Design of a secure-cloud remote medical monitoring system using the P-QRS-T electrocardiogram detection algorithm

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ABSTRACT

The COVID-19 pandemic has highlighted the limitations of traditional healthcare, resulting in higher mortality rates among children, the elderly, and healthcare workers. This situation has created a pressing need for urgent medical care from healthcare professionals. This paper presents a secure cloud-based remote medical monitoring system that integrates the internet of things (RMMS-IoT) with advanced P-QRS-T electrocardiogram (ECG) detection algorithms to enable real-time, accurate vital sign analysis. The system combines microcontroller devices, wearable sensors, and medical-grade equipment, leveraging hypertext transfer protocol secure (HTTPS) and Blynk bridge cloud technologies to ensure data security and interoperability. The RMMS-IoT system demonstrated high accuracy in monitoring vital signs by comparing its results with data from actual measuring devices, showing errors in body temperature readings below 1% and heart rate (HR) measurements below 2.8%. The algorithm used to detect P-QRS-T features from the ECG exhibited robust performance in differentiating between normal and abnormal ECG patterns in patients, and it achieved an accuracy rate of 90% in ECG classification.

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1. INTRODUCTION

The internet of medical things (IoMT) is a network of internet-based computer systems that connect health devices to healthcare systems, and it is expected to significantly impact the healthcare sector with innovative applications [1]. Projections suggest that there will be over 75 billion internet connections by 2025, indicating that internet of things (IoT) technologies could enhance patient care, streamline operations, and reduce costs [2]. The IoMT connects vital sign monitoring to decision support systems, helping doctors make quicker and more accurate diagnoses with fewer errors [3]. The advantages of IoMT include optimal pharmaceutical administration, reduced healthcare costs, improved patient experiences, superior diagnosis and therapy, effective disease management, and streamlined pharmacovigilance for chronic illnesses. Moreover, IoMT applications rely heavily on monitoring systems.

The patient monitoring system (PMS) is a vital component of the remote patient monitoring system (RPMS) within the IoMT network [4]. This system includes various functions such as disease management, anomaly detection, medical nursing and rehabilitation, screening, conditioning, remote treatment, and telemedicine, among others. It utilizes multiple devices to monitor patients' health through vital sign alert systems [5]. The rapid growth of RPMS can be attributed to several factors, including the emergence of highly contagious diseases like COVID-19, an increasing elderly population requiring long-term care, the system's effectiveness in assisting individuals with serious health conditions, and prevalent issues that diminish quality of life, such as busy schedules, epidemics, and pollution [6]. PMS allows healthcare providers to monitor patient health swiftly and remotely, transforming healthcare by reducing costs and enhancing patient outcomes. Researchers have been developing methods for the detection, monitoring, and tracking of PMS [7]. These innovations improve patient safety and provide caregivers with real-time data, enabling them to make informed decisions regarding treatment plans. However, RPMS often face challenges related to the quality of service (QoS) for real-time data monitoring. Additionally, there are concerns about reliability, privacy, and security. These factors are subject to regulations such as the Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR), which aim to protect privacy and mitigate risks associated with hacking. The issues encountered are primarily tied to the types of protocols utilized in RPMS.

Electrocardiogram (ECG) analysis is crucial for identifying and classifying heart disorders, aiding in early prevention and treatment. Advanced methods like the Pan–Tompkins technique [8], wavelet transform [9], and deep learning tools such as convolutional neural networks (CNNs) and deep neural networks (DNNs) help us quickly and accurately determine heart problems by identifying important features in ECG readings from patients being monitored remotely [10], [11]. However, these techniques face several challenges, including noise and artifacts, low-amplitude QRS complexes, irregular heart rhythms, high-frequency noise, and motion interference in the Pan–tompkins technique. Moreover, the selected wavelet basis influences the choice of the mother wavelet, as no single wavelet can effectively capture all ECG shape variations. Deep learning models, including CNNs and DNNs, have certain limitations. They require large labeled datasets of ECG data for training, which can be both expensive and time-consuming. Furthermore, these models may not be suitable for deployment on low-power devices. Deep learning techniques also frequently demand a significant amount of memory.

This study addresses the problems with current RPMS and the above-mentioned challenges of recognizing the P-QRS-T features of ECG signals to better detect heart disease. It does this by creating and testing a new remote medical monitoring system-IoT (RMMS-IoT) that uses a P-QRS-T ECG detection algorithm. This system enhances health monitoring, disease management, and medical response processes. Furthermore, it improves the QoS for real-time data monitoring and facilitates communication between patients and physicians by utilizing a combination of the hypertext transfer protocol secure (HTTPS) protocol and Blynk bridge cloud technology. This approach ensures strong encryption and follows standard security practices, thereby enhancing compliance with regulations such as HIPAA and GDPR. However, the preprocessing for the algorithm P-QRS-T ECG detection involves several filters. A bandpass filter, combining low-pass finite impulse response (FIR) and high-pass Butterworth filters, eliminates high-frequency noise and baseline variations. It determines the QRS complex, maintains the signal's baseline, and uses derivatives. A Hilbert transform (HT) and squaring reduce P and T wave influence, locating the R peak. T-wave discrimination is performed. The findings in this study suggest that this algorithm improves diagnostic accuracy in differentiating between normal and abnormal ECG patterns in patients and facilitates timely interventions by healthcare providers. The proposed RMMS-IoT system in healthcare facilities showed high accuracy in monitoring vital signs, with minimal errors in body temperature, heart rate (HR), and humidity. The world health organization (WHO) validated the data and compared it to recent RPMS systems, assessing its strengths and efficiency.

2. OVERVIEW OF THE CURRENT RPMS SYSTEMS

The IoT is revolutionizing healthcare by integrating medical equipment and health systems, leading to the development of a RPMS-IoT. This system uses sensors and networks to monitor patients' health, transferring data to smartphones or platforms using Arduino and ESP32 microcontrollers. This simple, scalable, and cost-effective method improves healthcare outcomes and patient satisfaction, enabling telemedicine and continuous monitoring for chronic diseases, especially in underserved or remote regions [12]. It also allows patients to be involved in managing their health by providing access to health data and encouraging self-monitoring. This enhances the quality of life for patients and improves the traceability of their information in healthcare. Ren *et al*. [13] indicates that sleep can be monitored using smartphone earphones, that human breathing sounds can be tracked remotely, and that telemedical assessments can be utilized for sleep apnea in patients. Research by Malasinghe *et al.* [14] provides a review of recent advances in remote healthcare and monitoring with both contact and contactless sensors, focusing on their applications to specific diseases. There have been several recent reports on the development of low-cost, non-invasive RPMS specifically tailored for elderly individuals, as well as activity monitoring systems [15]. An IoT-

RPMS design architecture consists of sensors, microcontrollers, cloud computing platforms, and wireless communication networks such as RFID, WSN, and ZigBee [16]. These systems can provide real-time remote medical monitoring, tracking patients' vital signs and physiological conditions. Healthcare facilities monitor humidity and temperature, while microcontrollers process sensor data using algorithmic design [17]. A sensor that tracks a patient's core temperature can alert clinicians to any temperature changes, facilitating prompt medical treatment. Reliable and secure delivery of crucial information necessitates timely detection systems [18]. The server transmits data to a mobile app and stores it in a patient database. Both applications can identify irregularities in patient data and display alerts, including their location. Figure 1 illustrates the system's functioning. The block diagram of the system depicts the use of the IoT as a RMMS.

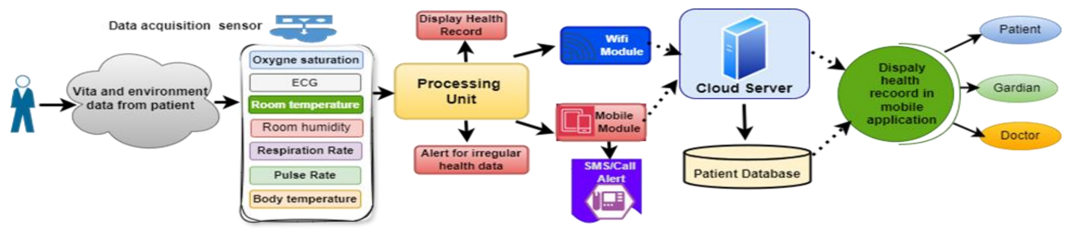


Figure 1. Block diagram of RMMS-IoT

This system enables the user to gather data from a patient or environment and subsequently transmit it to the cloud, which then reviews the patient's health data and the overall healthcare context. Wireless communication technology is essential for enhancing RMMS-IoT, which enable real-time patient monitoring and improve healthcare delivery [19]. Cloud computing strengthens healthcare systems by allowing faster data processing, better treatment of illnesses, and secure access to real-time patient information. Cloud-based systems provide scalability, security, and synchronized data sharing across platforms. Advanced algorithms, such as the one developed in our work to analyze ECG signals and identify critical features, ensure that vital information is readily accessible, thereby improving the efficiency of healthcare delivery. Medical servers and remote computers support real-time data monitoring and provide patient health recommendations.

3. DESIGN OF THE PROPOSED RMMS-IoT

The proposed RMMS utilizes the IoT to track real-time health data, improve security, and enhance patient care. It uses advanced algorithms, such as an ECG signal for recognizing P-QRS-T features, to display patient data securely via HTTPS from Blynk Cloud. This system enables doctors to respond quickly to patient needs, improving decision-making and resource allocation among healthcare providers. The primary objective is to monitor patients' health and their environment 24 hours a day, 7 days a week. Figure 2 demonstrates the design of the proposed system. The system design comprises three key components: i) a sensor and data handling unit, serving as the patient's device; ii) a data storage unit, represented by the Blynk Cloud server; and iii) an interaction unit, which is the data dashboard available on the mobile app.

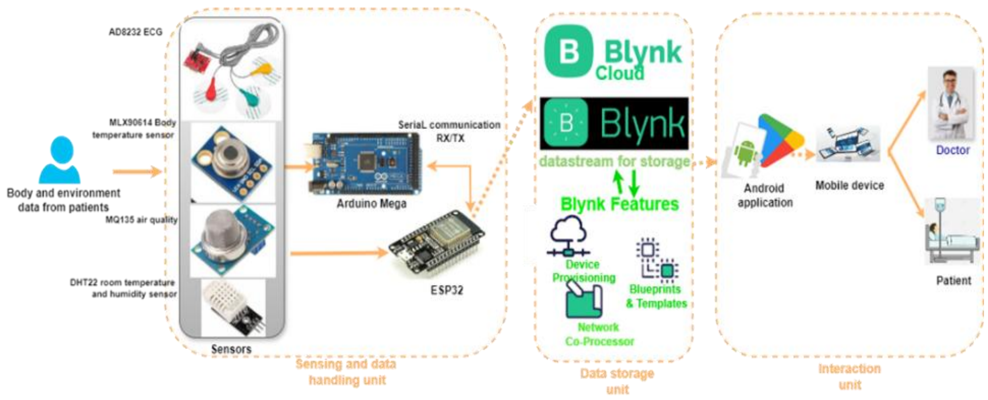


Figure 2. RMMS-IoT design architecture

3.1. Sensor and data handling unit

Important hardware components employed in the sensor and data handling unit to achieve the proposed system include:

- The Arduino Mega 2560 is a powerful electronic board with 54 digital I/O ports, 15 of which can be used as PWM outputs. It consists of an ATmega 2560 microcontroller, a 3-bus UART, a voltage regulator, a reset button, and a crystal oscillator.
- The ESP32 is an easy-to-use microcontroller board with integrated WiFi and Bluetooth modules. Its dual-core microprocessor, Xtensa Dual-Core 32-bit LX6, has 48 GPIOs and can send sensor data to the server as long as WiFi is available. The ESP32 functions as the system's processing unit, facilitating bidirectional serial communication with the Arduino Mega.
- The AD8232 ECG module HR sensor accurately measures heart electrical activity ECG. It uses an unconstrained operational amplifier to create a three-pole low pass filter (LPF) to remove noise and boost biopotential signals from the heart. Biomedical sensing electrodes on the skin connect to the sensor, which measures HR using three electrodes: red, green, and yellow. The signals are amplified and filtered for accurate PR and QT interval readings.
- The MLX90614 is an infrared thermometer for non-contact temperature measurements, featuring a low-noise amplifier, a 17-bit ADC, and a powerful DSP unit. It operates from 3.3 V to 5 V input and has a 10-bit PWM output resolution of 0.14 °C.
- The DHT22 healthcare facility temperature and humidity sensor is precise and stable, measuring temperatures from -40 to +125 °C and relative humidity levels from 0 to 100%. It communicates with a microcontroller via a single input/output pin, connecting to a power supply via a 4.7 KΩ pull-up resistor.
- The MQ135 air quality sensor monitors the air quality in healthcare facilities, detecting gases like CO_2 and nicotine. It has a sensitivity of 10-1000 ppm and features ground and +Vcc connections, analog A_0, and digital D_0 pins. It's part of a RMMS-IoT system.

3.2. Data storage unit

The proposed RMMS-IoT system uses Blynk Cloud's real-time database for data collection and storage and tracks real-time patient monitoring. It uses virtual channels and data streams, showcasing its versatility, ease of use, and multi-device compatibility for medical monitoring projects.

3.3. Interaction unit

This unit retrieves medical data from the Blynk Cloud, accessible to healthcare providers. It uses the Blynk App for iOS and Android, allowing users to interact with RMMS-IoT devices. This unit also allows users to create patient, guardian, or physician accounts and uses the Bridge feature for data transfer between devices.

4. IMPLEMENTATION OF A RMMS-IoT

The healthcare facility's RMMS-IoT system has successfully deployed a sensor and data handling unit that collects and processes sensor data, transmits results to the Blynk Cloud, and requires specific component assembly.

4.1. Hardware and software components of the RMMS-IoT

The RMMS-IoT system was developed by programming microcontrollers on an IoT board and connecting the necessary sensors, as illustrated in Figure 3. The prototype features an AD8232 HR ECG sensor, an MLX90614 infrared temperature sensor, an MQ135 air quality sensor, and a DHT22 temperature-humidity sensor.

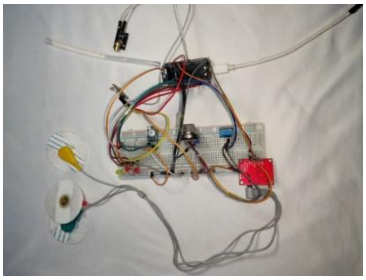


Figure 3. The hardware components utilized in the proposed prototype

The green electrode measures the heart's electrical activity, the red electrode measures body temperature, and the yellow electrode monitors the patient's ribcage. The system also monitors external environmental factors like temperature, humidity, and air quality in the patient room.

The software requires data storage and interaction units for its construction. The two components upload health records to the cloud and display them on the dashboard mobile app. The data storage unit can store patient data on Blynk Cloud using Datastreams, either temporarily or permanently. Later, we can analyze, visualize, or track this data. In Figure 4, the real-time Datastream captures health data from the equipment and transmits it to the Blynk Cloud.

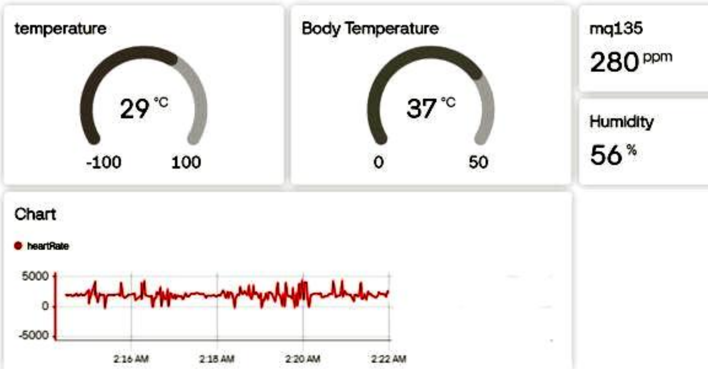


Figure 4. Real-time health data captured from various sensors in the Blynk Datastreams

4.2. Results and discussion

The RMMS-IoT system uses data from remote patient sensors and the Blynk platform to enhance efficiency and data handling accuracy. The system focuses on a sample of twenty patients. After consulting these patients, they consented to allow us to collect their vital signs. It is compatible with mobile health applications and sets benchmarks for emergency situations. The Blynk Bridge user interface features buttons for inputting patient information, deleting, viewing Firebase, and Blynk. The system generates a list of hospital patients based on personal information and location, aiding hospital reception staff and doctors in identifying patients and uploading their data to the Firebase database. Doctors can check on patients anytime but must update their status. The RMMS-IoT system was employed to evaluate the health status of twenty patients by analyzing real-time datasets gathered from various sensors. Absolute errors were found by comparing the data from the proposed system with the actual readings from forehead thermometers, HR monitors, hygrometers, and carbon dioxide meters in the healthcare facility. To assess the system's accuracy under different patient conditions, relative errors were also computed. The Blynk Bridge interface enabled access to this data.

Each patient has their body temperature measured using the MLX90614 infrared temperature sensor. A forehead thermometer is then used to compare these measurements with the actual body temperatures, as shown in Figure 5.

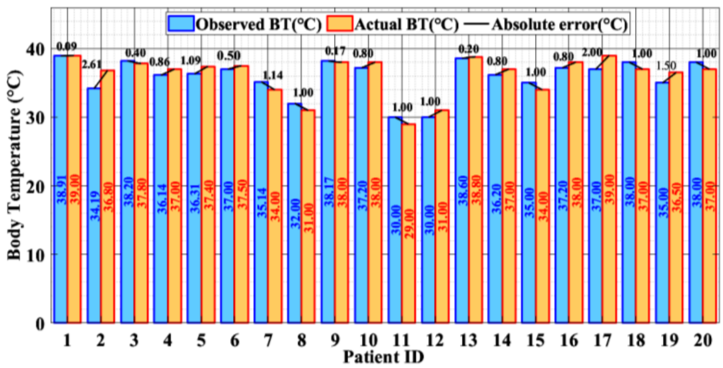


Figure 5. Bar graph with error bars comparing observed body temperature versus actual for each patient

The body temperature measured by the proposed system closely resembles the actual body temperature obtained with a forehead thermometer. The average absolute error is approximately 0.8 °C, and the relative error margin is less than 1%, indicating satisfactory consistency. The measurements align with the health standards established by WHO guidelines, highlighting their effectiveness for preliminary fever screening in public health assessments or triage. However, it is important to recognize that forehead thermometers typically offer less accuracy compared to the gold-standard rectal or oral thermometers. The HR readings from the HR monitor are compared with the data obtained from the AD8232 ECG module HR sensor, as shown in Figure 6.

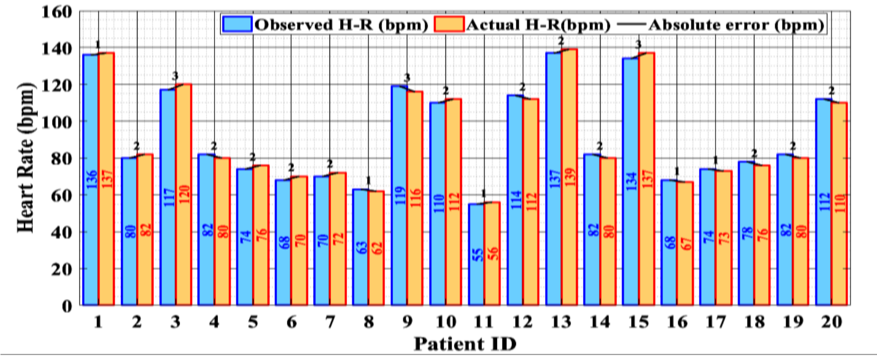
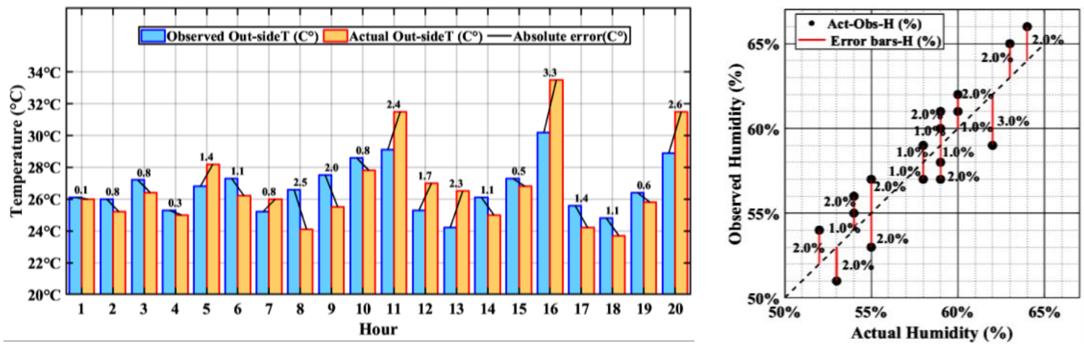


Figure 6. The bar chart with error bars compares the observed HR to the actual HR

The observed HR measured by the proposed system consistently tracks the actual HR across all patients, with an average absolute error of 1.9 bpm and relative errors of less than 2.8%, which demonstrates high accuracy. This performance meets the American heart association (AHA) standards and aligns with WHO recommendations, confirming its reliability for both clinical and personal use. Consequently, the system is suitable for medical diagnostics and continuous monitoring because it can detect subtle variations in HR that may indicate arrhythmias, stress, or cardiovascular strain while we integrate the proposed system with diagnostic algorithms, which will be discussed later in this study.

The outdoor temperature and humidity readings from the DHT22 sensor are compared with the actual data from the hygrometer inside the healthcare facility at different times throughout the day, as shown in Figures 7(a) and (b). Figure 7(a) displays a bar chart that compares actual outdoor temperatures with observed temperatures, featuring absolute error bars. In contrast, Figure 7(b) shows a scatter plot that illustrates observed humidity values against actual values, also including error bars.



(a) (b)

Figure 7. Comparison of environmental parameters obtained from the DHT22 sensor during healthcare monitoring: (a) temperature analysis—bar chart displaying error bars at different hours and (b) humidity analysis—scatter plot featuring error bars within the healthcare facility

The proposed system shows high accuracy in maintaining environmental conditions within a healthcare facility, with an average temperature deviation of 1.38 °C. This deviation is acceptable for general healthcare; however, tighter control may be necessary in sensitive areas such as operating rooms and neonatal ICUs to prevent bacterial growth and ensure patient comfort. Additionally, the 1.53% error margin for humidity is impressively good, aiding in infection prevention by reducing the transmission of flu viruses. These measurements align with weather forecast guidelines, indicating reliable performance for climate control in medical environments.

The carbon dioxide measurements taken from the carbon dioxide meter, along with the air quality readings from the MQ135 sensor inside the treatment room, are displayed in Figure 8.

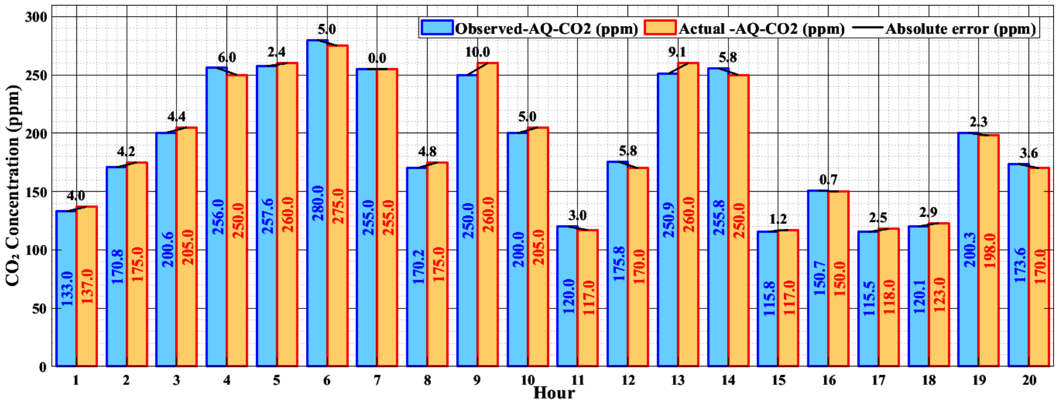


Figure 8. The bar graph with error bars compares the observed air quality versus actual air quality at different hours inside the healthcare treatment

These readings show that the measured CO_2 levels closely match the actual levels, with an absolute air quality error of about 4.6 ppm. This performance allows for clinically reliable CO_2 monitoring, helping healthcare facilities optimize ventilation, reduce infection risks, and enhance occupant well-being. These measurements comply with occupational safety standards, such as those set by OSHA and NIOSH, for indoor air quality in healthcare settings. Additionally, they suggest that the air quality is satisfactory and meets the Weather Foundation's standards, which define healthy air as having a CO_2 concentration between 0 and 1000 ppm.

The RMMS-IoT system uses the AD8232 ECG module HR sensor to monitor coronary heart disease. It extracts a patient's P-QRS-T features from the ECG, providing detailed information about heart health and necessary interventions. A new algorithm is implemented to facilitate ECG modeling, providing in-depth insights into heart health. This information is crucial for assessing patient health and identifying potential heart issues. Continuous monitoring of vital signs is essential for detecting arrhythmias, which can vary in severity and require immediate medical attention. The system integrates advanced analytics to deliver real-time alerts, enhance patient outcomes, and enable proactive healthcare interventions. MATLAB can access data from Blynk Cloud Datastreams using the Blynk Cloud HTTP API, improving modeling effectiveness. Figure 9 illustrates a normalized ECG obtained from the Blynk Cloud Datastreams.

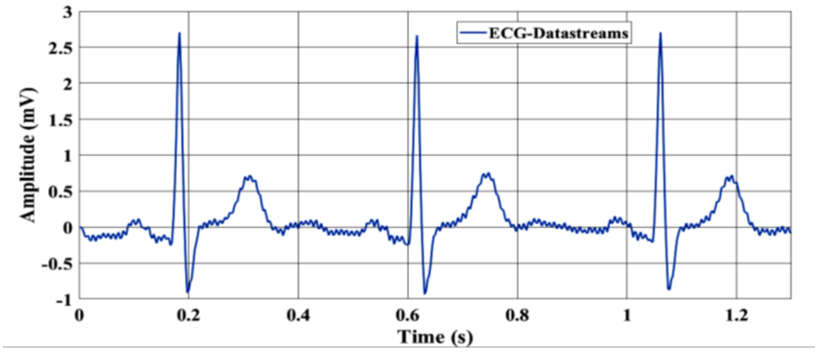


Figure 9. The ECG extracted from the Datastreams of the Blynk Cloud

The proposed RMMS-IoT framework incorporates a new algorithm that enables medical staff to extract the P-QRS-T components from an ECG. Physicians run the algorithm using MATLAB's "webwrite" function every 0.1 seconds, utilizing Blynk's HTTP GET tools. The ECG data from Figure 9 is first improved to get rid of noise from different devices [20], and then it is sampled at a rate of 360 Hz from the MIT/BIH database. Figure 10 shows the block diagram of the newly developed algorithm, which allows for the extraction of P-QRS-T features of ECG.

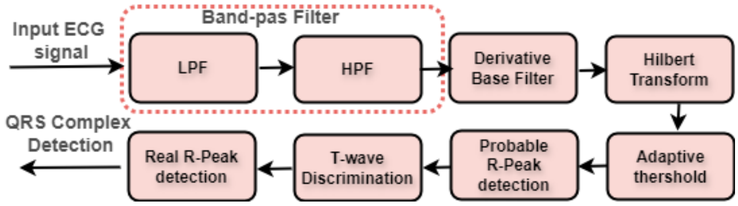


Figure 10. Block diagram representation of the developed algorithm for detecting P-QRS-T features of ECG

The model's algorithm consists of bandpass filtering, which includes cascading low-pass and high-pass filters (HPF), a derivative base filter (DBF), HT, squaring, and T-wave discrimination. The LPF effectively reduces higher-frequency noise components, particularly those from the 50 Hz power line and electromagnetic interference. The proposed LPF is a stable type of FIR filter, featuring a cutoff frequency of 22 Hz and an order of 12. The output FIR LPF is (1):

$$y(n) = 2y(n-1) - y(n-2) + 0.03.\left(x(n) - 2.x(n-6) + x(n-12)\right) \quad (1)$$

Figure 11 displays the ECG signal after the FIR and LPF. The ECG filtered signal shows a smoother waveform, indicating that high-frequency noise has been effectively removed.

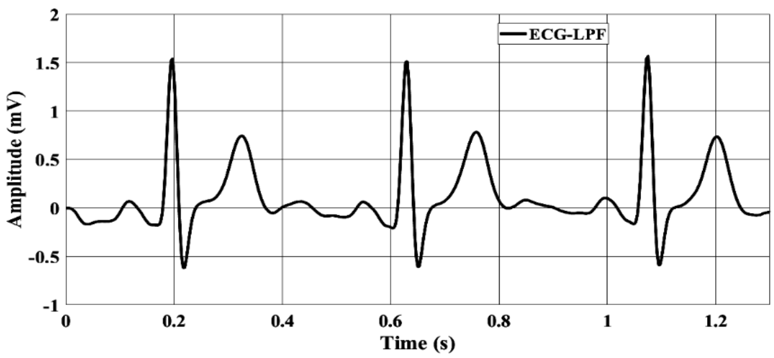


Figure 11. The ECG signal after the FIR LPF

The output of the FIR and LPF is directed into the Butterworth HPF with a minimal cutoff frequency of 0.5 Hz and order 33, which is suitable for removing baseline wander in ECG signals caused by motion artifacts. The output difference equation for the HPF is (2):

$$y(n) = y(n-1) - 0.03.\left(x(n) - 32.x(n-16) + 32.x(n-17) - x(n-32)\right) \quad (2)$$

The ECG signal after the Butterworth high pass-filter is shown in Figure 12.

A DBF of order 4 receives the filtered ECG signal to highlight its high-frequency components. This filter helps find the QRS complex in relation to the P and T waves and stops the signal's baseline from wandering. The output of DBF is expressed as (3):

$$y(n) = 0.25\left(x(n) - x(n-4)\right) + 0.125\left(x(n-1) - x(n-3)\right) \quad (3)$$

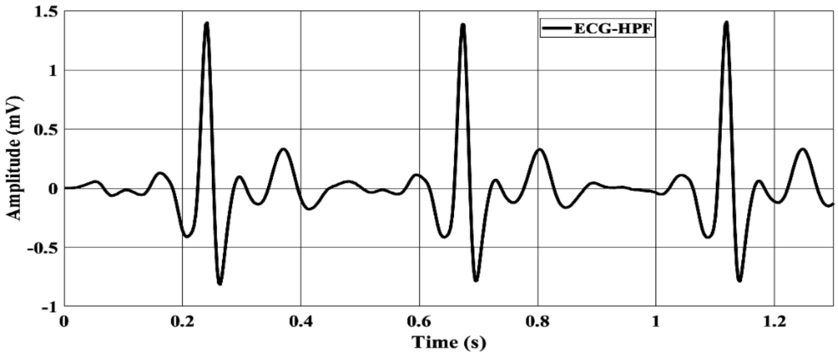


Figure 12. The ECG signal after Butterworth HPF

The ECG signal processed with the DBF is shown in Figure 13. The DBF enhances the clarity of R-peaks, aiding their identification in noisy signals. Additionally, it minimizes slow variations while preserving rapid changes in the QRS complex.

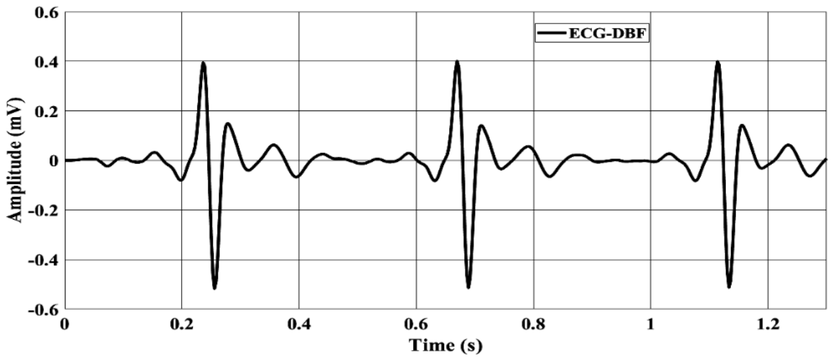


Figure 13. The ECG signal after DBF

The HT locates the R-peak of the derived ECG signal via the DBF filter. We square the output of the HT to accentuate the higher frequency components and diminish the lower frequency components. This method aids in attenuating the P- and T-waves. The probable R-peak is the signal's greatest value in a window after the HT point. The data shows that these peaks are fake and differ from the R-peak by a few milliseconds. We reduce HT output noise using an adaptive threshold. After identifying likely R-peaks, we apply RMS-ECG to distinguish the T wave. We set the maximum amplitude inside a 200-ms frame to identify true and potential R-peaks. Once the R-peak is detected, we select a window of 6 samples around the R-peak (3 samples to the left and 3 samples to the right). So, the Q-point is the minimum value in the left window (before the R-peak), and the S-point is the minimum value in the right window (after the R-peak). Figure 14 shows the detected P-QRS-T features within 3 R-R intervals via the developed algorithm.

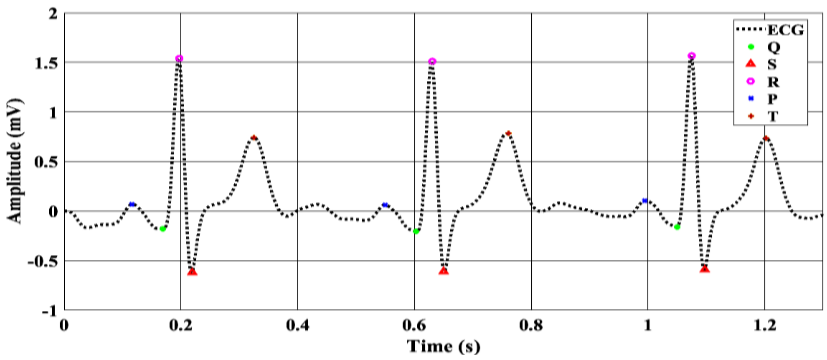


Figure 14. Detection of P-QRS-T features within 3 R-R intervals by the developed algorithm

The suggested algorithm detects P, QRS, and T waves in ECGs. The QRS complex has three waves Q, R, and S. The cardiac impulse running through the ventricles generates all these waves. P waves and QRS complex components are depolarization waves. T waves represent repolarization waves. Thus, depolarization and repolarization waves dominate the ECG. Table 1 shows how the proposed algorithm was tested by gathering patient ECG segments recorded in the Blynk Bridge interface and comparing them to standard ECG features.

Table 1. Amplitude and duration of waves, intervals, and segments of ECG from patients identified by the proposed algorithm

Patient N°	ECG Features								
	Amplitude (mV)			Duration (ms)					
	P-wave	QRS-complex	T-wave	P-wave	PR-interval	QRS-complex	ST-segment	T-wave	RR-interval
1	0.1	1.6	0.7	60	81	97	60	133	436
2	0.2	1.2	0.4	100	150	110	100	150	745
3	0.1	1.2	0.5	70	110	90	70	110	510
4	0.15	1.4	0.3	110	140	95	110	140	729
5	0.25	1.2	0.3	102	161	100	102	151	812
6	0.15	1	0.25	112	183	91	120	168	879
7	0.12	1.5	0.32	103	162	92	119	182	855
8	0.2	1.25	0.27	133	171	95	125	175	951
9	0.15	1.5	0.31	63	120	80	64	101	502
10	0.2	1.4	0.3	80	123	82	63	100	540
11	0.1	1.5	0.22	125	205	104	147	200	1095
12	0.15	1.3	0.25	75	120	80	67	102	520
13	0.12	1.2	0.3	70	110	82	49	104	435
14	0.2	1.5	0.27	107	155	85	92	132	730
15	0.15	1.7	0.2	73	121	79	63	105	445
16	0.2	1.3	0.3	110	180	90	120	160	880
17	0.13	1.5	0.28	100	162	95	119	147	810
18	0.2	1.43	0.3	98	151	90	122	153	765
19	0.17	1.52	0.26	104	160	105	124	154	729
20	0.19	1.4	0.25	85	115	82	61	120	530

A cardiac arrhythmia is characterized by abnormal contractions of the heart muscle, indicating any problem with heart rhythm. The sinoatrial (SA) node, located in the wall of the right atrium, is responsible for controlling cardiac rhythm. A regular sinus rhythm exhibits minor cyclical fluctuations and specific intervals: P-R intervals range from 0.12 to 0.20 seconds, T-waves from 0.01 to 0.25 seconds, RR intervals from 0.6 to 0.12 seconds, P-waves from 0.06 to 0.12 seconds, and both QRS complex and ST-segment durations from 0.08 to 0.12 seconds. Additionally, the amplitude of the QRS complex is typically less than 1.7 mV, while the amplitudes of the P and T waves range from 0.1 to 0.3 mV [11]-[21]. In a normal heart, atrial contraction is generally followed by ventricular contraction. Arrhythmias arise when this rhythm becomes irregular, excessively rapid (known as tachycardia, 300 ms≤RR-interval≤600 ms), or excessively slow (known as bradycardia 1000 ms≤RR-interval≤2000 ms) or when there is a divergence between atrial and ventricular beats. The diagnostic capability lies in the ability to correlate ECG signal characteristics with cardiac function.

The performance of the developed algorithm is evaluated using three statistical indices: accuracy (Acc%), sensitivity (Se%) and specificity (Sp%) [11].

- Accuracy (Acc%) measures the overall performance across all classes of heartbeats. It indicates the ratio of correctly classified patterns to the total number of patterns classified. This ratio offers helpful information regarding the effectiveness of the proposed algorithm for detecting the P-QRS-T features of the ECG and is written as (4):

$$Acc(\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (4)$$

where TP stands for true positive beats, signifying the accurate classification of normal ECG features as normal. FP denotes the number of false positives, meaning abnormal ECG features are incorrectly classified as normal. When we mistakenly label normal ECG parameters as abnormal, we display the number of false negatives (FN). Lastly, TN stands for true negatives, meaning abnormal ECG parameters are accurately classified as abnormal.

- Sensitivity (Se%), also known as recall, measures a model's ability to accurately identify true positive labels among all events and is expressed as (5):

$$Se(\%) = \frac{TP}{TP+FN} \times 100 \quad (5)$$

- Specificity (Sp%) measures how accurately the model identifies negative instances. A high level of specificity means that the algorithm detects false negatives with little to no false positives and is given by (6):

$$Sp(\%) = \frac{TN}{TN+FP} \times 100 \quad (6)$$

In the test shown in Table 1, we applied the P-QRS-T detection algorithm to ECG data from twenty patients and checked how it matched up with the standard P-QRS-T features in [13], [14]. Based on the confusion matrix, TP=10, TN=8, FP=1, and FN=1. Therefore, for the P-QRS-T data used, we get: Acc(%)=(10+8)/(10+8+1+1)×100=90%, Se(%)=10/(10+1)×100=90.9% and Sp (%)=8/(8+1)×100=88.88%.

The suggested RMMS-IoT can collect and analyze ECG data using a developed algorithm to detect ECG features. We tested it on 20 patients in treatment room, and it accurately identified 18 of them, achieving an overall accuracy of 90%. This evidence suggests strong overall performance in distinguishing between the two classes (normal and abnormal ECG patterns). The algorithm is excellent at finding real health problems, as it correctly identified 10 out of 11 actual abnormal cases and only missed 1, meaning it rarely overlooks abnormal ECG features. Furthermore, the proposed algorithm shows a good specificity of 88.88%; it correctly identified 8 out of 9 normal cases and only misclassified 1 normal case as abnormal FP. It suggests a satisfactory ability to confirm healthy cases with occasional overcalls.

5. CHALLENGES AND ISSUES OF THE PROPOSED RMMS-IoT SYSTEM

The proposed RMMS-IoT system offers potential personal health benefits; however, developing efficient and secure data-collecting schemes for IoT healthcare-monitoring systems continues to face several significant challenges. This section addresses various open research issues, including:

- The sample size of patients is crucial for data reliability and validity, but recruiting enough participants while maintaining privacy and security is a challenge. Effective data analysis requires external processing systems, robust data management protocols, and the adoption of 5G and 6G transmission technologies for real-time health monitoring and high transfer speeds in treatment rooms.
- Delays in data transfer can compromise patient information safety during IoT monitoring, as latency time is a key indicator of (QoS) for the proposed RMMS-IoT system. Monitoring memory consumption is essential to prevent leaks or improper data storage. Wireless connectivity issues can cause unexpected connections, weak signals, and slow network speeds, further affecting the QoS. Therefore, timely data transfer is critical to preserving the safety of patient information [22].
- The proposed system's devices consume significant power, causing issues like wireless interference when battery charge is low. The sensors lack sufficient power, causing problems [22]. To address this, green energy and renewable technology should be prioritized to enable IoT monitoring systems to function on low power.
- The RMMS-IoT system protects medical records from hackers, focusing on user authentication, data ownership, and preventing misuse. It adheres to HIPAA and GDPR regulations, ensuring secure data transmission and identity protection [22]. Figure 15 illustrates the design of our system, emphasizing a robust security framework that incorporates layer-level encryption, user authentication, and adherence to GDPR and HIPAA regulations.

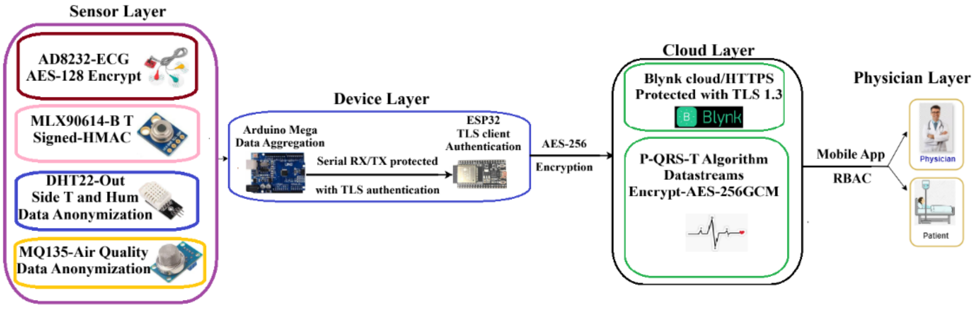


Figure 15. The proposed RMMS-IoT security architecture ensures compliance with GDPR and HIPAA while implementing measures for threat mitigation

The suggested system protects the sensor layer by using encryption on the connected Arduino Mega microcontroller. It uses AES-128 encryption for ECG data and hash-based message authentication code (HMAC) to sign each patient's body temperature reading. Additionally, the system anonymizes outside temperature, humidity, and air quality values. These measures are vital in healthcare facilities to balance clinical monitoring with privacy protection and to address potential threats. This encryption approach emphasizes security and ensures compliance with GDPR and HIPAA.

The device layer, which includes Arduino Mega and ESP32 microcontrollers, ensures the security of their serial communication (RX/TX) by utilizing the transport layer security (TLS) protocol. This protocol encrypts data transmission from the UART and I2C buses on the Arduino Mega. Additionally, ESP32 incorporates Secure Boot to prevent threat mitigation and firmware tampering. These measures are essential for GDPR/HIPAA.

The cloud layer, integrated with Blynk and HTTPS, is essential for ensuring the security, confidentiality, and compliance of medical data transmitted between an ESP32 and Blynk Cloud. This integration plays a vital role in preventing data interception by malicious actors. TLS 1.3 is used to encrypt all communications between the ESP32 and the cloud, utilizing either WiFi or Bluetooth and employing AES-256 as the encryption algorithm to secure the data. The Blynk Cloud chose AES-256-GCM for the secure P-QRS-T algorithm and the Datastream records, and they use ECDHE to safely share keys. For authentication purposes, Blynk provides a valid SSL certificate. Furthermore, the ESP32 has the option to implement a client certificate for mutual TLS (mTLS) [23]. The outlined requirements help maintain compliance with GDPR and HIPAA regulations.

The physician layer utilizes role-based access control (RBAC) as implemented by Blynk Cloud to enforce stringent data access policies between doctors and patients [23], [24]. This approach helps mitigate critical threats in the proposed RMMS-IoT system, ensuring that each patient can view their vital data without gaining access to others' information. This structure prevents data leakage between patients, thus preserving privacy in compliance with GDPR regulations. Doctors can access real-time data for their assigned patients; however, they are restricted from deleting or modifying raw data. Additionally, HIPAA mandates the protection of medical records from tampering.

The prototype for monitoring patients' vital signs, based on WHO guidelines, demonstrated efficient healthcare results, but challenges in data encryption and robust protocols remain. The reliability of the system in healthcare environments was assessed against other protocols, emphasizing data integrity and privacy, as well as compliance with HIPAA and GDPR, as detailed in Table 2.

Table 2. A comparative analysis of recent health monitoring systems and protocols, in relation to the proposed model, focuses on data integrity and privacy

Ref	Findings	Limitations
[3]	- Utilizes TLS encryption for data integrity. - Incorporates QoS levels for reliable message delivery in lossy networks. - QoS levels 1 and 2 ensure message delivery, despite additional overhead.	- MQTT effectiveness depends on proper implementation, with client errors or poorly configured TLS setups compromising security. - Can lead to unauthorized access to patient data. - Lacks HIPAA compliance audit logs. - Keep-alive packets can drain power from low-energy sensors.
[25]	- Provides strong encryption options: server-side encryption (SSE) and Amazon Web Services (AWS) Key Management Service. - Enables pre-encryption before upload using AWS SDKs. - Prevents unauthorized data access/modification. - It complies with stringent regulatory standards for data integrity as mandated by HIPAA and GDPR.	- The dependence on cloud services poses continuous risks to data security. - AWS does not provide automatic alerts for file modifications, which means that malicious actors could potentially alter data without being detected.
[26]	- The transport layer uses DTLS for data encryption. - Integrity depends on specific implementation and confirmable message utilization. - Block-wise transfer is beneficial for handling large payloads. - Data privacy encryption Protocol - This DTLS protocol ensures data privacy at the transport layer. - It aligned with HIPAA and GDPR requirements	- Privacy depends on specific implementation and data management. - Lower adoption rates compared to HTTPS and Blynk. - High risk of packet loss or leakage unless managed well. - Security weaknesses can arise from client errors or inadequate TLS configuration.
Our system	- Enhances telemedicine effectiveness, and it uses wearable technologies for health monitoring. - Employs HTTPS and Blynk Bridge clouds, where HTTPS encryption ensures strong encryption and security. - P-QRS-T characteristics in ECGs are identified through HTTPS encryption. - It is oriented to HIPAA/GDPR regulations.	RMMS-IoT faces these challenges - Latency and inaccurate readings. - Importance of security, reliability, and interoperability. - Potential impact on critical care decisions. - Resource-intensive, potentially impacting device responsiveness

6. CONCLUSION

This study presents a novel, secure, and multi-functional healthcare monitoring system featuring an integrated multi-sensor design. The system is capable of high-precision measurements that achieve medical-grade accuracy in compliance with AHA, WHO, and ASHRAE standards. It includes advanced P-QRS-T ECG feature detection to facilitate detailed cardiac analysis for early arrhythmia diagnosis with high accuracy. Additionally, it employs a secure IoT architecture that combines HTTPS and Blynk to ensure data privacy, integrity, and safety during real-time patient monitoring. However, to achieve its full potential, the system requires multicenter clinical validation across diverse patient demographics and health conditions. Immediate future work will focus on AI integration to enhance the ECG analysis with real-time arrhythmia prediction and automated disease detection. Subsequent development will pursue open dataset benchmarking and large-scale deployments in smart hospital ecosystems. Looking ahead, blockchain technology could enhance data security and facilitate seamless interoperability across healthcare networks, paving the way for next-generation preventive and diagnostic healthcare.

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All authors made significant contributions to the development of this paper. Rostom Khalef oversaw the conceptualization and supervision of this research. Additionally, all authors engaged in the review and editing of the manuscript. Rostom Khalef serves as the corresponding author and will manage all communication regarding this work.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state that they have no conflicts of interest.

INFORMED CONSENT

All participants in this paper gave their informed consent.

DATA AVAILABILITY

This paper does not involve any data that requires availability for admission.

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