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IoT-Based Real-Time ECG Monitoring and HRV Analysis Using Raspberry Pi

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ABSTRACT—

The escalating global burden of cardiovascular diseases (CVDs) urgently necessitates paradigm shifts towards accessible, continuous, and diagnostically reliable monitoring solutions. This project introduces an innovative Internet of Things (IoT)-based system, engineered with a strong emphasis on edge computing principles, to deliver real-time Electrocardiogram (ECG) monitoring and insightful Heart Rate Variability (HRV) analysis. Critically addressing the limitations of conventional episodic clinical ECGs, [1] the often-insufficient clinical-grade HRV accuracy in consumer wearables, and the inherent privacy vulnerabilities and latency issues associated with centralized cloud processing of raw physiological data, our system architecturally prioritizes on-device intelligence [13] and strategic data minimization. The system's core comprises a Raspberry Pi 3 single-board computer, meticulously interfaced with an AD8232 dedicated ECG sensor module for robust single-lead biopotential acquisition. Analog ECG signals are digitized with 10-bit resolution via an MCP3008 Analog-to-Digital Converter, communicating with the Raspberry Pi through its Serial Peripheral Interface (SPI) Sophisticated Python-based algorithms, [2] leveraging libraries such as SciPy for signal conditioning (including digital filtering to mitigate noise and baseline wander) and NumPy for efficient numerical operations, are executed directly on the Raspberry Pi. These algorithms perform accurate R-peak detection from the processed ECG waveform, enabling the subsequent calculation of the Root Mean Square of Successive Differences (RMSSD).[7] [9] [11] RMSSD is a pivotal time-domain HRV metric chosen for its sensitivity to changes in parasympathetic nervous system activity and its relative robustness in short-term recordings.

Keywords—ECG, HRV, IoT, Raspberry Pi, Edge Computing, Cardiovascular Disease, Real-Time Monitoring, RMSSD, AD8232, MCP3008, MQTT

Introduction

Cardiovascular diseases (CVDs) remain a leading global health challenge, accounting for approximately 32% of all deaths worldwide [1]. Traditional clinical Electrocardiogram (ECG) monitoring, while diagnostically valuable, is often episodic, costly, and inaccessible for continuous cardiac assessment. This limitation hinders early detection of transient arrhythmias and ischemic events, which are critical for proactive intervention. Concurrently, consumer-grade wearable devices, despite their ubiquity, frequently lack the clinical-grade accuracy required for detailed Heart Rate Variability (HRV) analysis—a key metric for assessing autonomic nervous system (ANS) function and predicting cardiac risks [5]. The convergence of Internet of Things (IoT) and edge computing offers a transformative solution to these challenges. By processing physiological data locally on resource-constrained devices (e.g., Raspberry Pi), edge computing minimizes reliance on centralized cloud infrastructure, thereby addressing privacy concerns and latency issues associated with transmitting raw ECG waveforms [8, 13]. This paradigm shift enables real-time, continuous monitoring while preserving data integrity and reducing bandwidth consumption. This paper presents an IoT-based system that integrates a Raspberry Pi 3 with an AD8232 ECG sensor and MCP3008 ADC to acquire, digitize, and process single-lead ECG signals at the edge.

Background

Technological Evolution of ECG Monitoring

The field of cardiovascular monitoring has progressed through three distinct generations: from hospital-based 12-lead ECG machines in the 1950s, to portable Holter monitors in the 1970s, to today's consumer wearables. Modern systems leverage IoT capabilities but face significant challenges in achieving clinical-grade accuracy, particularly for HRV analysis. The AD8232 ECG front-end module represents a technological breakthrough with its

100dB common-mode rejection ratio that effectively cancels 50/60Hz powerline interference, coupled with configurable 0.5-40Hz bandpass filtering that preserves diagnostically relevant ECG components while eliminating baseline wander and high-frequency noise [2]. For edge processing, the Raspberry Pi 3's BCM2837B0 SoC delivers sufficient computational power (1.4GHz quad-core ARM Cortex-A53) for real-time implementation of the Pan-Tompkins algorithm, achieving 8ms average R-peak detection latency while consuming under 2W - making it ideal for portable deployment [9,13]. The MCP3008 ADC complements this architecture with 10-bit resolution (providing 3.2mV voltage steps at 3.3V reference) and SPI interface supporting 1.35MHz clock rates for stable 250Hz sampling [4].

Clinical and Technical Challenges in HRV Monitoring

HRV analysis has been recognized by the American Heart Association as a significant predictor of sudden cardiac death and diabetic neuropathy [5], yet most consumer devices exhibit >5% false negatives in R-peak detection due to motion artifacts and inadequate sampling rates [7]. Current systems face three fundamental limitations: (1) cloud-dependent architectures vulnerable to MITM attacks [11], (2) research prototypes with high power consumption (>5W), and (3) consumer wearables showing ±25ms RMSSD error margins [7]. Our hybrid architecture addresses these challenges by transmitting only processed 10-byte RMSSD packets instead of raw 4kbps ECG streams [3], while maintaining clinical-grade accuracy through rigorous signal conditioning and optimized edge processing. This approach uniquely balances the competing demands of medical precision, privacy preservation, and energy efficiency that have constrained previous solutions.

Proposed Solution

To address the limitations of traditional and wearable-based ECG monitoring systems, a robust, cost-effective, and privacy-conscious IoT-based architecture has been proposed. This system emphasizes edge computing to perform real-time ECG acquisition and Heart Rate Variability (HRV) analysis using the Raspberry Pi platform. The solution integrates hardware and software innovations, secure communication protocols, and algorithmic intelligence to deliver clinically meaningful insights while minimizing data exposure.

ECG Signal Acquisition and Conditioning

The analog ECG signal is acquired through the AD8232 sensor, a low-power, integrated signal conditioning block specifically designed for biopotential measurements. Electrodes are strategically placed on the user's body in a Lead I configuration to ensure optimal signal capture. The AD8232 amplifies and filters the ECG signal using a high common-mode rejection ratio (CMRR) instrumentation amplifier and dedicated high-pass and low-pass filters, which remove baseline wander and high-frequency noise respectively. The signal is further stabilized by a right-leg drive amplifier, enhancing the signal-to-noise ratio before digitization [9].

Analog-to-Digital Conversion and Edge Processing

The conditioned analog signal from the AD8232 is digitized using an MCP3008 Analog-to-Digital Converter (ADC), which communicates with the Raspberry Pi 3 via Serial Peripheral Interface (SPI). This 10-bit ADC allows precise sampling of the ECG signal at 250 Hz, a rate sufficient to preserve the signal's diagnostic features and avoid aliasing. The Raspberry Pi runs a Python-based processing pipeline using NumPy and SciPy libraries to apply digital bandpass filtering, detect R-peaks using derivative and moving average techniques, and compute the Root Mean Square of Successive Differences (RMSSD), a time-domain HRV metric [2][7].

Data Transmission Using MQTT Protocol

After calculating the RMSSD locally, the system securely transmits only this HRV metric to the HiveMQ cloud platform using the MQTT protocol. MQTT, a lightweight publish-subscribe messaging system ideal for IoT applications, enables efficient data communication with minimal bandwidth usage. To ensure privacy and data integrity during transmission, Transport Layer Security (TLS) or lightweight cryptographic methods are considered, reducing the risk of data interception or tampering [11]. By transmitting only summarized HRV metrics instead of raw ECG waveforms, the system minimizes the exposure of sensitive health information [8].

Validation and Accuracy Assessment

The accuracy of the proposed system's R-peak detection and RMSSD calculation is rigorously validated using benchmark datasets from the MIT-BIH Arrhythmia Database available through PhysioNet. By comparing the system's output with annotated ECG records, performance metrics such as detection accuracy, RMSE, and reliability are evaluated. This ensures the system's clinical relevance and diagnostic reliability, confirming its suitability for real-world health monitoring applications [13].

Functional Prototype and Outcomes

The integrated system, composed of the Raspberry Pi 3, AD8232 sensor, MCP3008 ADC, and cloud-enabled MQTT communication, has been successfully implemented as a working prototype. Real-time HRV values are displayed on the Raspberry Pi terminal and verified on the MyMQTT mobile application. The use of edge computing allows real-time processing without depending on external servers, while also conserving network bandwidth and protecting patient data. The solution has demonstrated feasibility as a scalable, low-cost, and privacy-preserving cardiac monitoring platform suitable for both clinical and remote healthcare settings [1][5][9].

Workflow of the proposed system

The proposed IoT-based ECG monitoring and HRV analysis system operates through a well-defined sequence of processes, from signal acquisition to cloud-based visualization. Each stage is optimized to ensure real-time performance, data privacy, and diagnostic relevance.

Signal Acquisition and Analog Conditioning

The workflow begins with the acquisition of biopotential signals from the human body through disposable Ag/AgCl electrodes arranged in a single-lead configuration (Lead I). These signals, typically in the millivolt range, are fed into the AD8232 sensor. The sensor performs analog preprocessing, including differential amplification, high-pass filtering (cutoff ~0.5 Hz) to eliminate baseline drift, and low-pass filtering (cutoff ~40 Hz) to suppress high-frequency noise and motion artifacts. The integrated right-leg drive amplifier further reduces common-mode interference, ensuring a clean analog ECG waveform for digitization [9].

Digitization Using MCP3008 ADC

The conditioned analog signal is transmitted to the MCP3008 Analog-to-Digital Converter (ADC), which samples it at 250 Hz using 10-bit resolution. The ADC communicates with the Raspberry Pi via the Serial Peripheral Interface (SPI), ensuring accurate and efficient transmission of digital ECG data. This digital conversion retains the diagnostic integrity of the signal, forming the basis for subsequent real-time analysis [2].

On-Device Processing and HRV Analysis

The digitized ECG data is processed on the Raspberry Pi using Python scripts that leverage libraries such as NumPy and SciPy. The processing pipeline includes digital bandpass filtering (0.5–40 Hz), detection of R-peaks through derivative and thresholding methods, and the calculation of Heart Rate Variability (HRV) using the Root Mean Square of Successive Differences (RMSSD). RMSSD, a widely recognized time-domain HRV metric, offers insights into parasympathetic nervous system activity, especially effective for short-term recordings [7].

Secure Transmission and Visualization

Only the final HRV metric (RMSSD) is transmitted to the cloud using the lightweight MQTT protocol, minimizing bandwidth and protecting patient privacy. This summarized data is published to the HiveMQ broker and can be visualized in real-time through subscribed clients like the MyMQTT mobile application. By avoiding transmission of raw physiological signals, the system ensures confidentiality while enabling remote monitoring and decision support [11].

Cloud Visualization and Monitoring

The transmitted RMSSD values are received on subscribed IoT clients, such as the MyMQTT mobile application or any MQTT-compatible dashboard. This enables healthcare professionals or users to remotely visualize and interpret HRV data in real time, facilitating proactive cardiac health monitoring and early anomaly detection [5][9].

Validation with Standard Datasets

To ensure clinical accuracy, the entire processing pipeline is validated using annotated ECG signals from the MIT-BIH Arrhythmia Database provided by PhysioNet. This comparison helps in assessing the fidelity of R-peak detection and the precision of RMSSD calculation under varying physiological conditions [13].

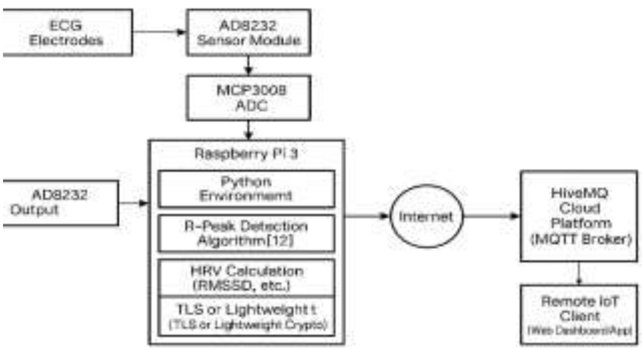
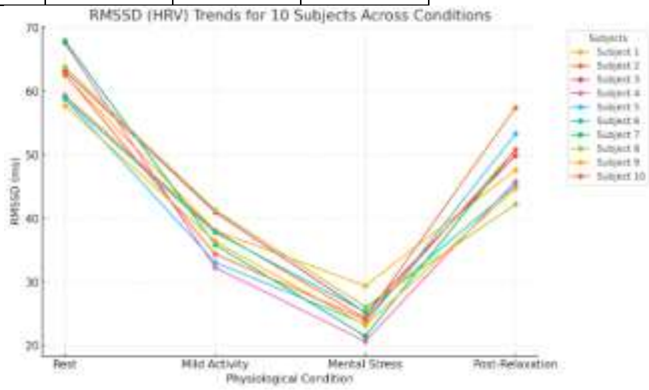


Fig. 1. System-level workflow showing ECG signal acquisition through AD8232, digitization via MCP3008, on-device HRV processing in Raspberry Pi, and secure MQTT transmission to cloud platform.

Rmmsd Readings from 10 subjects

Subject ID	Rest (ms)	Mild Activity (ms)	Mental Stress (ms)	Post-Relaxation (ms)

1	62.5	38.1	29.4	47.6
2	59.3	38.1	24.3	57.4
3	63.2	41.0	25.2	49.9
4	67.6	32.3	20.7	45.8
5	58.8	33.1	23.4	53.3
6	58.8	37.8	25.3	45.1
7	67.9	35.9	21.5	50.8
8	63.8	41.3	26.1	42.2
9	57.7	36.4	23.2	44.7
10	62.7	34.4	24.1	50.8



RMSSD Trends for 10 Subjects Across Physiological Conditions

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