charging. The design emphasizes low power consumption to support extended monitoring sessions. Power regulation and battery management ensure stable operation while protecting the device from overcharging and deep discharge.

D. Supporting circuitry

Complementary components such as resistors, capacitors, and connectors are integrated onto a compact PCB designed for wearable applications. The layout optimizes space, reduces interference, and ensures durability for daily use.

E. Hardware Integration and Wearability

All hardware components are integrated into a compact form factor suitable for wearable operation. The ECG sensor, microcontroller, and power module are arranged to minimize signal interference and improve user comfort during prolonged usage. Flexible electrode placement and lightweight construction enable unobtrusive continuous monitoring, making the device suitable for daily activities.

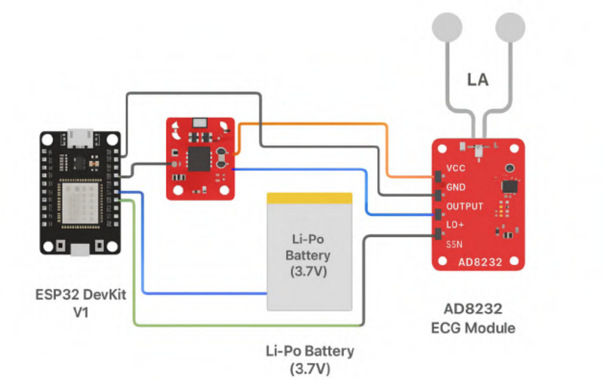

Fig. 1: Hardware circuit diagram of the PulsePatch system

V. Software Design

The software architecture consists of on-device firmware and a companion web-based application developed using React.

A. Embedded Firmware

The ESP32 is programmed using the Arduino framework in C/C++. It continuously samples the analog ECG signal from the AD8232 sensor using the internal 12-bit ADC. Leads-off detection is implemented through dedicated GPIO pins to ensure proper electrode connection. The digitized ECG samples are transmitted in real time via Bluetooth Serial (SPP profile). In the current implementation, the firmware performs data acquisition and transmission, while advanced signal analysis is handled at the application level. The firmware is designed to operate in a non-blocking manner to ensure consistent sampling rates and uninterrupted data transmission.

B. Web Application

The web application, developed using React, provides real-time ECG waveform visualization and basic heart rate monitoring. ECG samples received via Bluetooth are plotted dynamically for live observation. Arrhythmia detection is performed through interval-based analysis. Heart rate is calculated from RR intervals, and threshold-based logic is used to identify bradycardia (¡60 BPM) and tachycardia (¿100 BPM). ECG data can be exported for further offline analysis. The interface is designed with a modular component structure to support extensibility and cross-platform browser compatibility.

C. Backend Processing and API Layer

A lightweight backend service is implemented using Python and Flask to handle ECG data processing and arrhythmia classification. Uploaded or streamed ECG signals are preprocessed, normalized, and analyzed to extract temporal features such as RR intervals. A sliding window approach is employed for classification, and priority-based logic is applied to generate the final diagnostic output. The backend also generates annotated ECG plots, which are returned to the web application for visualization and user feedback.

VI. Methodology

The development of the PulsePatch system follows a structured workflow to ensure accurate ECG signal acquisition, efficient preprocessing, and reliable arrhythmia detection. The overall operational pipeline and user interaction flow are illustrated in Fig. 2. The methodology consists of following key stages corresponding to the ECG signal processing framework.

A. ECG Signal Acquisition

The first stage involves capturing the electrical activity of the heart using body-surface electrodes connected to the AD8232 ECG sensor module. The AD8232 functions as an analog front-end that amplifies low-amplitude cardiac signals and suppresses high-frequency environmental noise. The conditioned analog output is continuously sampled by the ESP32 microcontroller using its 12-bit ADC, producing a raw digital ECG waveform suitable for real-time analysis.

B. Signal Preprocessing

The acquired ECG signal undergoes preprocessing to enhance waveform quality and ensure reliable downstream analysis. This stage minimizes noise and signal distortion while preserving clinically relevant features.

- *Noise Reduction:* Suppression of motion artifacts, muscle noise, and power-line interference using digital filtering techniques.
- *Baseline Correction:* Removal of baseline wander caused by respiration or electrode movement to stabilize the ECG waveform.
- *R-Peak Detection:* Identification of QRS complexes using threshold-based or derivative-based algorithms for accurate heartbeat localization.
- *Heart Rate Computation:* Calculation of beats per minute (BPM) from RR intervals derived from detected R-peaks.

C. Feature Extraction and Analysis

Following preprocessing, temporal features are derived from the RR interval sequence, including heart rate variability statistics and short-term rhythm trends. To ensure robustness against transient noise, features are extracted using a sliding window approach, allowing localized rhythm variations to be analyzed over time. These features form the basis for detecting abnormal cardiac rhythm patterns.

D. Arrhythmia Detection

Arrhythmia detection is performed using a hybrid approach that combines machine learning–based classification with physiological rule-based analysis. Window-level predictions are generated from extracted features and aggregated to estimate atrial fibrillation likelihood. In parallel, average heart rate is evaluated against predefined clinical thresholds to identify bradycardia and tachycardia. A priority-based decision logic is applied, with atrial fibrillation detection taking precedence over heart rate abnormalities, followed by normal rhythm classification.

E. Data Transmission and Visualization

The processed ECG data and diagnostic outputs are transmitted wirelessly to the web-based monitoring interface. On the server side, ECG waveforms are rendered with annotated R-peak locations to aid visual interpretation. The interface displays heart rate metrics, arrhythmia classification results, and generates alerts for detected abnormalities, enabling real-time remote cardiac monitoring.

F. Software Algorithm and Web Application Workflow

The PulsePatch backend is developed using a Python-based web framework that processes ECG data, predicts arrhythmias, and generates visualizations. When a user uploads an ECG signal in CSV format through the web interface, the system extracts samples, removes missing values, and normalizes the signal using z-score normalization, followed by a digital bandpass filter to reduce baseline drift and high-frequency noise. R-peaks are detected using an adaptive peak detection algorithm to compute RR intervals and derive time-domain features, and if the signal length is insufficient, an error message is returned.

RR interval features are analyzed using a sliding window approach and fed into a pre-trained machine learning model to estimate atrial fibrillation probability. Physiological rules based on average heart rate are also used to detect bradycardia and tachycardia, with priority-based logic giving precedence to atrial fibrillation detection, followed by heart rate abnormalities and normal rhythm classification. Finally, a filtered ECG segment with marked R-peaks is plotted and saved on the server, and the prediction results, heart rate, atrial fibrillation probability, and ECG plot URL are sent to the frontend in JSON format for real-time visualization.

The use case diagram in Fig .2 illustrates the interaction between different system actors and the PulsePatch monitoring platform. The patient represents the primary data source, where ECG signals are continuously acquired using the wearable patch. These signals are processed to detect R-peaks and classify potential arrhythmias before being transmitted to the monitoring interface. The clinician (doctor) interacts with the system by viewing ECG waveforms, accessing reports, and reviewing detected abnormalities. In addition, authorized caregivers or relatives can receive alerts and access summarized ECG information for remote monitoring. This interaction model highlights the end-to-end flow of data acquisition, analysis, visualization, and alert generation within the PulsePatch system.

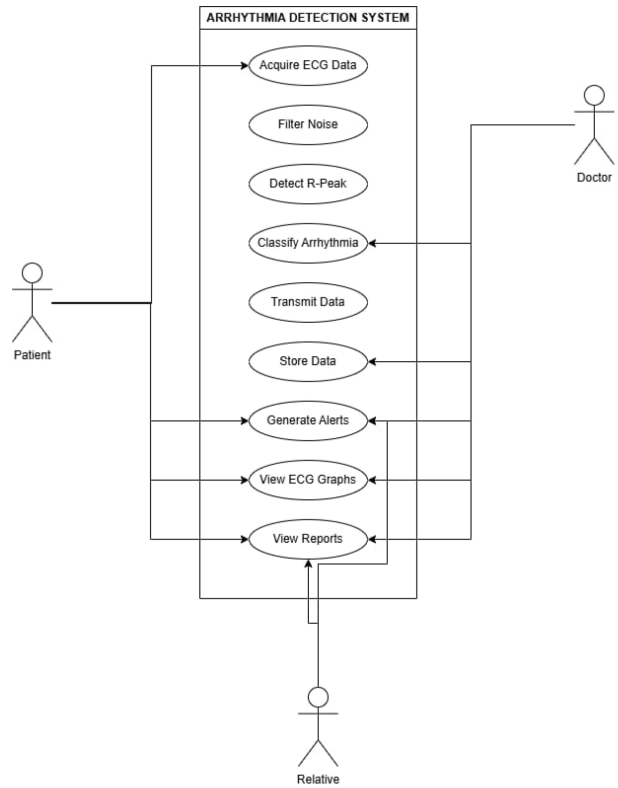

Fig. 2: Use case diagram of the PulsePatch system

VII. Dataset Description

The MIT-BIH Arrhythmia Database is utilized as a benchmark dataset for validating the ECG signal analysis methodology adopted in the PulsePatch system. The dataset consists of 48 half-hour ambulatory ECG recordings collected from 47 subjects, sampled at 360 Hz with high temporal resolution. The recordings include a diverse range of normal and abnormal cardiac rhythms, including atrial fibrillation, premature ventricular contractions, and other clinically significant arrhythmias. Each record contains expert beat-level annotations, enabling detailed analysis of RR intervals, rhythm irregularities, and waveform morphology.

In the context of this work, selected ECG records from the MIT-BIH dataset are used to study RR interval patterns and evaluate interval-based arrhythmia detection logic. The annotated R-peak locations provided in the dataset allow accurate computation of RR intervals and heart rate values, which serve as reference benchmarks for validating threshold-based detection of bradycardia and tachycardia.

VIII. System Integration

The system integration of PulsePatch combines ECG signal acquisition, embedded processing, wireless communication, and web-based visualization into a unified real-time monitoring platform. The integration ensures reliable signal capture from the sensor module, stable data transmission, and synchronized visualization within the user interface.

A. Hardware and Embedded Integration

At the hardware level, the AD8232 ECG sensor module captures low-amplitude cardiac electrical signals and performs initial analog amplification and filtering. The conditioned analog output is fed to the ESP32 microcontroller, where it is sampled using the internal 12-bit ADC. Leads-off detection is implemented through dedicated GPIO pins to monitor electrode connectivity and ensure signal reliability. The embedded firmware, developed using the Arduino framework in C/C++, manages continuous sampling and formats the digitized ECG values for wireless transmission.

B. Wireless Communication

For wireless communication, Bluetooth Serial (SPP profile) is used to stream ECG samples from the ESP32 to the web application. The firmware transmits sequential digitized samples at controlled intervals to maintain waveform continuity while preventing buffer overflow. Error codes are transmitted when electrode disconnection is detected, enabling real-time user notification.

C. Web Application Interface

A browser-based web application was developed to provide secure user access, ECG data management, and real-time visualization, ensuring cross-device compatibility and responsive design without requiring dedicated mobile applications. The user registration interface (Fig. 3) allows new users to create accounts securely with input validation and authentication mechanisms to maintain data integrity and controlled access. Existing users authenticate through the sign-in interface (Fig. 4), which verifies credentials and grants secure access to patient data and ECG monitoring features.

After login, the ECG dashboard (Fig. 5) enables users to upload ECG signals in CSV format or receive real-time data from the wearable device. It provides waveform visualization, arrhythmia analysis, and displays detection results with a layout designed for clarity, low-latency updates, and structured information presentation for both clinical and general monitoring tasks.

IX. Experimental Results

A functional prototype of the PulsePatch system was developed using an AD8232 ECG sensor module interfaced with an ESP32 microcontroller for real-time ECG data acquisition and wireless transmission. The analog ECG signal was sampled using the ESP32's 12-bit ADC and transmitted via Bluetooth Serial to a React-based web application for visualization. The system was configured with a sampling interval of approximately 50 ms, corresponding to a sampling frequency of 20 Hz. Although the sampling frequency is lower than that of clinical-grade ECG systems (typically 250–500 Hz), it was sufficient for demonstrating waveform morphology and basic rhythm monitoring in this prototype implementation.

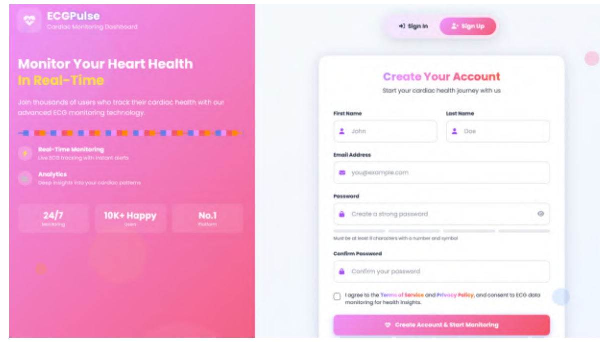

Fig. 3: User registration (sign-up) interface of the PulsePatch web application.

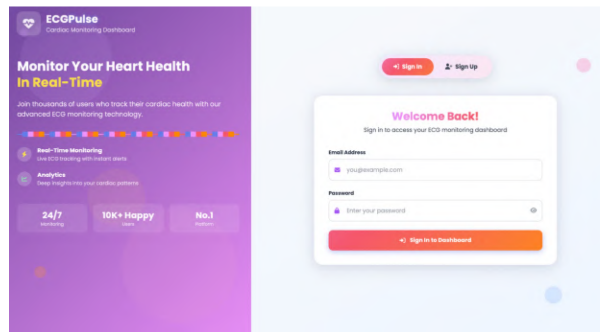

Fig. 4: User authentication (sign-in) interface for secure system access.

The prototype was evaluated under controlled indoor conditions using a healthy volunteer subject at rest. During testing, the system successfully captured ECG waveforms with distinguishable P, QRS, and T components. Although the sampling rate is lower than clinical-grade systems, the acquired waveform was sufficient to estimate heart rate and observe rhythm regularity. The average measured heart rate ranged between 72–84 BPM under resting conditions, consistent with expected physiological values.

As shown in Fig. 6, the acquired ECG waveform demonstrates stable morphology with clearly distinguishable cardiac cycles.

Wireless transmission performance was evaluated by monitoring continuity of received samples and visualization smoothness. Bluetooth Serial communication remained stable within a short-range indoor environment (approximately 5–8 meters). Real-time plotting in the web interface demonstrated minimal perceptible latency, and no significant packet loss was observed during short-duration monitoring sessions.

These results confirm the feasibility of integrating ECG acquisition hardware with wireless data streaming and browser-based visualization. While the current prototype focuses on reliable signal transmission and basic interval-based monitoring, further improvements in sampling frequency, digital filtering, and quantitative performance evaluation are required to enhance diagnostic reliability.

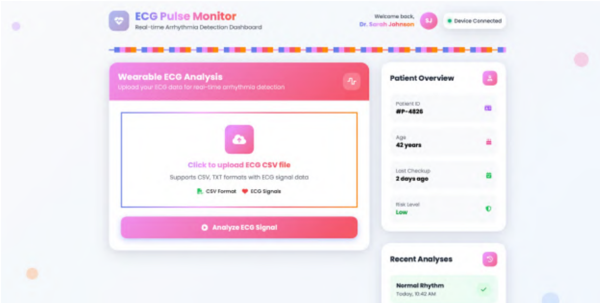

Fig. 5: ECG dashboard interface for data upload and waveform visualization.

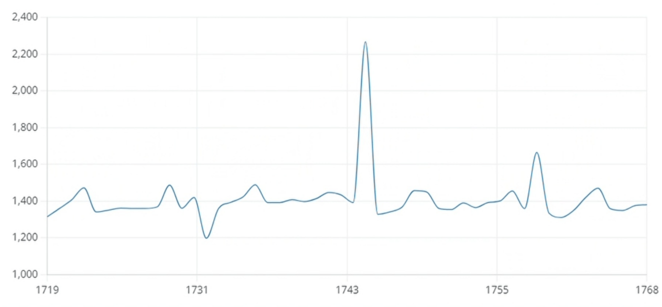

Fig. 6: Real-time ECG waveform acquired using the PulsePatch prototype under resting conditions.

X. Cost Analysis

The budget for the PulsePatch prototype was planned to ensure cost efficiency while maintaining reliable functionality. The main expenses were for hardware components used in ECG acquisition and wireless data transmission. The ESP32 microcontroller cost approximately INR 500, the AD8232 ECG sensor module cost INR 270, and ECG electrodes and accessories cost around INR 250.

The total hardware cost for the prototype was approximately INR 1,020. Software development and system integration were carried out using open-source tools, resulting in no additional software licensing costs. Compared to commercial wearable ECG devices and Holter monitoring systems, which typically cost several thousand rupees, the proposed system offers a significantly more affordable solution for real-time cardiac monitoring and research applications.

TABLE I: Approximate Hardware Cost

Component	Cost (INR)
ESP32 Microcontroller	500
AD8232 ECG Sensor	270
ECG Patch and Accessories	250
Total	**1,020**

XI. Future Work

Although the current PulsePatch prototype enables real-time ECG acquisition and wireless transmission, several improvements are planned to enhance accuracy and usability. Increasing the ECG sampling rate to clinical standards (250–360 Hz) will provide better waveform resolution and more accurate rhythm analysis.

Future work will focus on improved signal processing techniques, such as advanced band-pass and adaptive notch filters, to reduce motion artifacts and noise in wearable conditions. Real-time processing will also be enhanced by implementing R-peak detection and heart rate variability (HRV) analysis directly on the embedded device. Lightweight machine learning models trained on datasets like the MIT-BIH Arrhythmia Database will be integrated for better arrhythmia detection.

Additionally, future developments include secure cloud integration for long-term ECG storage and remote monitoring. Hardware miniaturization through custom PCB design, power optimization, and integration of additional sensors will further improve wearability and scalability of the system.

XII. Acknowledgment

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XIII. Conclusion

This paper presented PulsePatch, a wearable ECG patch designed for real-time arrhythmia detection and remote cardiac monitoring. The system integrates ECG sensing, embedded data acquisition, wireless communication, and a web-based visualization platform to provide a compact and cost-effective monitoring solution. A functional prototype was developed and experimentally validated, where the acquired ECG signals showed clear P, QRS, and T complexes, confirming effective signal acquisition and conditioning. Although the sampling frequency is lower than clinical-grade ECG systems, the captured signals are sufficient for heart rate estimation and basic rhythm analysis.

The arrhythmia detection framework identifies atrial fibrillation, bradycardia, and tachycardia using RR interval features, sliding window analysis, and priority-based decision logic, enabling real-time classification with minimal computational overhead. Future work will focus on improving robustness, reducing motion artifacts, increasing sampling frequency, integrating machine learning–based arrhythmia detection, and enabling secure cloud connectivity. Overall, PulsePatch provides a scalable and affordable solution for real-time wearable cardiac monitoring and supports the development of accessible preventive healthcare technologies.

References

[1] P. Busia *et al.*, "A tiny transformer for low-power arrhythmia classification," *IEEE TBCAS*, 2025.

[2] H. A. H. Baca and F. d. L. Palomino Valdivia, "Efficient deep learning-based arrhythmia detection using smartwatch ECG electrocardiograms," *Sensors*, vol. 25, no. 17, article 5244, 2025.

[3] M. A. O. Zishan *et al.*, "Dense neural network based arrhythmia classification on low-cost microcontroller," *arXiv:2504.03531*, 2025.

[4] B. Aldughayfiq *et al.*, "A deep learning approach for atrial fibrillation classification using multi-feature time series data from ECG and PPG," *Diagnostics*, vol. 13, no. 14, article 2442, 2023.
[5] H. Kim *et al.*, "A wearable ECG monitor for real-time cardiovascular disease detection," *arXiv:2201.10083*, 2022.
[6] D. H. Nguyen *et al.*, "Detecting atrial fibrillation in real time based on PPG," *IEEE Sensors Journal*, 2022.
[7] E. Jeon *et al.*, "A lightweight deep learning model for fast electrocardiographic beats classification," *JMIR Medical Informatics*, 2020.
[8] B. Hou *et al.*, "LSTM-based auto-encoder model for ECG arrhythmias classification," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 4, pp. 1232–1240, Apr. 2020.
[9] H. Li *et al.*, "A novel R-wave detection algorithm based on peaks of Shannon energy envelope," *Biomedical Signal Processing and Control*, vol. 8, no. 6, pp. 658–666, 2013.
[10] A. Lourenço *et al.*, "Unveiling the biometric potential of finger-based ECG signals," *Computers in Biology and Medicine*, vol. 43, no. 11, pp. 1498–1505, 2013.
[11] P. Rajpurkar, A. Y. Hannun, M. Haghpanahi, C. Bourn, and A. Y. Ng, "Cardiologist-level arrhythmia detection with convolutional neural networks," *Nature Medicine*, vol. 25, no. 1, pp. 65–69, 2019.
[12] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 664–675, 2016.
[13] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. E. W. Koh, and S. L. Oh, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Information Sciences*, vol. 405, pp. 81–90, 2017.
[14] M. Zihlmann, D. Perekrestenko, and M. Tschannen, "Convolutional recurrent neural networks for electrocardiogram classification," in *Proc. Computing in Cardiology Conference (CinC)*, 2017, pp. 1–4.
[15] Y. Yildirim, "A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification," *Computers in Biology and Medicine*, vol. 96, pp. 189–202, 2018.
[16] H. He, E. A. Garcia, "Learning from imbalanced data," *IEEE Transactions on Knowledge and Data Engineering*, vol. 21, no. 9, pp. 1263–1284, 2009.
[17] A. Faust, U. R. Acharya, H. Fujita, and Y. Hagiwara, "Automated detection of atrial fibrillation using long short-term memory network with RR interval signals," *Computers in Biology and Medicine*, vol. 102, pp. 327–335, 2018.
[18] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.
[19] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230–236, 1985.
[20] S. L. Oh, E. Y. K. Ng, R. San Tan, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heartbeats," *Computers in Biology and Medicine*, vol. 102, pp. 278–287, 2018.