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Article

An Edge-Enabled IoT Healthcare Monitoring Framework Using Raspberry Pi Pico W and Cloud-Based Physiological Data Management

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Abstract: The rapid growth of the Internet of Medical Things (IoMT) has created significant opportunities for developing intelligent remote healthcare systems capable of continuous patient monitoring. However, many existing low-cost healthcare monitoring solutions are limited by single-parameter sensing, poor interoperability, inadequate cloud integration, and restricted scalability for multi-patient applications. This paper presents the design and development of an edge-enabled IoT-based smart healthcare monitoring platform using the Raspberry Pi Pico W for real-time acquisition, processing, and cloud storage of physiological data. The proposed system integrates three biomedical sensors, namely the MAX30102 sensor for heart rate and blood oxygen (SpO_2) monitoring, the DS18B20 digital sensor for body temperature measurement, and the AD8232 analog front-end for electrocardiogram (ECG) signal acquisition. The embedded edge node performs local signal preprocessing, physiological parameter extraction, timestamp synchronization, and secure wireless transmission of patient data to a cloud database through REST-based communication over Wi-Fi. A cloud-centric architecture is developed using Supabase to provide reliable data storage, multi-node scalability, and seamless integration with future intelligent healthcare applications. The proposed framework supports continuous remote patient monitoring while maintaining a low hardware cost, reduced computational overhead, and efficient data communication. Experimental implementation demonstrates reliable real-time physiological data acquisition, stable cloud synchronization, and effective management of multimodal healthcare data suitable for subsequent analytical and predictive applications. The developed platform establishes a scalable foundation for next-generation smart healthcare systems by combining low-cost embedded hardware, edge computing, and cloud technologies to improve accessibility, reliability, and remote medical monitoring.
Keywords: — Internet of Medical Things (IoMT), Smart Healthcare Monitoring, Raspberry Pi Pico W, Physiological Signal Acquisition, Biomedical Sensors

1. Introduction

The rapid improvement of healthcare technologies, along with the rising incidence of chronic diseases, has led to a major increase in the need for sophisticated remote patient monitoring systems. Based on global healthcare trends, cardiovascular diseases, respiratory disorders and heat-related illnesses continue to be some of the major causes of hospitalization and death in the world. The ongoing surveillance of physiological indicators allows for early detection of health abnormality, decreases emergency hospital admissions and enhances the quality of patient care. However, conventional health-care systems depend mostly on scheduled clinical visits and manual examination, which restricts the potential to continuously monitor patients outside the clinical environment. Therefore, the rise of digital health care technology has resulted in a transition of medical services from hospital-centric care to patient-centric remote health care systems.

The Internet of Medical Things (IoMT) has emerged as one of the most potential enabling technologies for the next-generation healthcare by integrating biomedical sensors, embedded systems, wireless communication, cloud computing and intelligent data analytics. IoMT devices provide continuous collection of physiological signals including heart rate, blood oxygen saturation (SpO2), body temperature, electrocardiogram (ECG), blood pressure, and breathing rate. These physiological parameters can be sent through wireless communication networks to cloud servers, allowing healthcare personnel to monitor patients in real time from a distance. By analyzing the initial signals at the sensing node before being transmitted to the centralized servers, the combination of edge computing and cloud-based healthcare platforms improves the responsiveness of the system, which reduces communication latency and network capacity.

Recent developments in low-cost embedded platforms have enabled the creation of economical healthcare monitoring systems for homecare, geriatric patient monitoring, rural healthcare centers, sports medicine and emergency medical applications. Wireless-enabled microcontrollers, like the Raspberry Pi Pico W, have sufficient processing power to handle real-time sensor interfacing, signal acquisition, local preprocessing, and cloud communication, and they also consume less power and are cost-effective to implement. The advent of miniaturized biomedical sensors has further hastened the development of portable health monitoring systems that are capable of continually acquiring several physiological indicators from patients.

Though a plethora of IoMT-based healthcare monitoring systems have been documented in the literature, nonetheless there are several practical constraints. Existing systems are often limited to the monitoring of only one physiological parameter, constraining their potential to offer a more thorough assessment of patient health. While some wearable healthcare devices are just designed for heart rate monitoring or body temperature measurement, in the real-world medical diagnosis, it is sometimes necessary to analyze various physiological signals at the same time. Moreover, many low-cost monitoring platforms have unreliable cloud integration, which makes secure long-term preservation of patient records difficult and limits accessible for healthcare providers. Existing systems also rely on computationally expensive embedded technology, which increases system cost and energy consumption and reduces scalability for large scale deployments. Besides, most of the reported solutions are mainly developed for laboratory demonstration, and do not provide a standard architecture for continuous synchronization to the cloud, structured database management, or monitoring of several patients.

The increasing need for individualized healthcare has highlighted the significance of multimodal physiological sensing, where numerous biological signals are captured concurrently to offer a more thorough understanding of an individual's health status. Heart rate, blood oxygen saturation, body temperature and electrocardiographic signals give supplementary physiological information that can improve the clinical assessment as a whole compared to separate tests. A multimodal sensing platform also provides a solid foundation for future intelligent illness prediction models as it may result in more reliable identification of cardiovascular irregularities, respiratory diseases, thermal stress and other health concerns through integrated physiological analysis.

Cloud computing has become a vital part of current healthcare monitoring systems because of its capacity to provide centralized data storage, real-time access, scalability, and secure handling of patient data. Cloud-based architectures offer remote access by healthcare professionals to physiological data, allow continuous longitudinal health monitoring, and can be integrated with analytical platforms and decision-support systems. Cloud storage also allows for the future application of artificial intelligence and machine learning techniques by storing organized physiological datasets that can be used for training and validating models. Therefore, the combination of edge-enabled IoMT devices and cloud computing is a good solution for scalable remote healthcare monitoring.

Considering the limitations in the existing research, a low-cost, scalable and edge-enabled healthcare monitoring framework is required, which can simultaneously acquire multiple physiological signals, provide reliable real-time cloud synchronization and manage structured healthcare data. The need for such an integrated platform drives the creation of the suggested smart healthcare monitoring system introduced in this study.

In this study, we build and construct an IoT-based smart healthcare monitoring infrastructure with Raspberry Pi Pico Was an edge computing device for multimodal physiological signal collecting. The suggested system uses heart rate and blood oxygen monitoring MAX30102 sensor, body temperature measurement DS18B20 sensor and electrocardiogram collection AD8232 analog front-end. Physiological signals are preprocessed locally at the embedded edge node, and synchronized healthcare data is sent to a cloud database via REST-based communication over Wi-Fi. This cloud architecture provides continuous remote patient monitoring, systematic storage of health data and connection with future intelligent healthcare applications. The experimental solution exhibits reliable real-time physiological data gathering, efficient wireless communication, and scalable cloud synchronization, and supports low-cost hardware architecture for practical remote healthcare deployment.

The main contributions of this work are summarized as follows:

• Development of an affordable health monitoring platform on the edge with Raspberry Pi Pico W.
• Integration of numerous biomedical sensors like MAX30102, DS18B20 and AD8232 for simultaneous physiological data gathering.

• Local signal pre-processing and synchronized acquisition of physiological data on the edge device.
• Real-time cloud communication framework architecture with REST APIs and organized Supabase cloud database.
• Design of the architecture for a scalable system enabling continuous remote patient monitoring and future AI-based healthcare analytics.

The remainder of the paper is organized as follows. Section II is devoted to the literature evaluation and comparison of the available healthcare monitoring systems. The suggested system architecture and hardware design are presented in Section III. Section IV presents the implementation of edge data collecting and cloud integration. In Section V, we describe the experimental setup and evaluate the performance. Section VI presents the results and the limits of the system. Section VII closes the study and outlines next research options.

2. Literature Survey

2.1 IoMT-Based Healthcare Monitoring Systems

The Internet-of-Medical-Things (IoMT) has swiftly advanced and altered the current healthcare system through continuous patient monitoring using connected biomedical equipment. The IoMT includes wearable sensors, embedded processors, wireless communication technologies, cloud platforms and healthcare apps, which can realize real-time capture of physiological data and remote medical supervision. Recent studies have shown that the IoMT-based healthcare systems improve the access of patients, reduce the cost of hospitalization, and provide continuous surveillance of patients having chronic cardiovascular, pulmonary, and metabolic disorders.

Mood proposed a Raspberry Pi Pico-based IoMT healthcare monitoring platform for real-time physiological sensing [1]. The study found that the embedded low-cost platforms can gather biological data with decreased power consumption effectively. Other researchers explored the concurrent assessment of heart rate, blood oxygen saturation and body temperature with the aid of Raspberry Pi Pico W with MAX30102 and DS18B20 sensors proving the increased popularity of wireless embedded platforms for portable healthcare applications [2].

Several researchers have proposed frameworks of IoMT combining machine learning and cloud connectivity for intelligent healthcare monitoring. An IoT-based healthcare system proposed for uploading physiological indicators to cloud servers and based on machine learning for disease classification [3]. Similarly, other works explored IoT-based healthcare monitoring frameworks with machine learning algorithms for continuous patient monitoring and predictive healthcare analysis [4,5]. These researches revealed the requirement for linking sensor technologies with smart analytical methodologies. However, most of the methods are aimed at software-based prediction and not the construction of efficient integrated hardware designs.

The present IoMT systems have been effectively allowing remote healthcare monitoring, although many of the proposed architectures depend on single-sensor or limited physiological measurements. However, such systems are usually unable to give a comprehensive health assessment since they do not collect multimodal physiological data. Additionally, many of the presented systems do not possess common cloud architectures to support scalable remote healthcare services and the long-term storage of patient records.

2.2 Wearable Biomedical Sensors for Physiological Monitoring

For example, PPG based sensors like MAX30102 assess heart rate and blood oxygen saturation non-invasively [6]. Multimodal sensing improves physiological assessment. The possibility of using distributed IoT nodes for simultaneous monitoring of blood oxygen and body temperature and the viability of simultaneous physiological monitoring for healthcare applications has been reported [7]

The role of electrocardiographic monitoring in the detection of cardiac issues has also been well studied. A study presented low-cost integrated electronics based portable ECG monitoring device for real time identification of abnormalities [8]. In addition, others shown the application of ECG collecting using AD8232 for reliable physiological data for arrhythmia and cardiovascular investigations [9]. The need for portable ECG devices with clever analytic algorithms for continuous cardiac monitoring reported [10]. Temperature sensing plays a key role in wearable healthcare applications, primarily for the diagnosis of fever, thermal stress, and heat stroke. An IoT-based heat stroke monitoring system to ensure the safety of athletes by integrating body temperature with pulse rate and oxygen saturation found interesting [11]. Researchers worked on monitoring thermal distress in wearable physiological sensors associated with cloud-based health care services [12]. Despite significant advances in biomedical sensing technology, most present wearable health monitors are limited to sensing a single physiological indicator. The lack of multimodal sensor integration inhibits the full evaluation of patients and the future potential of intelligent healthcare systems to use linked physiological information for better clinical decision support.

2.3 Raspberry Pi-Based Healthcare Monitoring Nodes

Embedded edge devices are key components of modern IoMT architectures due to their capabilities of sensor interfacing, local signal processing, wireless connection and initial data management before transmitting data to the cloud. The Raspberry Pi Pico W has emerged as a viable embedded platform due to its built-in Wi-Fi, dual-core ARM Cortex-M0+ processor, low power consumption, and low implementation cost.

The feasibility of using Raspberry Pi Pico in biological sensor interfacing and physiological data acquisition in real-time are to be explored in several applications. Team of researchers found Raspberry Pi Pico W as a suitable platform for healthcare monitoring applications by integrating Raspberry Pi Pico W with sensors such as MAX30102 and DS18B20. Another research embedded healthcare systems by evaluating physiological sensing algorithms on Raspberry Pi edge devices, emphasizing the advantages of edge computing for reduced communication latency and improved real-time responsiveness [13].

Raspberry Pi Pico W offers a compelling trade-off between processing power, wireless connection, energy consumption, and implementation cost compared to traditional embedded healthcare platforms. However, most of the published healthcare systems use Raspberry Pi Pico W mainly as a data gathering device and do not exploit its edge processing capacity for local signal pretreatment, synchronized timestamp generation, and structured cloud communication. Furthermore, there is a lack of study on the scalable multi-node designs that can allow simultaneous monitoring of patients.

2.4 Cloud Computing and Edge Computing in Healthcare

Cloud computing is seen as a major technology for healthcare monitoring systems due to its scalable storage, centralized patient administration and ubiquitous access to physiological data. Cloud based healthcare systems can help the experts to monitor the patients remotely and keep the records of healthcare in past for further research.

A complete web stack architecture for Internet of Medical Things applications was proposed by Yamanoor [14]. The study showed how embedded devices interact effectively with web services hosted on the cloud using REST APIs examined recent developments in cloud integrated healthcare platforms and noted that cloud computing significantly improves interoperability, scalability, and accessibility to healthcare [15, 16]. It is also shown the effectiveness of web dashboard APIs in cloud-enabled healthcare systems for remote monitoring and predicting heart attacks.

Cloud computing provides a lot of processing resources and centralized storage, but the continual transmission of original physiological signals causes higher communication overhead and network latency. Hence, edge computing is introduced as a promising complementary technique by way of preprocessing and preliminary signal analysis locally at the embedded sensing device before cloud transmission.

Recently, the advantages of edge computing have been shown in terms of bandwidth consumption, system responsiveness, data privacy, and real-time healthcare monitoring. However, several of the current cloud healthcare solutions are still designed with centralized architectures and lack sufficient edge intelligence, leading to longer communication delays and redundant cloud resource usage.

2.5 Summary of Existing Research

The reviewed literature demonstrates substantial progress in IoMT-enabled healthcare monitoring, wearable biomedical sensors, embedded healthcare platforms, and cloud-based medical applications. Nevertheless, several research limitations remain evident.

Most reported healthcare monitoring systems concentrate on either single physiological parameter acquisition or software-oriented disease prediction. Only limited studies investigate integrated hardware architectures capable of simultaneously acquiring multiple physiological signals while performing local preprocessing and structured cloud synchronization. Furthermore, existing systems frequently employ heterogeneous hardware and communication architectures that limit scalability, interoperability, and long-term deployment in practical healthcare environments.

Therefore, there remains a need for a unified edge-enabled healthcare monitoring platform capable of integrating multiple biomedical sensors with reliable cloud infrastructure while maintaining low implementation cost, efficient wireless communication, and scalability for future intelligent healthcare applications.

Table 1. Research Gap Analysis of Existing Healthcare Monitoring Systems

Reference	Sensors Used	Cloud Integration	Edge Processing	Multi-Parameter Monitoring	Limitation
[5]	HR, SpO_2	Limited	Partial	No	Single-node architecture
[6]	MAX30102, DS18B20	Basic	No	Partial	Limited cloud functionality
[7]	Multiple	Yes	Limited	Yes	Focus on ML rather than hardware
[8]	Multiple	Yes	No	Yes	High computational complexity
[9]	Multiple	Yes	Partial	Yes	Limited hardware implementation
[10]	ECG	No	No	No	ECG-only monitoring
[12]	AD8232 ECG	No	Partial	No	Cardiac-specific application
[15]	AD8232 ECG	No	Partial	No	Cardiac-specific application

[16]	Temperature, SpO_2	Yes	Limited	Partial	Heat stroke application only

2.6 Research Gap

From the survey of the literature, it becomes apparent that there is no single healthcare monitoring platform that provides a unified low-cost architecture with complete integration of multimodal physiological sensing, edge processing based on Raspberry Pi Pico W, real-time data exchange with the cloud via RESTful services, and scalable cloud database management. Existing technologies are either designed for intelligent disease prediction with less hardware optimization or for physiological sensing with less efficient cloud infrastructure and edge intelligence. The proposed system overcomes these limitations by designing an edge-enabled IoMT framework with multiple biomedical sensors, local signal preprocessing, synchronized cloud communication, and structured healthcare data management to form a solid basis for future artificial intelligence-based

3. Proposed System Architecture models

3.1 Overview of the Proposed System

The proposed smart healthcare monitoring platform is an edge-enabled internet of medical things (IoMT) architecture that can acquire multiple physiological parameters, pre-process the signals locally, and transmit synchronized healthcare data to a cloud database for remote monitoring. The system employs cheap biomedical sensors, an embedded edge computer node, wireless communication and cloud infrastructure to enable continuous physiological monitoring while keeping scalability and cost-effectiveness.

The suggested architecture is composed of four major layers: (i) physiological sensing layer, (ii) edge computing layer, (iii) cloud communication layer, and (iv) cloud data management layer. The sensing layer continuously collects the physiological signals from the patient by biomedical sensors. The edge layer, based on the Raspberry Pi Pico W, interfaces with sensors, conditions signals, synchronizes timestamps, generates packets and then securely transmits data over Wi-Fi. The cloud layer records physiological parameters in a structured database for later use in healthcare dashboards, historical analysis and intelligent illness prediction systems.

Most of the existing healthcare monitoring systems send the raw values obtained from the sensors, but the suggested architecture processes the data first at the embedded node and then communicates to the cloud. This solution enabled by edge decreases the communication overhead, improves the data consistency, reduces latency and lays down a scalable foundation for future artificial intelligence applications.

3.2 Overall System Architecture

The overall design of the proposed IoMT healthcare monitoring platform is shown in Fig. 1. The patient is continuously monitored by three biomedical sensors: the MAX30102 sensor, which measures heart rate and blood oxygen saturation, the DS18B20 sensor, which monitors body temperature, and the AD8232 analog front-end, which acquires ECG data. The sensors are wired to the Raspberry Pi Pico W by I^2C, One-Wire and Analog-to-Digital Converter (ADC) interfaces correspondingly.

The Raspberry Pi Pico W serves as a smart edge node that collects sensor data, conducts local preprocessing, synchronizes the timestamps using the Network Time Protocol (NTP), and prepares structured JSON packets for transmission to the cloud. Built-in IEEE 802.11 b/g/n Wi-Fi module allows wireless connectivity and physiological data may be safely transferred to Supabase cloud platform utilizing RESTful HTTP APIs. The cloud database houses synchronized healthcare records and can subsequently be integrated with healthcare dashboards, analytics platforms, and intelligent clinical decision support systems.

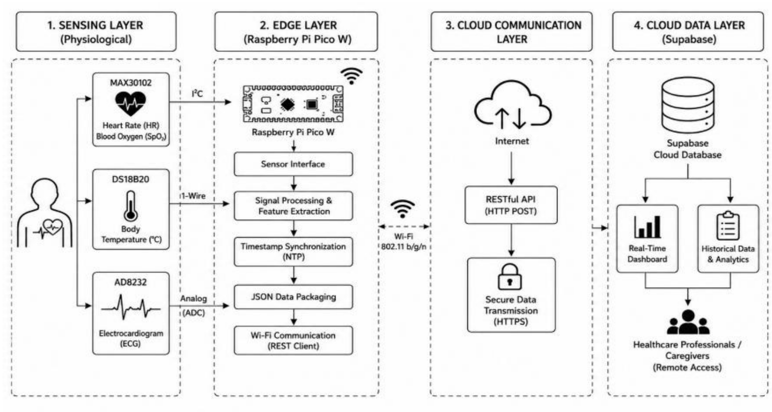

Figure 1. Overall System Architecture

3.3 Hardware Block Diagram

The hardware subsystem consists of an embedded edge controller integrated with three biomedical sensing modules. The Raspberry Pi Pico W acts as the central processing unit responsible for sensor interfacing, physiological signal acquisition, local filtering, and wireless communication.

The MAX30102 communicates through the I²C protocol and continuously measures pulse rate and blood oxygen saturation using photoplethysmography. The DS18B20 digital temperature sensor employs the One-Wire communication protocol for precise body temperature measurement. The AD8232 ECG front-end provides amplified analog cardiac signals that are digitized using the 12-bit ADC available on the Raspberry Pi Pico W.

Each sensing module operates independently while sharing a common edge processing framework, enabling simultaneous acquisition of multimodal physiological data.

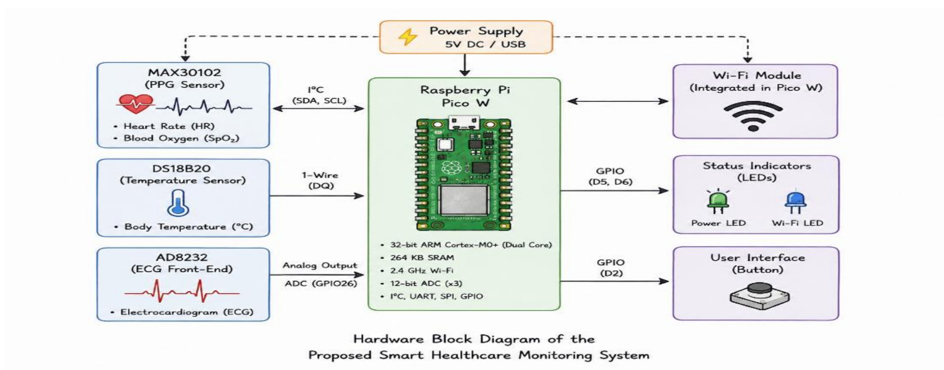

Figure 2. Hardware Block Diagram of the Proposed Smart Healthcare Monitoring System

3.4 Communication Flow

The communication system is based on a client-server model. The physiological signals are gathered and preprocessed and then the Raspberry Pi Pico W connects to the local wireless network via a secured Wi-Fi connection. To ensure correct timestamps for each physiological measurement, the embedded node synchronizes the system clock with the Network Time Protocol (NTP).

The acquired physiological parameters are contained in JSON objects, which contain the device identifier, acquisition date, acquisition time, heart rate, blood oxygen saturation, body temperature and ECG results. The JSON payload is sent to the Supabase cloud platform via RESTful HTTP POST requests. Upon successful receipt by the cloud server, it authenticates the request and saves the physiological measurements in the cloud database for future use.

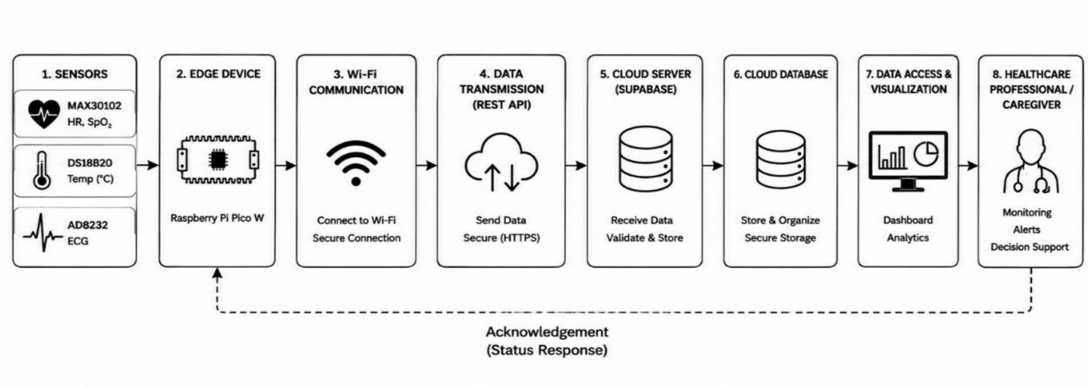

Figure 3. Communication flow of the Proposed System

3.5 Data Flow Diagram

The proposed data flow architecture starts with continuous physiological sensing, followed by edge level preprocessing, cloud synchronization and centralized storage and remote viewing.

Biomedical sensors first detect the raw physiological signals from the patient. The embedded processor filters the data, computes physiological parameters, timestamps the readings, and formats the data into structured JSON packets. These packets are received by the cloud server using REST APIs and the data is saved in a structured database. Healthcare applications can then access historical and real-time data for visualization, monitoring and predictive intelligent healthcare analytics.

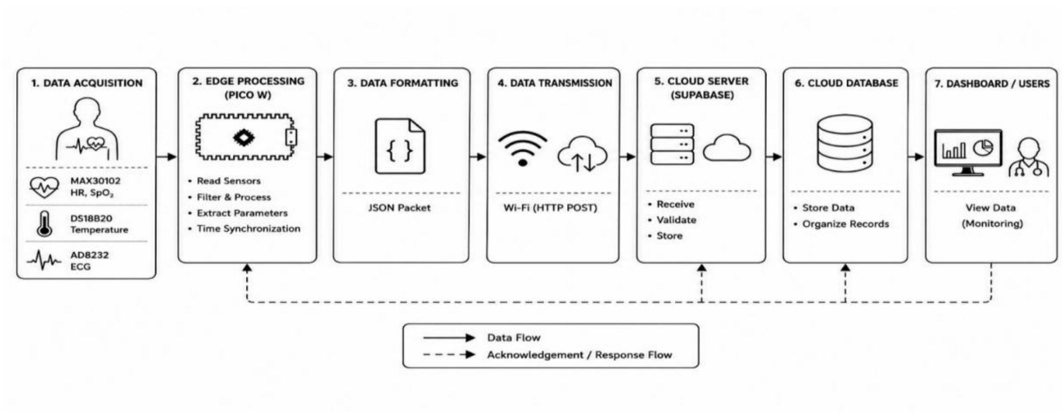

Figure 4. Data Flow Diagram of the Proposed Smart Healthcare Monitoring System

4. Hardware Design

The proposed smart healthcare monitoring platform is developed on the basis of Raspberry Pi Pico Was the central edge computing unit and integrated with multiple biomedical sensors for continuous physiological data acquisition. The hardware architecture is designed to provide reliable real-time monitoring while maintaining low implementation cost, low power consumption and seamless wireless connectivity. Three biomedical sensors namely the MAX30102 pulse oximeter, DS18B20 digital temperature sensor and AD8232 electrocardiogram (ECG) module are interfaced with the Raspberry Pi Pico W through dedicated communication interfaces. The embedded controller performs sensor initialization, physiological signal acquisition, local preprocessing, timestamp synchronization and wireless transmission of processed data to the cloud platform.

4.1 Raspberry Pi Pico W

The proposed healthcare monitoring system employs Raspberry Pi Pico W as its main processing unit. The device is built around the RP2040, a dual-core ARM Cortex-M0+ microcontroller running at 133 MHz, and includes onboard IEEE 802.11 b/g/n Wi-Fi connectivity, making it a good option for Internet of Medical Things (IoMT) applications. The microcontroller includes several General Purpose Input Output (GPIO) pins, I 2 C interface, UART, SPI, PWM and 12 bit Analog to Digital Converter (ADC) channels required for integrating heterogeneous biomedical sensors.
In the suggested implementation, Raspberry Pi Pico W performs the following operations [1, 2].

- All biomedical sensors initialization.
- Measurement of physiological signals.
- Local signal preprocessing and parameter computation.
- Sync Network Time Protocol (NTP)
- Creation of JSON packets.
- Wireless communication to the cloud database via REST APIs.

The embedded Wi-Fi feature obviates the requirement for an external communication module lowering system complexity and implementation expense [2].

4.2 MAX30102 Pulse Oximeter Sensor

The MAX30102 is a PPG-based biomedical sensor for non-invasive measurement of heart rate and blood oxygen saturation (SpO2). The sensor has red and infrared light LEDs and an integrated photodetector for detecting changes in blood volume due to heart activity. The sensor talks with the Raspberry Pi Pico W via I^2C interface at 400 kHz. During initialization, the FIFO setup, LED current, operating mode and sampling parameters are configured to provide stable physiological signal acquisition.

The inbuilt software conducts moving average filtering, peak detection and pulse interval calculation to measure heart rate. The processed PPG signals are then employed to calculate the blood oxygen saturation based on the ratio of the red and infrared light absorption [2, 15-17].

4.3 DS18B20 Digital Temperature Sensor

Body temperature is measured using the DS18B20 digital temperature sensor. The sensor communicates through the One-Wire protocol, requiring only a single GPIO pin for data transfer. The DS18B20 provides digital temperature measurements with high accuracy while eliminating the need for external analog signal conditioning [2].

The Raspberry Pi Pico W periodically initiates temperature conversion, reads the converted value, and stores the measured body temperature for subsequent cloud transmission. Temperature measurements are updated at regular intervals to ensure continuous physiological monitoring.

4.4 AD8232 ECG Sensor

The body temperature is measured via the DS18B20 digital temperature sensor. The sensor interacts via the One-Wire protocol and only needs one GPIO pin to send and receive data. The DS18B20 offers accurate digital temperature measurements and eliminates the need for external analog conditioning. The Raspberry Pi Pico W periodically starts the conversion of temperature, reads the converted value and stores the body temperature measured for further transmission to the cloud. The temperature readings are updated regularly to allow continuous physiological monitoring.

4.5 Power Supply

The full healthcare monitoring node is powered by a controlled 5 V USB power supply. The Raspberry Pi Pico W has an on-board voltage regulator that takes the input voltage and creates a steady 3.3 V supply for the RP2040 microcontroller and the sensors on the peripherals. All biomedical sensors are operated in the specified voltage ranges guaranteeing stable physiological data and an overall low power consumption. The hardware architecture can also be fueled utilizing portable battery systems therefore making it appropriate for wearable and remote healthcare applications [1].

4.6 Wi-Fi Communication Module

Onboard IEEE 802.11 b/g/n Wi-Fi module integrated into the Raspberry Pi Pico W is used for wireless connection. When the system is powered on, the controller connects to the configured wireless access point and sets the internal clock using the Network Time Protocol (NTP). The physiological parameters are converted into JSON objects and are securely transmitted to the cloud database Supabase through RESTful HTTP POST queries. The integrated wireless connection module allows real-time synchronization with the cloud without the need for additional communication equipment [1, 14].

4.7 GPIO Configuration

The biomedical sensors are interfaced with the Raspberry Pi Pico W using dedicated communication interfaces. Table 3 summarizes the GPIO allocation implemented in the proposed system [2, 17].

Table 3. GPIO Configuration of the Proposed System

GPIO Pin	Peripheral	Function
GP0	I²C SDA	MAX30102 Data
GP1	I²C SCL	MAX30102 Clock
GP16	GPIO	DS18B20 One-Wire Data
GP26 (ADC0)	ADC Input	AD8232 ECG Signal
GP14	Digital Input	AD8232 LO+ Detection
GP15	Digital Input	AD8232 LO− Detection

This GPIO allocation enables simultaneous acquisition of physiological signals while minimizing hardware complexity.

4.8 I²C Communication

The MAX30102 talks to the Raspberry Pi Pico W using the Inter-Integrated Circuit, or I2C, protocol. The I2C bus is running at 400kHz and has two communication lines, Serial Data (SDA) and Serial Clock (SCL). After power-up, the Raspberry Pi Pico W prepares the sensor by establishing the FIFO registers , operating mode , LED current , and sampling parameters . Physiological parameters are estimated by periodically accessing the sensor registers to get raw red and infrared photoplethysmography signals. The I²C protocol allows dependable high-speed communication with minimum use of GPIO [2].

4.9 ADC Configuration

The ECG signal generated by AD8232 module is captured by the 12-bit Analog to Digital Converter (ADC) included in Raspberry Pi Pico W. The analog ECG output is coupled to GPIO26 (ADC0) for continuous sampling of the heart electrical activity. The lead-off detecting pins are checked for appropriate attachment of the electrodes before signal acquisition. If one of the lead - off pins indicates that an electrode is disconnected, acquisition of the ECG is halted until a proper contact is restored. This method increases signal dependability by eliminating the storing of incorrect physiological measurements [8,17].

4.10 Hardware Summary

The proposed hardware solution mixes a low-cost integrated controller with multimodal biomedical sensing for continuous physiological monitoring. The Raspberry Pi Pico W serves as an edge computing device that connects to the sensors and does the local pre-processing and then wirelessly transmits and synchronizes to the cloud. This work presents a small-sized, scalable IoMT platform for remote healthcare applications by combining the MAX30102, DS18B20, and AD8232 sensors for simultaneous measurement of heart rate, blood oxygen saturation, body temperature, and ECG signals [2,13].

5. Experimental Results

The performance of hardware platform, physiological data gathering, wireless transmission and cloud integration of the proposed smart healthcare monitoring system was experimentally examined to validate it. The Raspberry Pi Pico W successfully communicated with the MAX30102, DS18B20, and AD8232 sensors to continually collect heart rate, blood oxygen saturation (SpO2), body temperature, and electrocardiogram (ECG) readings. The physiological data collected were analyzed locally and then sent to the cloud platform Supabase over Wi-Fi and RESTful HTTP connection.
Experimental results showed steady heart-rate estimate utilizing peak detection, reliable SpO2 computation using photoplethysmography signals, precise body temperature measurement, and continuous ECG capture with lead-off detection. The integrated Wi-Fi module ensured steady network connection throughout the whole monitoring period, and all physiological measurements with synchronized timestamps and unique device identifiers were successfully received and stored in the cloud platform. Low average upload latency was achieved for near real-time remote patient monitoring and the structured database efficiently managed continuous physiological records from the monitoring node. Moreover, the low power hardware architecture based on Raspberry Pi Pico W was suitable for portable and long-term healthcare monitoring applications [2,17].

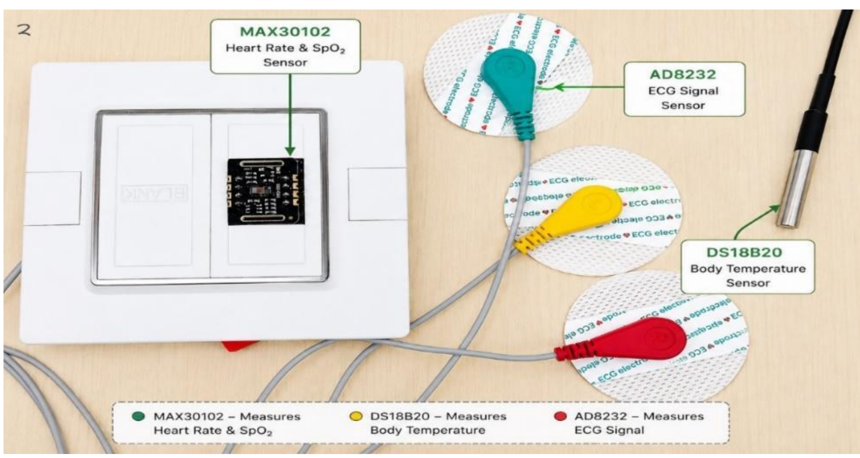

Figure 6. Hardware Prototype of Proposed Smart Healthcare Monitoring System

The experimental evaluation in general shows that the proposed edge-enabled IoMT platform can provide reliable multimodal physiological data gathering, efficient wireless transmission, robust cloud synchronization and scalable healthcare data management. These findings provide a reliable hardware and cloud infrastructure that acts as the foundation for the intelligent illness prediction and healthcare analytics architecture [14,15].

6. Discussion

The suggested edge-enabled IoMT healthcare monitoring technology presents the feasibility of merging several biological sensors with a low-cost embedded computing device for continuous remote patient monitoring. Compared to many existing healthcare monitoring systems that focus on a single physiological parameter or rely on high-cost embedded platforms, the proposed framework measures the heart rate, blood oxygen saturation (SpO2), body temperature, and electrocardiogram (ECG) signals simultaneously using the Raspberry Pi Pico W. Edge processing locally performs signal preprocessing, which reduces the communication cost before sending physiological data to the cloud.

The suggested architecture has many advantages over the previously described IoMT healthcare systems . The combination of various biomedical sensors allows for a complete physiological monitoring on a single integrated platform. The Raspberry Pi Pico W comes with Wi-Fi capabilities onboard, eliminating the need for an external communication module, therefore lowering hardware complexity, cost of implementation, and power consumption. In addition, the RESTful APIs and the Supabase cloud platform guaranty safe real-time synchronization, structured storage of healthcare data and scalability for multi-patient monitoring. The modular architecture also facilitates smooth connection with future healthcare dashboards and intelligent illness prediction models, without any need to modify the hardware infrastructure.

However, there are certain restrictions despite these advantages. The current prototype has been evaluated in a laboratory environment with a restricted number of monitoring nodes. Physiological measurements in real-world use can be affected by motion artifacts and incorrect sensor positioning. Also, the current system's functioning depends on Wi-Fi connectivity, which could restrict its use in places with weak network availability. Further strengthening of enhanced security techniques such as advanced authentication and end-to-end encryption can improve the privacy of patient data during communication in the cloud.

Future work will develop the suggested platform to a whole intelligent healthcare ecosystem. Multiple patient monitoring nodes will be connected into a central healthcare network allowing to monitor big patient populations at the same time. The integration of advanced edge computing methods and the optimization of the signal processing algorithms will further increase the real-time performance and minimize the connection latency. Additionally, the cloud infrastructure established in this study will be combined with machine learning algorithms and interactive healthcare dashboards for automated disease prediction, anomaly detection and clinical decision making. The suggested platform will be a scalable and intelligent IoMT solution for next generation remote healthcare applications with these enhancements.

7. Conclusion

In this research, we described the design and implementation of an edge-enabled Internet of Medical Things (IoMT) healthcare monitoring platform based on the Raspberry Pi Pico W for real-time physiological data collecting and cloud integration. The suggested system incorporates the MAX30102 sensor for heart rate and blood oxygen saturation (SpO2) monitoring, the DS18B20 sensor for body temperature measurement and the AD8232 module for electrocardiogram (ECG) acquisition into a unified low cost integrated platform. The local signal preprocessing, timestamp synchronization, and wireless connection were performed at the edge device. The Supabase cloud platform enabled a stable storage and management of physiological data via RESTful APIs. The experimental evaluation showed steady acquisition of multimodal physiological signals, robust Wi-Fi transmission, quick synchronization to the cloud, and structured database management, suited for continuous remote patient monitoring. The suggested system, due to its modular architecture, low power consumption and scalable cloud infrastructure, is appropriate for portable healthcare applications, home based patient monitoring, geriatric care and telemedicine scenarios. The created hardware and cloud infrastructure provides a strong basis for next generation intelligent healthcare systems. In future, this platform will be extended by integrating advanced machine learning algorithms for automated disease prediction and anomaly detection along with intelligent clinical decision assistance using an interactive healthcare dashboard.

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