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IoT-Enabled Remote Health Monitoring: Blood Glucose and Other Vital Parameters in Chronic Patients

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ABSTRACT

Chronic diseases such as diabetes, cardiovascular conditions, and respiratory ailments are increasing globally, necessitating continuous and efficient health monitoring. This research develops a multi-sensor IoT-based system for remote, real-time monitoring of vital health parameters including non-invasive blood glucose, heart rate, oxygen saturation (SpO2), and body temperature. The system integrates the MAX30100 sensor for blood glucose, heart rate, and SpO2 measurement, and the DS18B20 sensor for body temperature, all interfaced with a Raspberry Pi 4B microcontroller. Additionally, a SIM7600E GSM/GNSS module provides patient location tracking to enhance emergency response. Data are securely transmitted and stored on a cloud platform and accessed via a cross-platform mobile application, facilitating timely clinical interventions and personalized care. Validation against clinical hospital tests showed approximately 90% accuracy for non-invasive glucose monitoring and over 96% accuracy for other vital signs, demonstrating reliable performance. This low-cost, portable, and pain-free monitoring solution addresses the limitations of traditional invasive methods, improving chronic disease management, reducing hospital visits, and supporting proactive healthcare delivery, particularly in underserved regions. The proposed system was evaluated on 80 participants (male and female, aged 1–80 years) and its performance was compared with standard medical devices. Following calibration using a regression model, glucose readings achieved an overall accuracy of approximately 90%, while the mean errors for SpO_2, heart rate, and body temperature were 2%, 4%, and 3%, respectively. These findings demonstrate that the system provides reliable performance for most physiological parameters. Future work will focus on incorporating advanced machine learning algorithms to enhance glucose prediction, extending the system to monitor additional parameters such as ECG and blood pressure, and conducting large-scale trials with diverse patient populations to confirm its reliability and clinical applicability.

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1.Introduction

The rapid advancement of communication and information technologies has profoundly impacted various fields worldwide. Among these innovations, the Internet of Things (IoT) has emerged as a transformative technology, enabling the connection and interaction of diverse devices and systems through the internet. This interconnectivity facilitates real-time data collection, monitoring, and automated control across numerous domains, enhancing efficiency, accuracy, and decision-making processes (Mamdiwar et al., 2021, Siam et al., 2021).

In healthcare, IoT plays a particularly crucial role by integrating sensor-based equipment with software systems to support real-time health monitoring and data collection. IoT-enabled healthcare systems improve the accuracy and efficiency of diagnoses, promote proactive and remote patient care, and expand access to continuous health monitoring beyond traditional hospital settings. This functionality is especially vital for managing chronic diseases, reducing hospital visits, and addressing the challenges posed by limited medical personnel and rising healthcare costs.

Traditional healthcare models rely on scheduled, periodic monitoring, usually within hospital settings. This approach often leads to delayed detection of health deterioration, limited patient engagement, and increased burdens on healthcare facilities, especially for managing chronic diseases (Mukhopadhyay et al., 2021, Waleed et al., 2023).. Additionally, limited medical personnel and rising healthcare costs hinder timely and efficient care delivery. These challenges highlight the need for continuous, remote monitoring solutions that can provide real-time health data and facilitate proactive medical intervention.

The implementation of the IoT into the healthcare system will enable the collection of data on vital health-related indicators, data processing, and data assessment on a real-time basis and aid timely clinical interventions. The IoT enabled health monitoring infrastructure will consist of a variety of sensors that will evaluate this kind of value such as blood glucose, the body temperature, heart rate, and SpO2 (Salih Hasan, 2024). Such systems depend on cloud networks and mobile applications to transmit health records to health care professionals with the purpose of remote diagnosis and response. Machine learning algorithms integrated with IoT platforms have shown exceptional promise in healthcare applications, with systems achieving high accuracy rates for patient monitoring through cloud-based diagnosis and emergency ward applications (Shafi et al., 2024, Singh et al., 2024, Chen et al., 2020).

Continuing needs in terms of care are associated with such diseases as diabetes, heart disease, stroke, cancer, respiratory diseases, which might produce life-threatening issues in case no care is provided. The random nature of these diseases and the lack of medical attention to some regions make continuous remote medical attention important. IoT is a reliable action of early diagnosis and treatment of the patient to improve the health status of patients with chronic ailments. Advanced IoT-ML systems have demonstrated exceptional accuracy in health prediction, with some achieving up to 99.45% accuracy in cloud-based diagnosis (Singh et al., 2025), while deep learning approaches show promise in early cardiac disease detection (Islam et al., 2020, Sharma et al., 2023, Siam et al., 2021), as shown in Table 1.

The proposed project is a Multi-Sensor IoT System of Continuous Health Support to the Chronic Patients with the assistance of a Raspberry Pi 4 Model B microcontroller. The system has multiple sensors to constantly monitor the core vitals such as blood glucose, heart rate, SpO 2 as provided by the MAX30100 sensor and body temperature as provided by the DS18B20. Moreover, a SIM7600E GSM/GNSS tracker module allows tracking the location of patients and improves the efficiency of emergency response (Shafi et al., 2024, Li et al., 2021).

Blood glucose monitoring is necessary with checking frequently to control the occurrence of diabetes mellitus and avoid complications such as cardiovascular issues and renal failure. Conventional glucose monitoring is painful and not comfortable, and continuous glucose monitors are still expensive. The MAX30100 sensor provides a painless and affordable non-invasive solution, where infrared light absorption is measured to supply blood glucose, in addition to measuring the heart rate and SpO2 levels accurately with a simple finger tap, such sensor would be a renewable option to use with chronic patients (K. M et al., 2024, Laha et al., 2022)

Raspberry Pi 4B is the most suitable to use in the area of IoT healthcare because it is cheap, portable, and well supported by the community. Leveraged with Python-based application and MySQL cloud database the system has the benefit of secure real time data transfer as well as data access through a cross platform mobile application between both doctors and patients. Integrating the MAX30100 sensor on the EK with its heart rate and SpO 2 monitoring capabilities, as well as glucose and temperature sensors, this system is a complete approach to continuous health monitoring, emergency calls, and chronic disease management that can take place beyond the walls of a healthcare facility (Mohammed and Hasan, 2023, Vineela et al., 2018).

2- Literature Survey

Recent years have witnessed substantial progress in the field of non-invasive glucose monitoring (NIGM), with optical and signal-processing approaches emerging as the most promising alternatives to invasive finger-prick testing. Leung *et al.* (2025) reported on the clinical evaluation of a polarization-based optical sensing system for glucose monitoring, which demonstrated feasibility but revealed significant inter-subject variability, with accuracy generally below 85% under dynamic conditions, thereby highlighting the difficulty of achieving consistent clinical performance.(Leung et al., 2025).Parallel to optical polarization methods, several studies have employed photoplethysmography (PPG) signals combined with advanced machine learning. Zeynali *et al.* (2025) introduced a deep learning framework using short (1-second) PPG segments analyzed with CNN-LSTM and ResNet models. Their approach achieved an RMSE of 19.7 mg/dL and 100% clinical acceptability according to Clarke Error Grid analysis, although overall accuracy remained below 90%. Similarly (Zeynali et al., 2025), Satter *et al.* (2024) applied empirical mode decomposition (EMD) features extracted from wrist-worn PPG signals with CatBoost regression, obtaining a strong correlation (r = 0.96, MAE = 8.01 mg/dL), but without reaching 90% accuracy. In a broader context (Satter et al., 2024), Moses *et al.* (2024) provided a comprehensive review of NIGM technologies, concluding that most existing systems achieve only 70–85% accuracy, with values exceeding 90% reported only in isolated, highly controlled studies.(Moses et al., 2024)

Taken together, these investigations emphasize both the potential and the limitations of current NIGM methods. While optical and PPG-based strategies demonstrate considerable promise, reliable accuracy above 90% remains uncommon. In contrast, the present study advances the field by integrating a MAX30100 PPG sensor with regression-based calibration, achieving approximately 90% accuracy with 10% error, and further extending the approach through multi-sensor fusion and IoT-enabled deployment for chronic patient monitoring.

Alarcón -Paredes et al. develop a non-invasive glucose-monitoring system based on the use of IoT through a Raspberry Pi Zero micro controller, a visible laser beam, and a Raspberry Pi camera that captures fingertip image. Processing of the data is implemented as an artificial neural network (ANN) as a Flask-based microservice trained with TensorFlow, whereas remote real-time monitoring is facilitated by a smartphone app which offers a minimal, patient-oriented remedy to people with diabetes. (Alarcón-Paredes et al., 2019)

Jose-Luis Bayo-Monton et al. (2018), in their review, analyzed in detail so-called wearable health sensors integrated into Internet-of-Things infrastructures to support eHealth functions. The authors constructed a remote diagnostic tool with five devices (sensors in healthcare) through Arduino and Raspberry Pi 3 as single-board computers. The findings reported that Raspberry Pi transmitted data at faster rates compared to desktop computers and reported low failure rates hence proving that it is suitable in continuous tracking of the chronic patient. (Bayo-Monton et al., 2018)

Gamessa and Suman proposed a phenomenon involving a non-invasive blood-glucose monitoring process that consists of a human visible laser of 650 nm and a photodiode sensor to query the level of glucose through light refraction. Laboratory tests and biological reviews confirming empirical results have shown that there is close correlation between optical technique and other conventional methods of blood glucose measurements which depict that the system has a prospect of continuous but non-invasive blood-sugaring measurement (Gamessa and Suman 2019).

Siam et al. introduced a secure IoT-based health monitoring system designed to track heart rate, SpO_2, and body temperature. Powered by an ESP8266 microcontroller, the system encrypts patient data using the Advanced Encryption Standard (AES) algorithm and transmits it via Wi-Fi. A dedicated dashboard allows authorized healthcare providers to remotely monitor patient vitals, particularly beneficial for elderly or isolated individuals (Siam et al., 2021).

Singh et al. (2024) presented a comprehensive healthcare system integrating machine learning and IoT technologies for enhanced healthcare efficiency in emergency ward situations. Their system employed multiple sensors for continuous patient data collection, with the ANN model achieving 92% accuracy, followed by SVM at 89%. The integration of real-time data and predictive analytics significantly improved healthcare efficiency and enabled customized patient treatment plans (Singh et al., 2024).

Singh et al. (2025) developed an IoT and machine learning-based health monitoring system for protecting patients' vital organs through cloud diagnosis. The system connected multiple sensors to patients, transmitting real-time data for cloud-based analysis. The ANN model demonstrated exceptional predictive ability with 99.45% accuracy, while SVM, NB, and DT models achieved 96.5%, 94.34%, and 91.2% accuracy respectively, enabling early detection and improved patient outcomes (Singh et al., 2025).

Sharma et al. (2023) introduced a novel approach for early cardiac disease diagnostics combining IoT technologies with deep learning algorithms. Their CNN model effectively utilized sensor data from 30 patients monitored over 10 days to accurately detect and predict various cardiac conditions including Normal Beat, Premature Beat, and Early Ventricular Contraction. The results demonstrated potential for early interventions to prevent serious health complications, transforming healthcare from reactive to proactive approaches (Sharma et al., 2023)

Wang et al. proposed a multi-sensor wearable decision support system combining a MAX30102 sensor for heart rate, SpO_2, and skin temperature monitoring with a DHT22 sensor for environmental data collection. An STM32F103C6T6 microcontroller processes the data, which is wirelessly transmitted using the USART protocol and stored on a microSD card. Data reporting occurs in real-time, and thus visualized on the software architecture of the host system, and as such present a simplified and reliable platform to clinical surveillance. (Wang et al., 2021)

3- System hardware component

3.1 Microcontroller (b)

In this study, Raspberry Pi 4 Model B is used as the main communicating and processing (CPU) unit of the real-time, IoT-based health-monitoring system aimed at connecting patients and clinicians. This gadget communicates with clinical sensors i.e. the MAX30100 and the DS18B20 to obtain physiological data continuously such as glucose levels, heart rate, SpO 2 and body temperature. The obtained data can be securely transmitted by 4G or Wi-Fi to the MySQL database on the cloud. A cross-platform mobile or web application enables patients and clinicians to access both real-time and historical health records, making it possible to monitor patients remotely, provide them with medical feedback in a timely manner, and send emergency alerts by the fact of abnormal readings. As a result, the Raspberry Pi 4 Model B device, not only facilitates sustained data collection but also, makes the necessary connection between the patients and healthcare providers, thus enhancing the chronic disease management and in emergency contacts beyond standard clinical practice, as shown **in Figure 1**

(Raspberry Pi Foundation, 2025, Ashna Sahdi and Dler Salih, 2023).

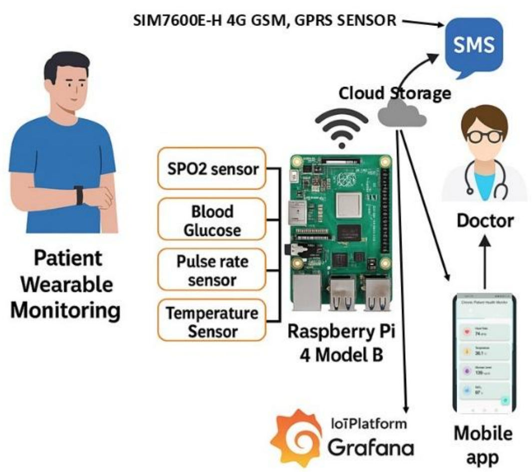


Figure 1: System Architecture

3.2 Sensors

3.2.1 IR, Red, and Photodiode Sensors for Blood Sugar Level Monitoring

This paper explores a noninvasive method for continuous blood glucose monitoring using IR and red LEDs with a photodiode sensor. The system relies on glucose's light absorption properties and applies photoplethysmography (PPG) via the fingertip, chosen for its strong reflective characteristics. To ensure accuracy, calibration is performed using models, which establishes a relationship between sensor readings and known glucose values. Controlled experiments on diabetic and non-diabetic subjects were conducted using glucose solutions to validate performance. External factors such as hand posture, movement, and sensor alignment significantly affect measurement reliability. Standardized conditions—using the right hand while seated—help improve consistency. Data collection and processing are handled by a Raspberry Pi 4 Model B, enabling real-time glucose level monitoring. While some limitations remain, the results demonstrate the potential of this low-cost, noninvasive system for diabetic health tracking. (Mohammed, 2024, NASR et al., 2021).

3.2.2 Sensor Max30100 (d) for Heart Rate and SPo2 Monitoring

Max30100 sensor can be used to monitor heart rate and SpO2 (blood oxygen saturation) levels. Max30100 is a photoplethysmography (PPG) sensor that works on two wavelengths of light: one that is visible and one that is invisible. These two LED lights are placed beside a photo-detector. When the lights fall on the blood vessels, patient's skin and tissue, different amounts of light get absorbed at different rates and the reflected light or the light that passes through tissue is detected by the photo detector. Max30100 sensor can operate between 1.8 to 2V and its operating temperature is around -40 to +85 degrees Celsius and also a current consumption of around 600 microamperes.

90% of the patients of the hospitals in developed countries are said to be monitored using pulse oximeters, as a thick cable is connected to the patients' finger. By this, real-time data is only displayed in the monitoring machine and the patient or the patient's family doesn't know the real-time health condition. In this project, SpO2, heart rate and sensor temperature value and blood glucose are displayed in the SSH terminal of Raspberry Pi with real-time readings. If any abnormal values are found, an alert indication SMS is also sent to the registered mobile number with the patient's hospital number from the Raspberry Pi.

3.3 Pulse Oximeter

The max30100 technical device along with other pulse oximeter devices incorporates two high-intensity LEDs (RED and IR with distinct wavelength values) paired with a photodetector. Two LEDs with wavelengths of 660nm and 880nm operate in the sensor **in Figure 2.**

The MAX30100 functions through shining two light wavelengths onto the fingers while its photodetector measures resulting light reflection intensity.

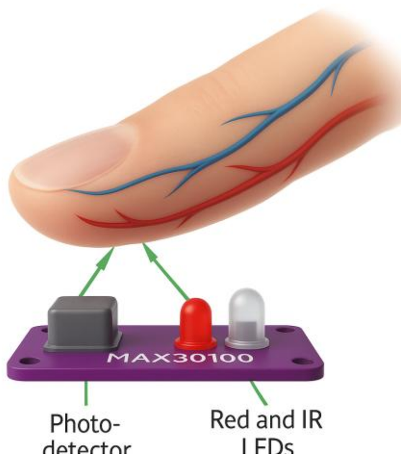
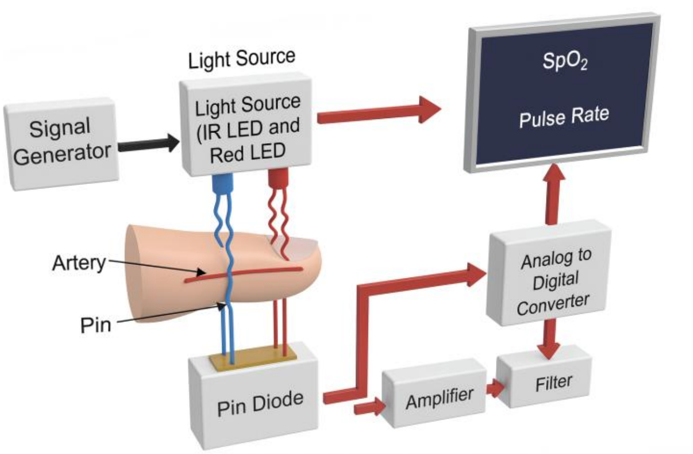


Figure 2: Pulse Oximeter (Paneru et al., 2024)

3.4 Heart Rate Measurement

Oxygenated hemoglobin (HbO2) within the arterial blood demonstrates a specific capacity to absorb infra-red light. The volume of IR light absorption rises directly with increased blood hemoglobin content, as shown in Figure 3 Mitigation of the blood flow caused by heartbeat results in modified light reflectance which produces pulse waveform output from the photodetector. Maintaining external light exposure and photodetection measurements enable you to observe a heart-beat (HR) pulse



pattern.

Figure 3: Heart Rate Measurement (Emon et al., 2024)

3.5 Pulse Oximetry Chart

Pulse oximetry uses the fact that blood with various oxygen levels absorbs distinct amounts of RED and infrared light. A chart exhibits both the absorption patterns of HbO2 (oxygenated hemoglobin) along with Hb (deoxygenated hemoglobin).

The data in the graph, as shown in Figure 4, deoxygenated blood takes up higher amounts of 660nm RED light while oxygenated blood absorbs greater 880nm IR light. The photodetector measures IR and RED light ratios to compute blood oxygen level (SpO2).

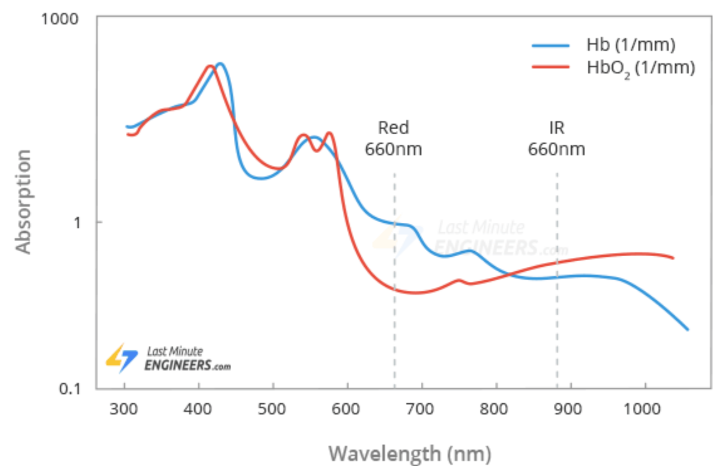


Figure 4: Pulse Oximetry chart (Paneru et al., 2024)

3.6 Glucose measurement (d)

In this project, the MAX30100 sensor is employed for noninvasive glucose monitoring due to its capability to emit both infrared (IR) and red light, enabling simultaneous detection of SpO_2 and pulse rate—key indicators in optical biosensing. The glucose measurement process combines reflection and scatternet methods, utilizing an optical path centered around 850 nm, which falls within the near-infrared (NIR) range (700–1000 nm). This wavelength is chosen for its effective skin penetration and interaction with blood vessels. Light passing through the human tissue hits hemoglobin, as presented in Figure 5, which absorbs certain frequency of light, and consequently, it makes it the ability to extract SpO 2. At the same time reflected, refracted and absorbed light forms scatternet data which is modulated by glucose presence in the skin. A combination of the SpO 2 measurements with the corresponding scatternet data enables the use of derived formulae to calculate glucose concentration using this joint analysis. The MAX30100 sensor is quite suitable to this use-case, at least in terms of its small size, low power demand and capacity to provide real-time optical measurement, making it quite suitable to the role of inclusion in a low-cost, transparent, and wearable glucose-monitoring platform. (Abdulmalek et al., 2022, Rajeswari and Vijayakumar, 2024, Ramazi et al., 2021)

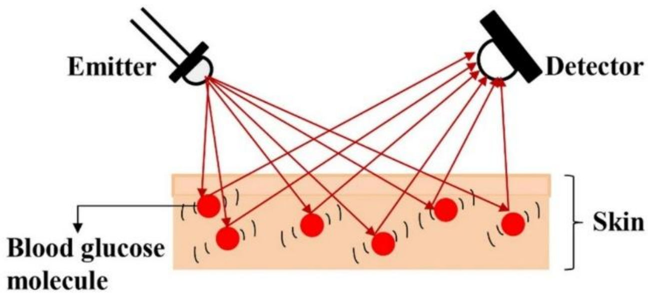


Figure 5: Glucose measurement (Rajeswari and Vijayakumar, 2024)

3.7 DS18B20 sensor (c)

This paper takes advantage of the DS18B20 digital temperature sensor as the main piece of an Internet-of-Things (IoT)-based health-monitoring platform to be able to continually monitor the body temperature of patients remotely. This choice of the sensor is explained by its high level of accuracy (0.5 0 C), the physiologically suitable range of measurements, and the possibility of easy connection to the Raspberry Pi microprocessor. The 64-bit serial which supports Mult tolerance in several sensors can run up to multiple sensors on the same GPIO pin, which makes it scale up. Importantly, the DS18B20 presents high-resolution (12-bit) digital output with the fastest measurement speed (mechanical dispensing rate), and it does not require analog-to-digital conversion or secondary calibration, which means sure and cost-effective to use in the long-term continuous monitoring with lower power consumption.

3.8 Hardware Extension (a):

A 4G GSM, GPRS, and GNSS HAT module has been integrated with the Raspberry Pi 4B in the present study that assembled a platform based on real-time wireless health data transmission and location detection based on GNSS and Raspberry Pi 4B. This integration helps in providing constant remote monitoring of the vital signs and it also allows the healthcare professionals to sense the status of their patients and allow them to respond in the emergent situations with the high precision of the location, hence, improving the communication and accessibility in the healthcare sector.

3.9 Key Features of the 4G GSM, GPRS, and GNSS HAT Module (a)

The opportunity to use a 4G GSM, GPRS, and GNSS HAT module has greatly increased the communications infrastructure of the healthcare monitoring project, which is the focus of the investigation, with the provision of high-speed LTE connectivity and real-time GPS monitoring. These functions allow the medical staff to track the health conditions and location of the patients, which is the valuable feature, especially when it comes to unexpected situations. Its easy compatibility with Raspberry Pi makes it carry out an effective data transfer through sensors and proper delivery to the cloud services to be used by healthcare experts.

The cross-platform dial-up support in the module enables authorized professionals to retrieve patient data in a secure environment on various systems. Furthermore, the use of various communication protocols, specifically, TCP/UDP, FTP/FTPS, HTTP/HTTPS ensures safe transfer of encrypted data (Kareem and Z. Ghafoor, 2021). An added bonus to the process of doctor-patient interaction is the addition of call and SMS features that have the benefit of alerting to abnormal readings and allowing face-to-face interaction during consultations, increasing response time and overall quality of care delivery.

3.10 Significance in Continuous Health Support for Chronic Patients

The module serves as a crucial part of a multi-sensor IoT system for continuous health support for chronic patients, telemedicine and care solutions because it enables real-time data transfer and security measures and patient tracking capabilities.

3.11 Raspberry Pi 4 model B 4Go (b) : technical specifications

In this project the Raspberry Pi 4 model B in Figure 6 used, features a quad-core 1.5GHz processor, 4GB RAM, dual-band Wi-Fi, Bluetooth 5.0, and Gigabit Ethernet. The device provides 40 GPIO pins while supporting dual transmission of 4K HDMI signals and multiple

USB 3.0 ports and camera/display access points. The device supports Micro SD storage and has USB-C powering capabilities while Power over Ethernet remains optional.

3.12 Technical Specifications of Max30100 (d)

The MAX30100 sensor in Figure 6 (d), functions between 3.3V and 5.5V supply voltage while it consumes approximately 600 microamps for operation but only requires 0.7 microamps in standby mode. The sensor system functions through the combination of a 660nm red LED and an 880nm IR LED for detection purposes. This device performs its operations within a temperature range from -40°C up to +85°C.

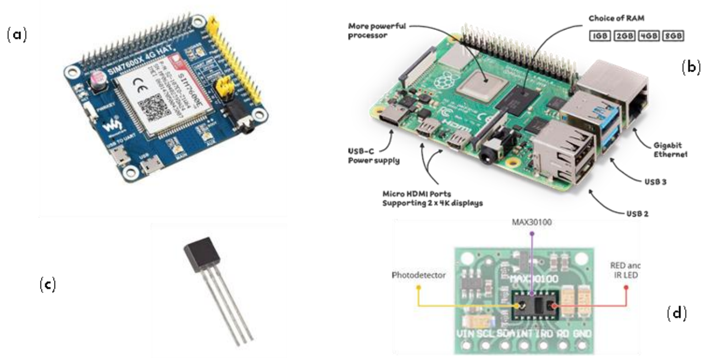


Figure 6: Raspberry Pi 4 Model B paired with a SIM7600E-H 4G GSM, GPRS, and GNSS HAT module, along with a DS18B20 digital body temperature sensor and a MAX30100 pulse oximeter sensor.

4- Software and programming language

4.1 Python

In this project, the Python programming language is used to operate the Raspberry Pi microcontroller, managing sensor inputs and system functions. Python scripts read sensor data—such as glucose levels heart rate, Spo2, and body temperature—before transmitting it to cloud storage, where it can be accessed by doctors for remote monitoring. The Python-based libraries simplify sensor integration and ensure accurate data collection from the patient. Python's cross-platform capabilities allow the same application to run on Windows and Unix-like systems, including Linux and macOS, providing flexibility for healthcare providers to monitor patients across various platforms. Its wide applicability in web, mobile, and scientific applications supports scalable healthcare solutions, enhancing communication and interaction between patients and doctors (Packt_Publishing, 2018).

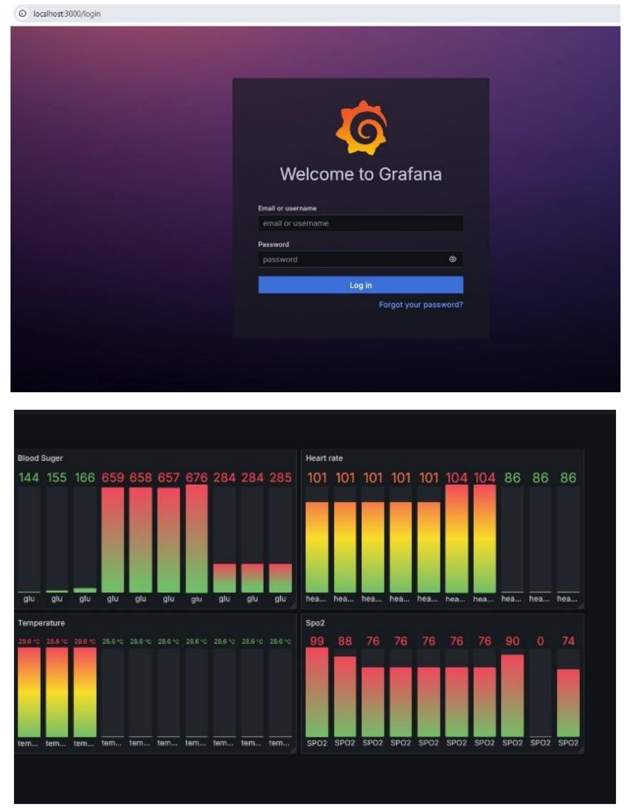


Figure 7: Grafana Platform Analysis Data

4.2 Flutter and Dart Flutter

Flutter and Dart Flutter operates as an open-source platform that relies on Dart for its programming language development. Developers can generate natively built applications and cross-platform applications using a single codebase on their platform. Flutter Google developed both Flutter and its original programming language Dart (Chen et al., 2020). The recommended framework incorporates the pair of Flutter alongside Dart programming language. The development used Flutter and Dart to build a unified mobile application which functions on Android and iOS operating systems. for displaying real-time health parameter values, alerts, and notifications for both patients and paramedics/doctors.

4.3 Grafana

Grafana, as shown in Figure 7, operates as an open-source solution that functions for real-time analysis and visualization of time-series data from multiple origins. The platform lets its users design adjustable dashboards which show trends between data points and trigger alerts using interactive graph and gauge visuals. Grafana functions as a versatile instrument for IoT-based health monitoring applications because it interacts with numerous data sources that encompass MySQL, Influx DB, and Prometheus. Live visual data streams provide healthcare providers or researchers with clear and precise patient vital monitoring of glucose levels alongside heart rate and blood oxygen saturation and body temperature measurement.

Grafana serves as the central component in a multi-sensor IoT system for continuous health support for chronic patients because it presents real-time remotely accessible dashboards which show critical patient health metrics collected from MAX30100 (d), DS18B20 (c) and non-invasive glucose sensors linked to Raspberry Pi devices. Grafana enables doctors to gain easy visibility into patient health changes through dynamic visualizations which allows caregivers to create alert thresholds while studying historical health patterns for making improved healthcare decisions. The integrated system provides greater emergency care capabilities and disease prevention mechanisms through its constant data visualization solution that remains accessible and well-organized. (Rajeswari and Vijayakumar, 2024)

4.4 MySQL (Online Host)

These days, MySQL stands as the leading open-source database system worldwide. Whether for small startups, growing tech firms, or large organizations, MySQL implementations offer scalable, reliable, and cost-effective database solutions. In this proposed system, the application employs MySQL cloud storage hosted on online host, which serves as a secure and efficient database platform to store information obtained from multiple sensors and devices. The Raspberry Pi microcontroller processes input from the sensors, then transmits and stores this data directly into the Hostinger-hosted MySQL database via Wi-Fi. (Rghioui et al., 2020).

The Online Host MySQL cloud environment ensures stable, remote-accessible storage for critical patient health data, doctor and paramedic details, and records of abnormal measurements. It also maintains a comprehensive archive of previous patient histories, allowing authorized medical staff to retrieve and review recorded information at any time. This cloud-based storage approach enhances system reliability, accessibility, and performance, making it ideal for continuous healthcare monitoring and emergency response management.

5. Methods and Proposed system

Important healthcare parameters are remotely tracked in real-time and their measured values are presented to doctors and patients through a system-specific mobile application. The primary healthcare parameters include SPO2, heart rate, body temperature, and non-invasive blood glucose levels. For glucose monitoring, the system uses the MAX30100 sensor as a key component, functioning not only as a pulse oximeter and heart rate sensor but also as a primary module for estimating blood glucose levels through near-infrared light absorption analysis and red light.

This integrated glucose monitoring system enables continuous patient monitoring without invasive sampling, ensuring accurate glucose level estimation through model analysis applied to revised data collected from sensors and cross-referenced measurements. The hardware setup involves connecting all sensors to a Raspberry Pi microcontroller, including a 4G GSM, GPRS, and GNSS HAT Module, which communicates with a MySQL database via Wi-Fi. The Raspberry Pi and sensors are programmed using Python for efficient data gathering, analysis, and transfer. Each sensor is strategically placed on the patient's body — the temperature sensor on the skin, the pulse oximeter and glucose monitoring sensor on the fingertip. After health parameters are measured, values are compared to normal reference ranges and displayed on the mobile application. If any reading, including glucose levels, falls outside the normal range, as presented in Table 2, an emergency alert with the patient's location is instantly sent via SMS to doctors, paramedics, and relatives, enabling timely, life-saving medical decisions without the need for clinic or hospital visits. Flowchart of proposed system, as presented in Figure 8.

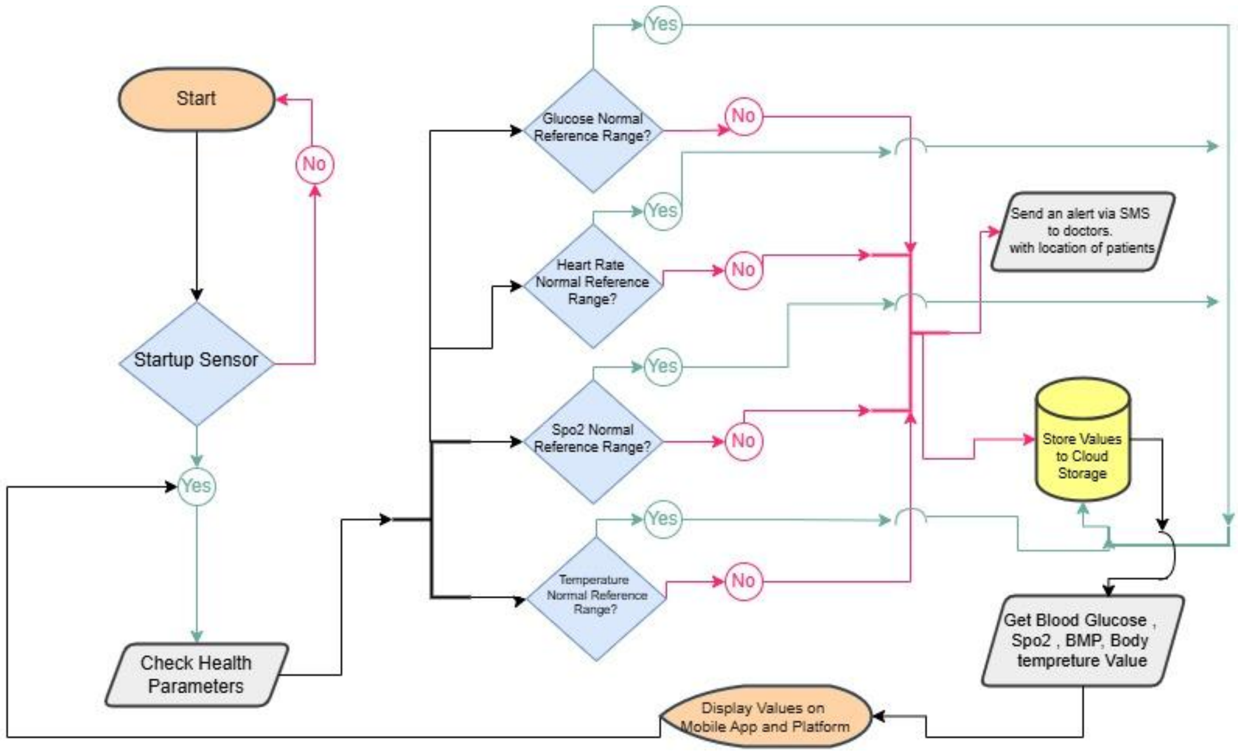


Figure 8: A Multi-Sensor IoT System for Continuous Health Support for Chronic Patients Flowchart

6. Testing and results

The monitoring system was implemented by connecting all sensors to a Raspberry Pi microcontroller in Figure 9, supported by a portable power bank to ensure reliable operation. Medical reference ranges were first established, followed by meticulous sensor calibration to enhance measurement accuracy. After calibration, the system efficiently acquired vital signs, processed the data through the microcontroller, and transferred the outputs to secure MySQL servers for storage and further analysis.

The performance of the proposed IoT-based health monitoring system was evaluated on a sample of 80 participants (40 male, 40 female) with ages ranging from 1 to 80 years. This distribution was selected to ensure a balanced representation across different genders and age groups, thereby enhancing the generalizability of the findings. Demographic details were further categorized into four age groups (1–20, 21–40, 41–60, and 61–80 years) to examine system performance under varied physiological conditions shown in Figure 10 and Table 3.

The developed non-invasive monitoring system, alongside FDA-approved reference devices, was used to simultaneously measure each participant's vital signs, including blood glucose, heart rate, SpO_2, and body temperature. To enhance accuracy and data reliability, multiple readings were obtained from every patient.

The system displayed real-time Glucose and SpO2 and heart rate and body temperature values through its system-defined mobile application shown in Figure 11. When a patient's measured values exceeded normal reference limits the system generated automatic SMS alerts which transmitted the abnormal results together with patient position information to doctors, paramedics and family members for fast medical reactions and decisions.

The system enabled healthcare staff to receive warning alerts combined with continuous real-time observation of all healthcare data collected through remote monitoring. The system upgrade enabled better supervisory capabilities and superior patient care administration over remote distances. Sending the patient's location to the system enabled quick dispatch of ambulances when critical situations arose. Fifteen subjects participated in health data recording activities during testing as shown in Table 4 depicts live data collection linked to a participant.

To validate the effectiveness of the proposed multi-sensor IoT system, a series of experiments were conducted involving both diabetic and non-diabetic subjects. The system's sensor readings were compared against standard clinical devices to assess accuracy. The results demonstrated that the non-invasive blood glucose monitoring using the MAX30100 sensor achieved an average accuracy rate of 90%, reflecting the inherent challenges of non-invasive glucose measurement and the need for further calibration. For SpO_2 (blood oxygen saturation) measurements, the system exhibited a high average accuracy rate of 98%, while the heart rate monitoring achieved an average accuracy of 96% then the body temperature achieved an average accuracy of 97%. These results indicate that the system is highly reliable for heart rate and SpO_2 and body temperature monitoring and shows promising potential for non-invasive blood glucose estimation. Continued refinement of the calibration protocol and additional testing are expected to further enhance the accuracy and reliability of the system, particularly for blood glucose measurement.

In Figure 12, the scatter plots demonstrate strong agreement between the proposed system and reference devices. The non-invasive glucose measurement achieved an average accuracy of around 90%, reflecting the challenges of glucose estimation. Meanwhile, the other parameters—SpO_2, heart rate, and body temperature—consistently exceeded 95% accuracy, highlighting the system's reliability and robustness in monitoring vital signs.

Figure 9: Testing of proposed system

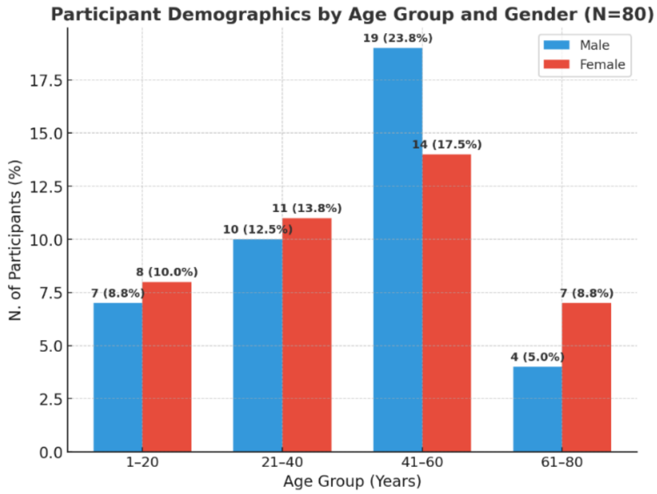


Figure 10: Participant Demographics by Age Group and Gender

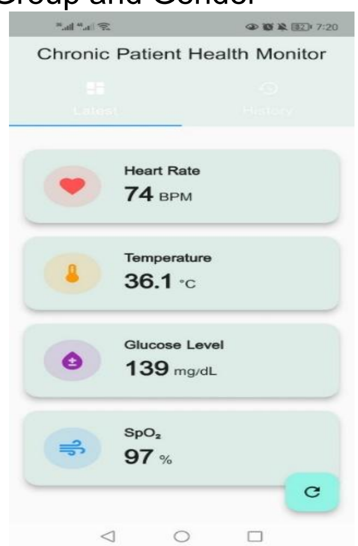


Figure 11 : Mobile App Interface

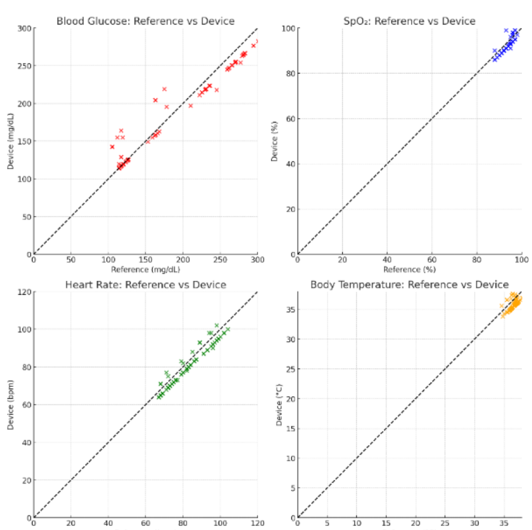


Figure 12: Scatter Plot for All Parameters

Discussion

This study proposes a novel IoT-enabled health monitoring system that leverages non-invasive biosensors to provide continuous tracking of vital parameters, including blood glucose, heart rate, SpO_2, and body temperature. The key innovation lies in replacing painful, invasive techniques such as finger-prick glucose testing with a painless optical sensor approach, making the system significantly more comfortable and patient-friendly. Unlike traditional methods that are costly, inconvenient, or limited to clinical environments, this research delivers an affordable, portable, and secure architecture capable of supporting chronic patient care in real time. By combining regression-calibrated non-invasive glucose estimation, multi-sensor integration, cloud-based visualization, and automated GPS-enabled alerts, the system ensures proactive healthcare delivery while prioritizing patient comfort and accessibility.

The findings of this study confirm the feasibility of a multi-sensor IoT-enabled system for chronic patient monitoring, with strong performance in SpO_2 (98%), heart rate (96%), and body temperature (97%) accuracy. These results underscore the reliability of integrating MAX30100 and DS18B20 sensors with the Raspberry Pi 4B for continuous real-time health monitoring. Importantly, the non-invasive glucose monitoring achieved an average accuracy of 90%, placing it closer to clinical standards compared with earlier non-invasive approaches. This improvement addresses a well-documented challenge, as previous studies by Alarcón-Paredes et al. (2019) and Waktola & Suman (2019) noted calibration difficulties and susceptibility to motion and light interference when using optical glucose sensing.

Recent advances in NIGM reinforce these challenges. Leung et al. (2025) demonstrated the feasibility of a polarization-based optical system but reported accuracy generally below 85% due to significant inter-subject variability. Similarly, Zeynali et al. (2025) applied deep learning to short PPG segments, achieving RMSE values around 19.7 mg/dL with 100% clinical acceptability by Clarke Error Grid, yet still below 90% accuracy. Satter et al. (2024) showed improved correlation (r = 0.96, MAE = 8.01 mg/dL) using CatBoost regression on wrist-worn PPG signals, but again, accuracy remained under 90%. A comprehensive review by Moses et al. (2024) concluded that most NIGM systems currently achieve only 70–85% accuracy, with values above 90% reported only under highly controlled conditions. In comparison, the present study contributes by integrating the MAX30100 PPG sensor with regression-based calibration and achieving about 90% accuracy (≈10% error margin), while extending this through multi-sensor fusion and IoT deployment for real-world chronic patient support. This positions our system at the higher end of current NIGM performance benchmarks.

Beyond glucose monitoring, the proposed design introduces several practical enhancements. Earlier systems, such as those reported by Bayo-Monton et al. (2018) and Mukhopadhyay et al. (2021), demonstrated the potential of IoT-linked sensors for healthcare data transmission but lacked robust emergency communication. By integrating the SIM7600E GSM/GNSS module, our system adds real-time alerting and geolocation tracking, significantly improving doctor–patient interaction and emergency response capabilities. Likewise, Siam et al. (2021) emphasized secure data transmission in IoT health systems, which we complemented with cloud-based MySQL storage and Grafana visualization for accessibility and real-time decision-making.

Looking forward, studies by Singh et al. (2024, 2025) and Sharma et al. (2023) highlight the transformative potential of combining IoT with machine learning, reporting predictive accuracies up to 99.45% in cloud-based systems. While our current prototype relies on regression calibration, its cloud infrastructure and modularity allow for integration with machine learning pipelines in future iterations. Such upgrades could help overcome the remaining accuracy gap in NIGM, particularly by applying adaptive calibration, sensor fusion, and AI-driven error correction.

In summary, this study strengthens the case for low-cost, IoT-enabled multi-sensor health systems. The strong reliability of SpO_2, heart rate, and temperature monitoring validates the approach, while the glucose monitoring results, at 90% accuracy, demonstrate progress toward clinically viable non-invasive solutions. Compared to prior work, the inclusion of real-time alerts, GPS tracking, and a cross-platform mobile app represent clear advances in clinical applicability. Nonetheless, larger-scale clinical validation and integration of advanced learning algorithms remain crucial to elevating non-invasive glucose monitoring to true clinical readiness.

Conclusion

The integration of non-invasive health monitoring technologies with IoT infrastructure presents a transformative solution for managing chronic conditions like diabetes and other critical health issues. By combining sensors such as the MAX30100 for glucose estimation, heart rate, and SpO_2 measurement with the DS18B20 for body temperature, the proposed system offers continuous, real-time patient monitoring through a cross-platform mobile application. Enhanced by Wi-Fi and cloud-based connectivity, this system ensures the remote collection, analysis, and visualization of vital health data, while providing instant SMS alerts with location information in emergency situations. This innovation reduces the need for physical hospital visits, enables timely medical interventions, and empowers clinicians to make life-saving decisions remotely significantly improving healthcare accessibility, patient safety, and chronic disease management in both developed and developing regions.

Table 1: Comparison of Healthcare Monitoring Sensor Systems and Their Performance

Researchers (Year)	Methodology	Sensors Used	Parameters Monitored	Platform/Hardware	Communication Protocol	Results/Performance
Islam et al. (2020)	Hospital room monitoring system	BT sensor, HR sensor, Environmental sensors	Body Temperature, Heart Rate, CO, CO_2, Humidity	Not specified	Not specified	~95% agreement between monitored and actual data
Gupta & Parikh (2018)	Real-time monitoring for obese adults	MAX30100, LM35, BP monitor	BP, BT, Pulse Rate, SpO_2	Atmega 328, Keypad, LCD	IEEE 802.11 (Wi-Fi)	Can store data of multiple patients simultaneously
Alamsyah & Ikhlayel (2019)	Vital signs monitoring system	MCP3008, HRM-2511E, DS18B20, MPX5050DP	HR, BP, BT	Raspberry Pi	IEEE 802.11 (Wi-Fi)	Mobile access for medical staff via Android
Sangeethalakshmi et al. (2021)	Real-time patient tracking system	LM35, AD8232, MAX30100, BP sensor	Temperature, HR, ECG, BP, SpO_2	ESP32	Wi-Fi/802.11	Real-time alerts for abnormal readings
Vaneeta et al. (2022)	Rural healthcare monitoring system	Temperature, BP, HR, SpO_2 sensors	BT, BP, HR, SpO_2	Not specified	Not specified	Relative errors: HR (2.89%), BT (3.03%), SpO_2 (1.05%)
Mostafa et al. (2021)	Contactless monitoring system	DS18B20, Max30100, IR sensor	BT, HR, SpO_2	NodeMCU	Wi-Fi to Blynk	System takes only one minute to provide readings
Proposed System (Saeed & Hasan, 2025)	IoT-enabled continuous health monitoring	MAX30100, DS18B20, SIM7600E GNSS HAT	Blood Glucose (non-invasive), HR, SpO_2, BT, Patient Location	Raspberry Pi 4B, Mobile App, Grafana Dashboard	Wi-Fi, 4G/GNSS, MySQL Cloud	98% (SpO_2), 96% (HR), 97% (BT), 90% (Blood Glucose), real-time alerts with SMS + GPS tracking

Table 2. The reference ranges for the involved health parameters (Geneva et al., 2019, Averdunk et al., 2020, ElSayed et al., 2023)

Parameter	Child (1–12 yrs)	Teen (13–17 yrs)	Adult (18+ yrs)	Abnormal Values
Blood Glucose	Fasting:70–100 mg/dL Post:<140 mg/dL Random:<200 mg/dL OGTT: <140 mg/dL	Same as child	Same as teen	Fasting: ≥126 mg/dL Post: ≥200 mg/dL Random: ≥200 mg/dL OGTT: 140–199 mg/dL (prediabetes); ≥200 mg/dL (diabetes)
SpO_2	95–100%	95–100%	95–100%	< 90% indicates hypoxemia
Heart Rate	70–120 bpm (varies by age)	60–100 bpm	60–100 bpm	Bradycardia < 60 bpm; Tachycardia > 100 bpm (adult)
Body Temperature (Oral)	36.1–37.8 °C (97–100 °F)	36.1–37.5 °C	36.1–37.2 °C	Fever: ≥ 38 °C (100.4 °F); Hypothermia: < 35 °C

Table 3: Test Results of proposed System Based on Age Distribution by Gender

Gender	1–20 Years	21-40 Years	41-60 Years	61-80 Years	Total
Male	7 (8.75%)	10 (12.5%)	19 (23.75%)	4 (5.0%)	40 (50.0%)
Female	8 (10.0%)	11 (13.75%)	14 (17.5%)	7 (8.75%)	40 (50.0%)
Total	15 (17.75%)	21 (26.25%)	33 (41.25%)	11 (13.75%)	80 (50.0%)

Table 4: Recorded Data for Blood Sugar , Spo2 , Heart rate , Body Temperature by Proposed System Device and Medical Device (References)

PN	Gender	Blood Sugar Reference	Blood Sugar Device Calibrated	Spo2 reference	Spo2 Device	Heart Rate Reference	Heart Rate Device	Body Tempt. Reference	Body Tempt. Device	Error on BG %
P1	Male	277	254	88	86	97	93	37 °C	36.8 °C	8.3
P2	Male	119	154	95	93	73	70	36.2 °C	36.8 °C	29.4
P3	Male	166	160	95	96	71	77	35 °C	34.3 °C	3.6
P4	Male	265	250	91	89	71	68	36.7 °C	36.1 °C	5.7
P5	Female	230	219	96	97	75	72	37 °C	36.4 °C	4.8
P6	Male	260	195	95	93	77	73	37 °C	37 °C	25.0
P7	Male	279	263	95	93	80	82	37 °C	37 °C	5.7
P8	Male	162	157	92	90	96	90	36.9 °C	36.1 °C	3.1
P9	Male	231	219	93	99	72	69	36.5°C	36.0 °C	5.2
P10	Female	114	119	90	90	101	96	37 °C	37.6 °C	4.4
P11	Male	325	304	96	94	93	89	36.9 °C	35.9 °C	6.5
P12	Female	300.63	282	96	97	91	87	37 °C	37 °C	6.2
P13	Female	117	163	94	93	79	83	36.8 °C	36.4 °C	39.3
P14	Female	124	123	95	91	82	78	37.1 °C	36.7 °C	0.8
P15	Male	112	127	95	94	85	88	37.3 °C	37.3 °C	13.4

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