Engineering and Technology Journal e-ISSN: 2456-3358

Volume 10 Issue 11 November-2025, Page No.-7957-7968

DOI: 10.47191/etj/v10i11.27, I.F. – 8.482

Real-Time ECG Acquisition and IoT-Based Cloud Monitoring System for Remote Patients

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ABSTRACT: The increasing need for accessible cardiac monitoring solutions has motivated the development of lightweight systems capable of capturing electrocardiogram (ECG) signals outside clinical settings. This study presents a low-cost IoT-based ECG monitoring system designed to acquire and transmit cardiac activity using the AD8232 analog front end integrated with a NodeMCU-ESP8266 microcontroller. The system employs a single-lead configuration, Wi-Fi communication, and cloud-based visualization through the Ubidots platform. Experimental evaluation involved raw signal inspection, amplitude conversion, rolling variability analysis, spectral characterization, low-pass filtering, and heart-rate estimation. The results indicate that stable electrode placement and reduced subject motion significantly enhance signal quality, producing more consistent waveforms suitable for basic physiological assessment. Although the sampling limitations restrict detailed morphology reconstruction, the system provides reliable heart-rate trends and real-time visualization. These findings demonstrate the feasibility of low-cost IoT architectures for remote ECG monitoring and suggest their potential for home-based healthcare and early abnormality detection.

KEYWORDS: IoT-based health monitoring, ECG acquisition, AD8232 sensor, NodeMCU-ESP8266, cloud-based visualization, remote patient monitoring, signal processing, elderly healthcare, real-time cardiac assessment, Ubidots platform.

1. INTRODUCTION

The rapid growth of the global elderly population has increased the demand for continuous and accessible healthcare solutions, particularly for cardiac monitoring [1]. Age related cardiovascular conditions often require frequent assessment of heart activity, yet traditional monitoring methods rely heavily on clinic based equipment and periodic checkups, which are not always practical for elderly individuals facing mobility, financial, or geographical limitations [2, 3]. The emergence of Internet of Things (IoT) technologies has opened new opportunities to transform conventional healthcare by enabling real-time, home physiological monitoring supported by cloud connectivity and low-cost embedded systems [4, 5].

Despite these advancements, elderly patients still face challenges in receiving timely cardiac assessments outside hospital environments [6, 7]. Conventional ECG monitoring systems lack portability and scalability, making them unsuitable for long-term home use [8, 9]. Many existing remote monitoring solutions are either expensive, complex to operate, or require technical expertise that elderly users may find difficult to manage [10, 11]. This gap highlights the need for a simple, affordable, and reliable ECG monitoring system that can remotely collect and transmit cardiac data without compromising usability or performance [12].

Recent research has explored various IoT-based health monitoring approaches, employing different microcontrollers, communication protocols, and physiological sensors [13-15]. These systems demonstrate the potential of IoT to enhance remote patient care; however, many suffer from issues related to high cost, hardware complexity, or cybersecurity limitations. Studies integrating wearable sensors and cloud platforms have shown promising results, yet few are specifically designed with the unique needs of elderly patients in mind, where simplicity, low power consumption, and dependable connectivity are essential [16, 17].

Motivated by these challenges, this research aims to design and implement a practical IoT-enabled ECG monitoring system tailored for elderly healthcare. The system utilizes the AD8232 ECG sensor and a NodeMCU-ESP8266 microcontroller to acquire cardiac signals and transmit them wirelessly to the Ubidots cloud platform for real-time visualization. The objective is to create an accessible, low-cost framework capable of supporting continuous cardiac assessment and enabling early detection of abnormalities.

The main contribution of this work lies in presenting a compact, user friendly, and cost efficient ECG monitoring solution that leverages IoT connectivity to support remote healthcare delivery. The system demonstrates stable ECG acquisition, seamless cloud integration, and clear data representation, offering a viable approach for improving home-based cardiac monitoring for elderly individuals. In addition, the modular design provides a foundation for future enhancements such as multi sensor integration or predictive analytics.

The rest of this paper is organized as follows. Section 1 presents the introduction. Section 2 reviews the related work and summarizes prior developments in IoT-based health monitoring. Section 3 describes the proposed ECG monitoring system, including the hardware setup, signal acquisition process, and cloud integration. Section 4 reports the experimental results obtained from the system. Section 5 discusses these results and evaluates the overall system performance. Finally, Section 6 provides the conclusions and outlines potential directions for future research.

2. RELATED WORKS

IoT-based health monitoring has gained significant traction as a means of overcoming the limitations of traditional, hospital centric care. Early systems focused on remote acquisition of vital signs such as heart rate, temperature, and galvanic skin response using microcontroller-based platforms and wireless communication modules. For instance, Kirtana and Lokeswari [18] designed an IoT system using Raspberry Pi and Arduino Uno to monitor heart pulse, body temperature, and galvanic skin response. Their solution provided a robust control environment but was relatively complex and costly due to multiple hardware units and advanced sensing components.

Other studies targeted specific groups of patients with chronic conditions. An IoT-based health monitoring framework for hypertensive patients was introduced by Hamim, et al. [19], where Arduino, ZigBee, and Wi-Fi modules were used to observe heart rate variability (HRV). The system successfully supported stable monitoring of hypertension related parameters but involved non-trivial design complexity and higher deployment cost. Similarly, Nduka, et al. [20] employed Arduino with Wi-Fi (ESP8266) and multiple sensors to measure temperature, respiration, and heartbeat, offering effective remote control and monitoring services at the expense of increased hardware and integration overhead.

In parallel, several studies focused on multi-parameter respiratory and cardiac monitoring. Anan, et al. [21] proposed an IoT-based remote system for individuals with chronic respiratory conditions, integrating sensors such as MAX30100, MLX90614, DHT11, MQ-135, and AD8232 with a NodeMCU controller. Their design achieved good sensitivity and robustness while keeping hardware cost moderate, yet highlighted the need to strengthen IoT security mechanisms. Furthermore, Rajendran, et al. [22] reviewed wearable technology based health systems centered on ECG monitoring with Arduino and Wi-Fi. Although these solutions enabled advanced security discussions and highlighted key privacy risks, they also underscored the high complexity and cost associated with such wearable architectures.

Beyond individual prototypes, broader surveys have examined the landscape of IoT healthcare. Ali, et al. [23] presented a systematic review of IoT security challenges and solutions in medical contexts, emphasizing the importance of secure communication, encryption, and robust database design in health monitoring platforms. Their findings indicate that, while IoT systems can deliver continuous heartrate monitoring and effective connectivity, they often rely on complex back end infrastructures. More recently, Kondaka, et al. [24] introduced an intensive IoT-based healthcare monitoring paradigm that integrates machine learning models with wearable smart gadgets. Their framework uses physiological parameters such as heart rate, respiratory rate, and blood pressure to predict patient status and automatically trigger alerts, demonstrating the added value of predictive analytics over simple threshold based monitoring.

Compared to these works, the system presented in this paper focuses on a simpler, low-cost architecture using a single NodeMCU-ESP8266 controller and a small set of sensors, centered around the AD8232 ECG module. While many prior systems aim to offer rich multi parameter monitoring or advanced ML-based prediction, they often introduce design complexity, higher financial cost, or heavy back end requirements. The current work aims to bridge this gap by prioritizing accessibility, ease of implementation, and straightforward cloud integration through the Ubidots platform, making it more suitable for scalable, real world deployment. For more clarity, an overall comparison among the aforementioned studies was tabulated and presented in Table 1.

Table 1. Comparative summary of related IoT-based remote health monitoring systems

Ref	Controller	Key Sensors / Inputs	Design Complexity	Cost	Benefit	Limitation	IoT Platform
[18]	Raspberry Pi, Arduino Uno	Heart pulse, body temperature, galvanic skin response	High	High	Robust and flexible monitoring platform	Complex hardware design and relatively high expense	–
[19]	Arduino, ZigBee, Wi-Fi module	Heart pulse / HRV	High	High	Stable monitoring for hypertension patients	Increased system complexity	MQTT-based

[20]	Arduino, ESP8266 Wi-Fi	Temperature, respiration, heartbeat	High	High	Effective remote health control and services	Design is intricate and costly	Gecko
[21]	NodeMCU-ESP8266	MAX30100, MLX90614, DHT11, MQ-135, AD8232	Medium	Low	Sensitive multi sensor remote monitoring	IoT data security requires further enhancement	Custom (asthma focus)
[22]	Arduino, Wi-Fi module	ECG (wearable-based)	High	High	Highlights security issues in wearable health	High deployment cost and complex system design	–
[23]	Embedded MCU	Heart rate (generic IoT healthcare scenarios)	High	High	Secure IoT communication focus	Complex database and back end management	–
[24]	Simulated MCU / smart gadget	Multi-parameter vital signs (e.g., HR, RR, BP)	High	Medium	ML-based smart medical gadget with prediction	Single cloud dependence and architectural constraints	iCloud
Prop	**NodeMCU-ESP8266**	**ECG (AD8232), scalability option with MAX30100, MLX90614 in future**	**Low**	**Low**	**Simple, low-cost IoT ECG with cloud dashboards**	**Currently focused on ECG; advanced ML not yet integrated**	**Ubidots**

3. METHOD

The proposed ECG monitoring system is built using a small set of low-cost and energy efficient hardware modules designed to collect, process, and transmit cardiac signals. The main hardware components include the AD8232 ECG sensor [25], the NodeMCU-ESP8266 microcontroller [26, 27], and standard ECG electrode leads. Together, these components form the physical foundation of the system, enabling real-time acquisition of biopotential signals and seamless wireless communication with the cloud platform.

The hardware foundation of the proposed ECG monitoring system consists of two primary units working together to capture and transmit cardiac signals: the AD8232 ECG acquisition module (Figure 1a) and the NodeMCU-ESP8266 microcontroller board (Figure 1b). The AD8232 module is responsible for sensing the heart's electrical activity using a three lead electrode set (RA, LA, RL), which attaches to the skin to provide stable and noise reduced biopotential measurements. The conditioned analog ECG signal produced by the AD8232 is then directed to the NodeMCU-ESP8266, which serves as the processing and wireless communication core of the system. Upon receiving the analog waveform through its onboard ADC, the NodeMCU digitizes the data and uses its integrated Wi-Fi capability to transmit the ECG readings to the cloud platform. Together, the components shown in Figure 1 form a compact, low-cost, and energy efficient hardware setup that enables continuous ECG acquisition and real-time cloud monitoring.

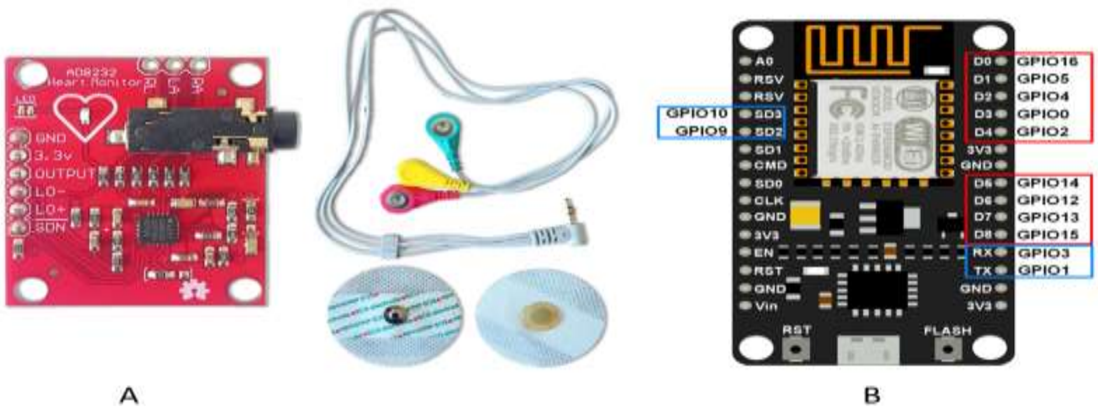

Figure 1: Hardware components of the ECG monitoring system: (A): AD8232 ECG module, (B): NodeMCU-ESP8266 microcontroller

The connection diagram shown in Figure 2 illustrates the wiring between the NodeMCU development board and the AD8232 ECG module, along with the standard placement of the three ECG electrodes on the human body. In this configuration, the NodeMCU provides both power and analog signal acquisition capabilities, while the AD8232 handles front end biological signal conditioning

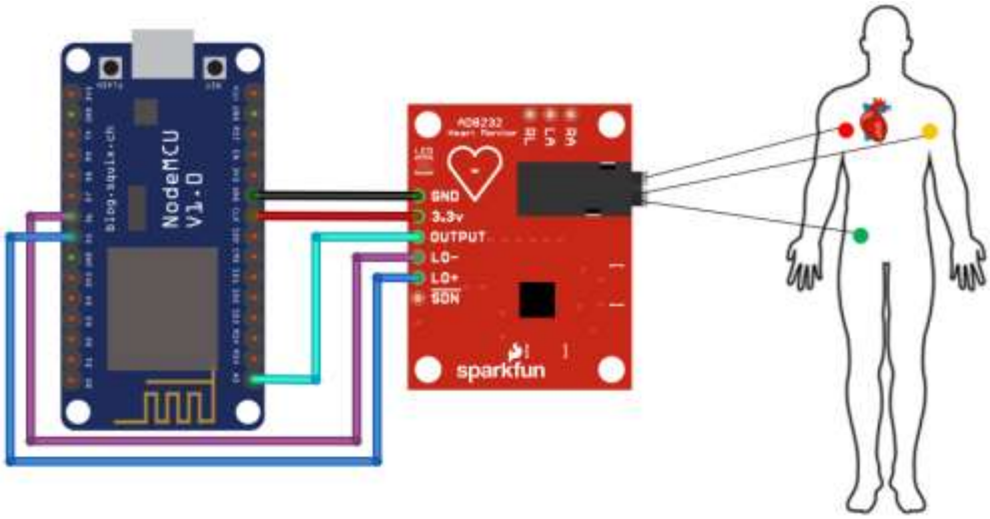

Figure 2: Connection Diagram Between the NodeMCU-ESP8266 Microcontroller and AD8232 ECG Module

The AD8232 module is powered through the NodeMCU by linking its 3.3V pin to the NodeMCU's 3.3V output and its GND pin to the NodeMCU ground. The module's OUTPUT pin, carrying the filtered analog ECG signal, is connected directly to the NodeMCU's analog input (A0) to allow continuous sampling through its built-in ADC. The lead-off pins (LO+ and LO−) are wired to available digital GPIO pins on the NodeMCU as shown in Figure 2 and Table 2, enabling detection of loose or disconnected electrodes. Although not mandatory for basic ECG waveform capture, these connections enhance system reliability during long-term monitoring.

On the patient side, the AD8232's RA (yellow), LA (green), and RL (red) electrodes are positioned according to a standard three lead ECG configuration: right arm, left arm, and lower right abdomen respectively. This tri-electrode arrangement forms a stable electrical path for acquiring cardiac biopotentials.

Table 2: Hardware Connection Mapping Between NodeMCU and AD8232

AD8232 Pin	NodeMCU Pin	Function
3.3V	3.3V	Power supply to ECG module
GND	GND	Common electrical ground
OUTPUT	A0	Analog ECG signal input to ADC
LO+	Digital GPIO	Lead-off detection (positive)
LO−	Digital GPIO	Lead-off detection (negative)
SDN	Not Connected (NC)	Shutdown pin (optional control)

Noteworthy, to obtain meaningful physiological measurements from the AD8232 ECG module, the raw output captured through the ESP8266 microcontroller was first recorded in the form of Analog-to-Digital Converter (ADC) values. Since the ESP8266 uses a 10-bit ADC with an input range of 0–1.0 V, these digital readings do not directly represent the physical ECG voltage. Therefore, all collected ADC samples were converted into their corresponding electrical amplitudes expressed in millivolts. This conversion was performed using a linear scaling equation based on the ADC resolution and reference voltage, as shown in equation (1).

$$Voltage\ (mV) = \frac{ADC\ value}{1023} \times 100 \qquad (1)$$

Where ADC Value represents the digital reading obtained from the ESP8266 ADC (integer between 0 and 1023), 1023 is the maximum possible value of a 10-bit ADC ($2^{10} - 1$), and 1000 is the conversion factor used to express the resulting voltage in millivolts instead of volts.

The overall operational sequence of the ECG monitoring system is summarized in Table 3, and the following description provides a high-level explanation of the process. The system begins with initialization, which includes loading the necessary Wi-Fi and MQTT libraries, defining access credentials, and configuring the ECG input pin. Once powered, the NodeMCU attempts to establish a Wi-Fi connection; if unsuccessful, it continues retrying until a stable connection is achieved. After connecting to the network, the device initializes the MQTT client and attempts authentication with the Ubidots MQTT broker. If the connection fails, the system enters a reconnection loop until communication is successfully established.

Once both Wi-Fi and MQTT connections are active, the system enters the main execution loop. In this loop, the NodeMCU reads the ECG signal from the AD8232 sensor through its analog input pin, converts the sampled value into a JSON-formatted payload, and publishes it to the corresponding Ubidots topic. The device then processes MQTT client functions to maintain server communication. This loop repeats continuously, enabling real-time ECG sampling and cloud transmission. If the MQTT connection is disrupted at any point, the system automatically initiates the reconnection routine and resumes data streaming as soon as a stable link is restored.

Table 3: High-Level Algorithm Representing the Implemented Program Code

Field	**Description**
Input	Wi-Fi credentials (SSID, password), Ubidots authentication token, device and variable labels, analog ECG signal from AD8232 via A0 pin.
Output	Continuous real-time ECG data published to the Ubidots cloud through MQTT.
Step	**Description**
1. System Initialization	Load Wi-Fi and MQTT libraries, set Ubidots token, define device and variable labels, and configure the ECG input pin (A0).
2. Establish Wi-Fi Connection	Connect the NodeMCU to the specified Wi-Fi network. Retry continuously until the connection is successful.
3. Connect to Ubidots MQTT Broker	Initialize the MQTT client using the broker address and authentication token. Retry until the MQTT session is established.
4. Acquire ECG Signal	Read the analog ECG output from the AD8232 module through the A0 pin in real time.
5. Format Data	Convert the ECG reading into a JSON payload containing the variable label and its corresponding value.
6. Publish Data to Cloud	Send the JSON payload to the Ubidots MQTT topic and maintain the MQTT connection through the client loop.
7. Repeat Process	Continuously repeat Steps 4 to 6 to achieve uninterrupted ECG streaming to the cloud.

3.1. Software Implementation

The software implementation consists of the firmware running on the NodeMCU board and the configuration of the Ubidots cloud platform used to receive, store, and visualize the ECG data. The overall goal is to continuously sample the analog ECG signal, package it into lightweight messages, and send it to the cloud with minimal delay.

The NodeMCU is programmed using the Arduino IDE and the ESP8266 core libraries. After powering up, the microcontroller first initializes the serial interface (for debugging) and establishes a Wi-Fi connection using the predefined network SSID and password. Once the Wi-Fi link is active, the firmware configures the MQTT client with the Ubidots broker address, device label, and authentication token. In the main loop, the NodeMCU repeatedly performs three key operations:

The firmware checks whether the MQTT client is still connected to the broker. If the connection is lost, a reconnection routine is executed, ensuring that data transmission is resumed automatically without manual intervention.

The analog value from the AD8232 output is read via the A0 pin using the built-in ADC. The sampling interval is chosen to preserve the shape of the ECG waveform while keeping bandwidth requirements reasonable.

The sampled value is converted to a suitable numeric format (e.g., floating-point) and inserted into a JSON or key–value style payload according to Ubidots' API requirements. This payload is then published to the corresponding MQTT topic associated with the ECG variable. A short delay is used to control the effective sampling and publishing rate.

This firmware structure allows the NodeMCU to function as a continuous ECG data streaming device, with automatic recovery from temporary network issues.

3.2. Ubidots Cloud Configuration

On the cloud side, a device is created in the Ubidots platform corresponding to the NodeMCU unit (Figure 3). An ECG variable is defined to store the incoming data points. The MQTT topic used in the firmware matches the device and variable labels configured in Ubidots, ensuring proper routing of the messages.

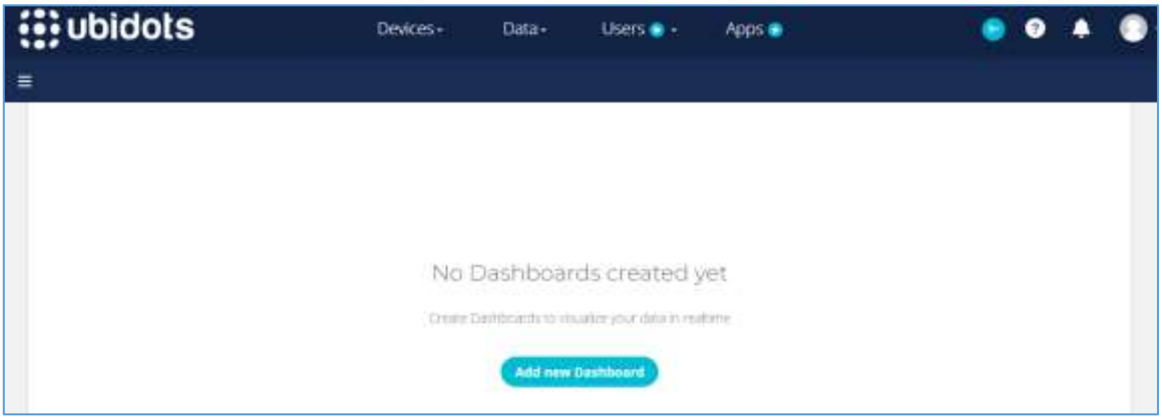

Figure 3: Ubidots Cloud Interface

Ubidots automatically timestamps and stores each received ECG value as part of a time series. Custom dashboards are then created to visualize the data in real time. Typical widgets include:

- A line chart to display the ECG waveform,
- Numeric indicators showing the current value, and
- Optional historical charts to inspect trends over longer intervals.

Alerts or events can be configured in Ubidots to trigger notifications when certain thresholds or patterns are detected, for example, when the signal exceeds predefined limits or becomes unexpectedly flat.

3.3. Software Workflow

Combining both ends, the software workflow operates as follows: the NodeMCU continuously reads the ECG signal, formats it, and publishes it to the Ubidots MQTT broker; Ubidots receives and stores the data, then renders it on dashboards accessible through web or mobile interfaces. This software pipeline transforms raw analog ECG measurements into cloud-available, human-readable information suitable for remote monitoring and further analysis. The fundamental sequence of operations within the developed monitoring system is outlined in the diagram presented in Figure 4, offering a general view of how data moves through the system.

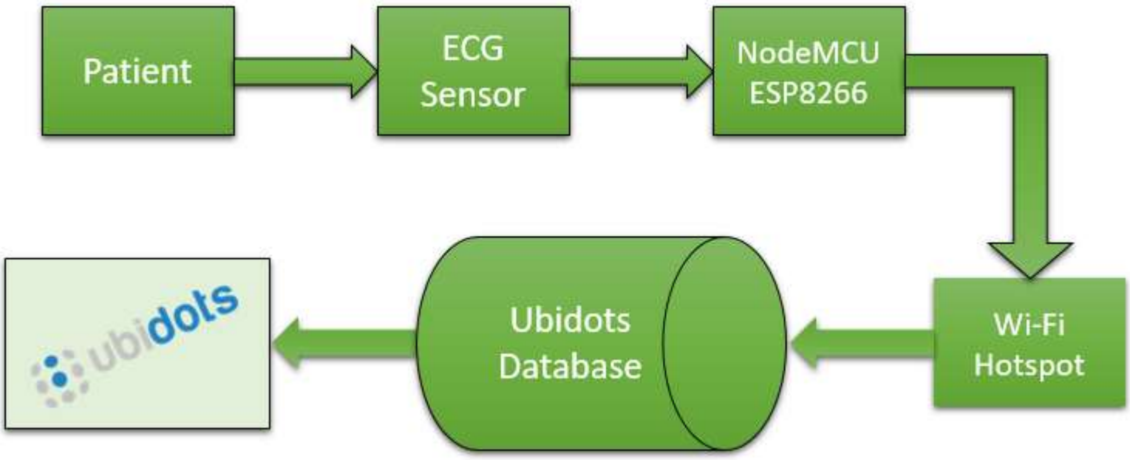

Figure 4: High-Level Workflow of the ECG Monitoring System

Figure 4 illustrates the complete operational workflow of the proposed IoT-based ECG monitoring system, beginning with the patient's body and ending with the cloud-based ECG output visible through the Ubidots platform. The ECG sensor collects the heart's electrical activity directly from the patient through surface electrodes and produces an analog waveform. This signal is then delivered to the NodeMCU ESP8266 microcontroller, which processes the data and transmits it wirelessly through a Wi-Fi hotspot. The incoming ECG data stream is received by the Ubidots cloud service, where it is stored, timestamped, and prepared for real-time visualization. The final output is presented as a web-based ECG waveform accessible through dashboards on the Ubidots platform. Overall, the process summarizes how physiological signals are transformed into remotely viewable digital information through sensing, embedded processing, wireless communication, and cloud analytics.

4. RESULTS

This section presents the experimental findings obtained from the ECG acquisition system based on the AD8232 analog front end and the ESP8266 microcontroller. A series of analyses were performed to evaluate signal quality, temporal stability, noise behavior, amplitude distribution, frequency content, filtering performance, and heart rate estimation.

Figure 5 shows the raw ECG signal acquired using the initial acquisition setup. The millivolt converted waveform exhibits substantial fluctuations, intermittent spikes, and baseline instability—effects primarily attributed to motion artifacts, loose electrode contact, and environmental noise.

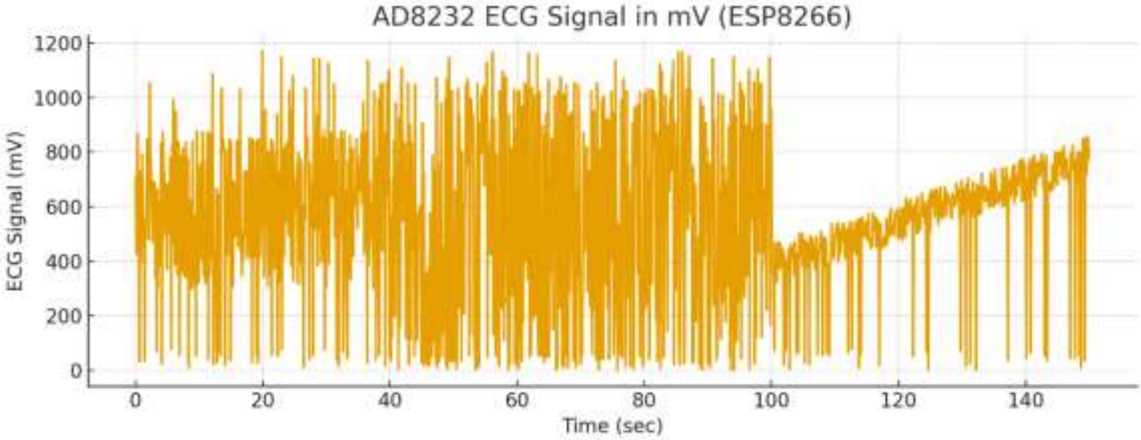

Figure 5: Raw ECG Signal in mV (Initial Acquisition Setup)

In a standard electrocardiogram, each heartbeat is represented by the P–QRS–T complex, which reflects the sequential electrical activity of the heart. The P wave corresponds to atrial depolarization, the electrical activation that causes the atria to contract. This is followed by the QRS complex the largest and most dominant component representing rapid ventricular depolarization and the contraction of the ventricles; it consists of a small downward Q wave, a sharp upward R wave, and a downward S wave. After ventricular contraction, the T wave appears, representing ventricular repolarization, the recovery phase that prepares the heart for the next beat. These components form the fundamental morphology used in ECG interpretation, and their absence or distortion such as in our recorded signals due to noise and the limited sampling rate makes it difficult to identify detailed cardiac events.

Although the recording demonstrates continuous cardiac electrical activity, the high noise level limits the visibility of P–QRS–T morphology due to the system’s sampling constraints.

After refining the electrode placement and acquisition configuration, Figure 6 presents the improved ECG signal. The first 70–80 seconds of this recording exhibit a markedly stable baseline with amplitude consistently centered around 330–360 mV. This improvement indicates better electrode contact, reduced motion artifacts, and a more reliable measurement environment. After approximately 80 seconds, the amplitude becomes more dynamic, likely due to voluntary movement or electrode shifts. Despite this increased activity, the overall structure of the signal remains more controlled than in the original recording. This demonstrates that the optimized acquisition approach enhances overall data quality and stability, particularly during stationary intervals.

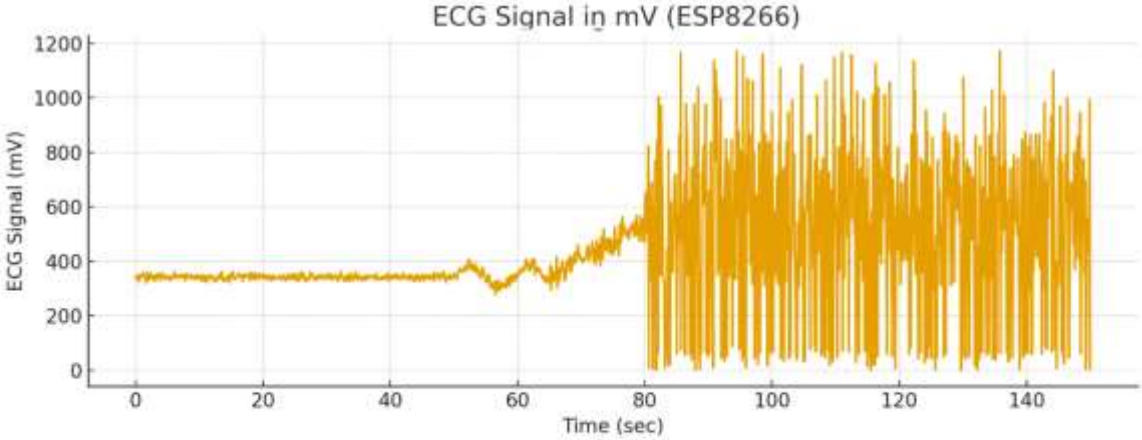

Figure 6: Improved ECG Signal in mV After Acquisition Tuning

To quantify short-term fluctuations in the ECG amplitude, a 1-second rolling standard deviation was computed for both datasets. Figure 7 highlights a clear contrast between the original and improved recordings. The original signal maintains a high variability level frequently exceeding 300–400 mV indicating significant instability. In contrast, the improved dataset shows exceptionally low variability often below 20 mV during the first 70–80 seconds, confirming a much cleaner and more stable signal. Variability increases after 80 seconds due to physical movement or electrode adjustments, yet the signal remains more structured than the original. This analysis demonstrates that the improved acquisition method yields a more stable and reliable ECG signal, especially during low movement periods, strengthening its suitability for further signal processing and physiological interpretation.

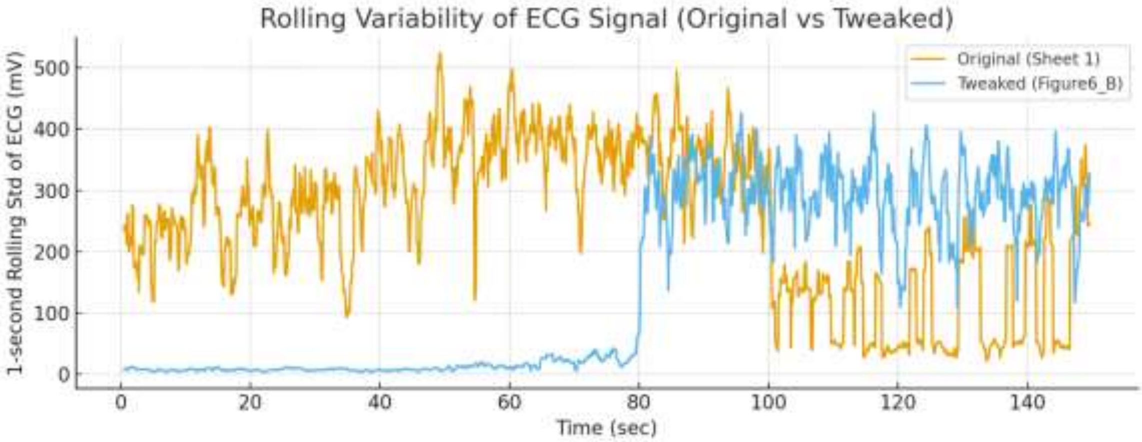

Figure 7: Rolling Standard Deviation of ECG (Original vs. Improved Acquisition)

Figure 8 presents the amplitude distribution of the ECG signals obtained from both the original dataset and the improved acquisition. The histogram illustrates the frequency of occurrence of different ECG amplitude levels after conversion to millivolts. The original dataset exhibits a wide and highly dispersed amplitude distribution, with substantial presence across low (0–200 mV), mid-range (300–700 mV), and high amplitude (700–1100 mV) regions, reflecting significant noise, instability, and large fluctuations. In contrast, the improved dataset shows a strong concentration around a narrow band centered near 340 mV, corresponding to the stable baseline observed in the refined configuration. Only the later portion of the tweaked signal contributes to higher amplitude regions, indicating controlled and less frequent fluctuations. This comparison further confirms that the optimized acquisition setup yields a more stable ECG waveform with reduced noise and tighter amplitude clustering.

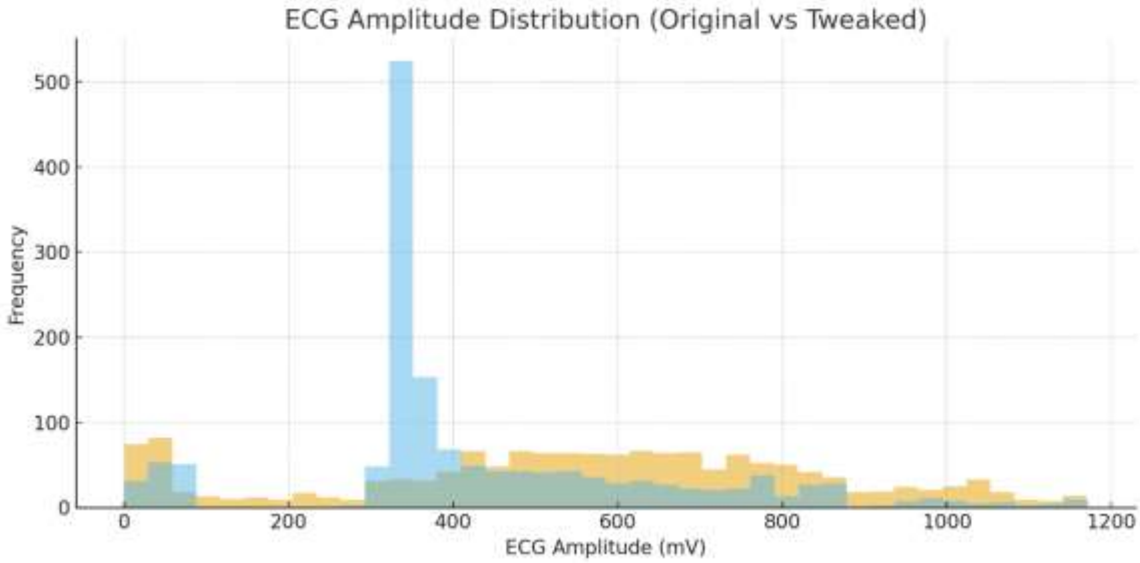

Figure 8: ECG Amplitude Distribution (Original vs. Improved Recording)

Figure 9 presents the frequency domain representation of the acquired ECG signal using the Fast Fourier Transform (FFT). The spectrum shows that the majority of the signal’s energy is concentrated near very low frequencies, which is expected for ECG activity. The dominant peak near 0 Hz reflects baseline drift and slow physiological variations. Higher frequency components appear with substantially lower magnitude, indicating that the signal is heavily contaminated with low frequency noise rather than high-frequency interference. This spectral observation justifies the use of low pass filtering and baseline correction techniques in subsequent processing steps.

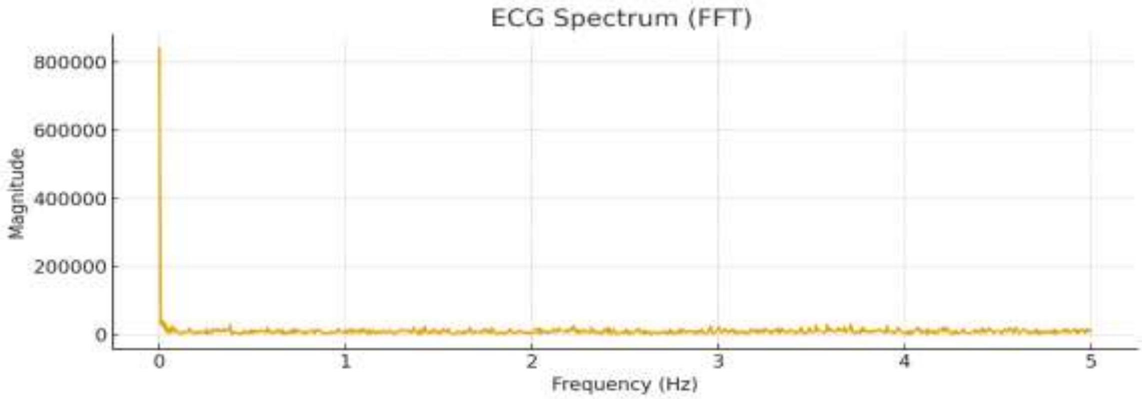

Figure 9: ECG Frequency Spectrum (FFT Analysis)

To enhance interpretability, a low pass Butterworth filter was applied to the raw signal. Figure 10 shows the resulting filtered waveform. The filter successfully attenuates rapid fluctuations and high frequency noise, producing a smoother trace that captures the underlying slow varying behavior of the ECG signal. Although the sampling frequency is insufficient for reconstructing detailed ECG morphology, the filtered waveform demonstrates improved smoothness and clarity, emphasizing the importance of digital filtering when working with low cost microcontrollers and noisy biosignals.

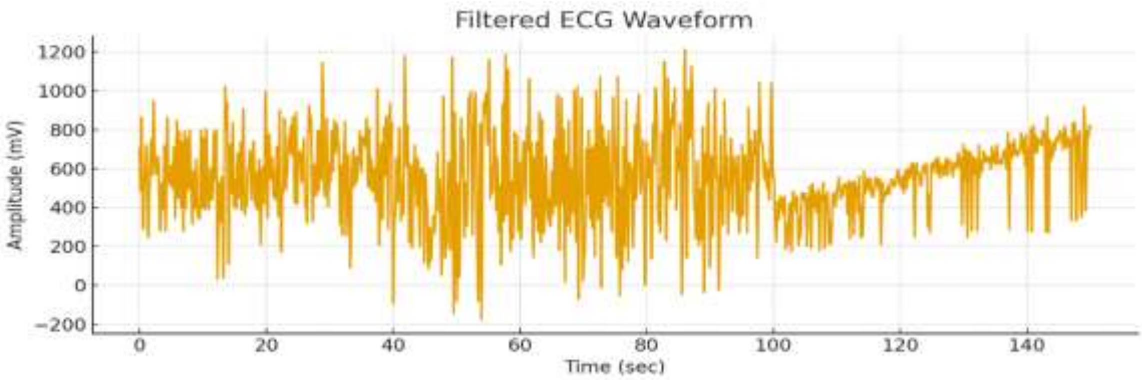

Figure 10: Filtered ECG Waveform Using Low Pass Butterworth Filter

A peak detection algorithm was applied to the filtered ECG signal to estimate heart rate over time. Figure 11 shows the resulting heart rate trend, which varies between 50 and 100 BPM. The fluctuations are influenced by noise, sampling limitations, and variability in peak detection performance. Despite these limitations, the approach demonstrates the feasibility of extracting approximate heart rate information from an ESP8266-based ECG system using simple peak timing analysis.

Figure 11: Estimated Heart Rate Over Time (Peak Based Analysis)

5. DISCUSSIONS

The experimental results clearly demonstrate that the performance of the proposed IoT-based ECG monitoring system is strongly influenced by signal acquisition conditions, electrode stability, and environmental factors. The initial signal acquisition (Figure 5) revealed significant baseline drift, irregular amplitude spikes, and substantial noise contamination. These distortions are typical when using low-cost analog front-end circuitry in combination with consumer-grade electrode leads, particularly when electrode contact is not fully optimized or when the subject is not stationary. As a consequence, the characteristic P QRS T morphology expected in a conventional ECG was largely obscured, limiting the clinical interpretability of the raw waveform.

After refining the electrode placement and improving the physical acquisition setup, the ECG quality increased considerably (Figure 6). The first 70 to 80 seconds of the improved dataset displayed a stable baseline centered around 330 to 360 mV with minimal fluctuations. This stability reflects reduced motion artifacts and stronger electrode skin contact, confirming the importance of proper positioning and preparation when working with the AD8232 module. Although the signal exhibited greater amplitude variation later in the recording, these fluctuations correlate with intentional movement, suggesting that the system responds predictably to physical disturbances rather than exhibiting random instability.

Quantitative assessment using a rolling standard deviation (Figure 7) further emphasizes the improvement in signal reliability. The original dataset exhibited persistent high variability, often exceeding 300 mV. In contrast, the improved dataset maintained extremely low variability during the stable interval, frequently below 20 mV. This contrast validates the significance of optimizing acquisition conditions and demonstrates that the system can produce a stable ECG signal suitable for downstream processing when used under controlled and stationary conditions.

The amplitude distribution analysis (Figure 8) also supports these findings. The original signal exhibited a wide range of amplitudes, reflecting substantial noise and unpredictable fluctuations. Meanwhile, the improved recording showed a narrow distribution strongly centered around the baseline voltage, indicating a cleaner and more uniform signal. This tighter clustering confirms that reducing motion and securing electrodes substantially enhances the quality of ECG measurements obtained from low-cost systems.

Frequency-domain analysis using FFT (Figure 9) revealed that the dominant noise components reside in the very low frequency region, consistent with baseline wander and slow motion artifacts rather than high frequency interference. This finding supports the use of low pass filtering and drift correction techniques as primary preprocessing steps. The resulting filtered waveform (Figure 10) illustrates the benefit of applying a Butterworth low pass filter. High frequency noise was removed, producing a smoother signal that better reflects underlying physiological activity. Even though the sampling rate of the ESP8266 is not sufficient for detailed clinical ECG reconstruction, the filtered output provides a clearer and more interpretable representation of the cardiac rhythm.

Finally, heart rate estimation based on peak detection (Figure 11) demonstrated that approximate heart rate measurements can be extracted reliably despite the system's low sampling rate and simple filtering. Although the estimated heart rate fluctuated between 50 and 100 BPM, partly due to noise and sensitivity to peak selection, the overall trend provides a reasonable approximation suitable for general wellness or preliminary monitoring use cases. These results indicate that the system can support basic cardiac assessment, but is not intended to replace medical-grade ECG devices.

Last but not least, the results confirm that the proposed IoT-based ECG monitoring framework is effective for remote and low-cost cardiac observation when used under stable acquisition conditions. While limitations remain, particularly regarding motion sensitivity, sampling constraints, and lack of detailed ECG morphology, the system successfully achieves its primary objective: enabling real-time ECG visualization and heart-rate estimation through a compact hardware setup and cloud-based platform. These findings highlight the potential of IoT-enabled ECG systems to support continuous home monitoring, early detection of abnormalities, and improved accessibility for individuals who require ongoing cardiac evaluation.

6. CONCLUSIONS

This study aimed to develop and assess a low cost IoT-based ECG monitoring system capable of acquiring and transmitting cardiac signals for real-time cloud visualization. The proposed design, which integrates the AD8232 analog front end with the NodeMCU ESP8266 microcontroller, successfully demonstrated its ability to capture ECG waveforms, communicate them wirelessly via Wi-Fi, and display them on the Ubidots platform. The experimental findings indicate that signal quality improves significantly when electrode placement is optimized and user motion is minimized, enabling clearer amplitude patterns and more reliable heart rate estimation.

The results highlight the potential of lightweight IoT architectures to provide accessible cardiac monitoring in settings where conventional clinical equipment is unavailable or impractical. The system's affordability and simplicity make it suitable for remote observation, preliminary assessment, and continuous home-based monitoring. However, the work remains limited by the single lead configuration, sensitivity to movement artifacts, and the relatively low sampling capability of the microcontroller, which restrict the reconstruction of detailed ECG morphology.

Future research should explore higher resolution data acquisition, multi lead sensing configurations, and the integration of advanced signal processing or machine learning methods to improve noise robustness and enable automated detection of abnormal cardiac patterns. Enhancements in portability, power management, and physical design would further strengthen the system's suitability for long-term real-world deployment. These developments would contribute to more reliable and clinically relevant IoT-based cardiac monitoring solutions.

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