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NON-INVASIVE GLUCOSE MONITORING USING ESP32 AND NIR SENSOR

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Abstract:

The rapid advancement of the Internet of Things (IoT) and embedded systems has significantly improved modern healthcare solutions. This paper presents the development of a non-invasive glucose monitoring system using an ESP32 microcontroller and a near-infrared (NIR) sensor to estimate glucose levels in real time. Unlike traditional invasive methods, which require blood samples, the proposed system uses NIR technology to analyse light absorption through human tissues, providing a painless and convenient alternative for diabetic patients. The system combines a MAX30102 PPG sensor, which measures heart rate and oxygen saturation (SpO_2), and a temperature sensor to measure body temperature to increase the accuracy and reliability of health monitoring. These supplementary parameters will help in a more thorough examination of the health status of the patient. The ESP32 microcontroller is the central processing unit, and it receives the data, processes it and works with the IoT platforms (ThingSpeak) to see the results in real-time and monitor the system remotely. The system can also be used to send alerts in case of abnormal health conditions such as an increase in glucose levels. Overall, the proposed system is easy to use and affordable, and this feature could serve to monitor a person constantly, making it a practical solution for smart healthcare and preventive medical applications.

Keywords:

Non-Invasive Glucose Monitoring, ESP8266, Near Infrared (NIR) Sensor, Glucose Estimation, DHT11 Sensor, Body Temperature, IOT Cloud Platform, ThingSpeak, Real-Time Monitoring.

1. Introduction

One of the most common chronic metabolic disorders in the world is diabetes mellitus, which has captured millions of victims of all ages. The disease is characterised by abnormal blood glucose regulation due to insufficient insulin production or impaired insulin response. It is important to constantly check the level of glucose to avoid such complications as cardiovascular diseases, kidney failure, neuropathy, and loss of sight. The traditional glucose monitoring systems are dependent on the invasive finger prick, which is painful, uncomfortable, and inconvenient to patients. Consecutive invasive testing usually deters consistent monitoring, particularly in the elderly population and children. As healthcare systems move toward preventive and patient-centred care, there is an increasing demand for painless, continuous, and user-friendly monitoring solutions. The recent technological developments in the field of embedded systems and IoT-based healthcare systems have provided new opportunities for non-invasive diagnostic systems. The integration of optical sensing technologies with microcontrollers has enabled innovative biomedical applications. Therefore, developing a reliable non-invasive glucose monitoring system is not only a technological advancement but also a

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critical step toward improving the quality of life for diabetic patients globally [1].

Non-invasive glucose monitoring techniques primarily focus on optical methods such as Near Infrared (NIR) spectroscopy, which measures the absorption characteristics of biological tissues. The absorption of certain wavelengths of near-infrared light by the glucose molecules can be correlated with the concentration of glucose in the blood and alterations in the absorption strength, which can be attributed to changes in the concentration of glucose in the blood. Compared to invasive electrochemical sensors, systems based on NIR are painless and more convenient to use since they do not require blood samples. However, the optical sensing can be problematic in measuring the glucose level due to the variation in skin thickness, hydration, temperature and tissue composition. The algorithms and methods of signal processing and calibration are also needed to enhance the reliability of measurements. Innovations in embedded microcontrollers such as ESP32 have made it possible to acquire, filter, and transmit data in real time and wirelessly. These controllers have Wi-Fi connectivity and can be used in healthcare monitoring systems based on the IoT. Non-invasive glucose monitoring systems can be used to offer continuous and real-time health-related information by using NIR sensing and intelligent data processing without interfering with user comfort and portability [7].

The advent of the Internet of Things (IoT) has greatly changed the modern healthcare system as it opens the possibility of interconnected smart medical devices. Health monitoring systems based on IoT enable the transmission of the data in real time, remote monitoring of patients, and the early detection of abnormalities. The IoT platforms reduce the instances of patients visiting a hospital when seeking medical attention to chronic conditions and enable the carer to check on the health of the patient remotely. The systems are user-friendly with graphical views of the data, data logging and alert systems which are made available in cloud-based systems like ThingSpeak and Blynk. IoT will enable tracking the continuity of data and history analysis in the instance of glucose monitoring systems, which are of utmost importance in clinical decision-making. When the glucose levels are above the predetermined limits, real-time notifications can be created to provide prompt action. Further, the IoT connection enhances the availability of data, and patients and healthcare experts can access readings in mobile applications or dashboards with the help of the IoT connection. The combination of embedded sensors with wireless communication technologies is thus crucial in creating smart healthcare ecosystems, which place a focus on preventive care and active management of a disease [8].

Although the main goal of diabetic treatment is glucose monitoring, other physiological indicators have a great impact on general health status. Along with glucose monitoring, other physiological variables like heart rate, oxygen saturation (SpO_2) and body temperature are also important in assessing general health conditions [9]. Besides, the metabolic alterations are susceptible to the surroundings and temperature shifts, which may alter the glucose levels. The suggested system will not only approximate glucose but also provide holistic health monitoring since it will comprise different sensors. This multi-sensor system improves safety for the patient, as the metabolic monitoring is cross-linked with physical activity analysis, which has formed a complete health care monitoring system that is applicable in the home care environment [10].

Modern portable medical devices are based on embedded systems. The ESP32 microcontroller has

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a higher processing speed, has built-in Wi-Fi and Bluetooth, and has several analogue-to-digital converter (ADC) channels that allow interface to sensors. ESP32 is more efficient in terms of data throughput and energy consumption than the older microcontrollers, and it can be implemented in wearables and portables in the healthcare industry. Its dual-core design makes its sensor data and wireless communication be captured at once with no delays. The microcontroller collects analogue signals captured by the NIR sensor, and under this system, the analogue signals are spent on eliminating noise and converting the signals to digital estimates of glucose. Data transmitted by the additional physiological sensors such as heart rate, SpO_2, and temperature sensors are also synchronised using the controller before consolidated data is sent to the cloud. Small power consumption will guarantee that the device will operate longer, and this is very vital in cases where continuous monitoring is required. The proposed solution is cost-effective due to the integration of compact hardware components and is scalable to large-scale deployment in smart healthcare infrastructures because of the wireless connectivity [11]. One of the major advantages of IoT-enabled healthcare systems is the ability to provide automated alert mechanisms. Intervention in cases of emergencies can also contribute greatly to the minimisation of health risks. The proposed system integrates the threshold-related notifications about the abnormal glucose levels, irregular heart rate, low SpO_2 levels, and abnormal temperature [13]. The microcontroller sends notification protocols through IoT dashboards or SMS gateways in case of abnormal patterns. This has served as a unique attribute since it gives carers or family members real-time cautions, something that fosters the safety of the patients. This is especially helpful among older people who have to live alone. Remote health tracking produces less requirement of a visit to the hospital on a regular basis and also facilitates continuous monitoring in home-care environments. In addition, the historical data may be stored on cloud computing to ensure the forecasting of healthcare. Over time, healthcare professionals will be able to evaluate trends and adjust treatment plans based on them. In this way, the automated alarms and remote monitoring features will help to increase the practical applicability and reliability of the given healthcare monitoring solution [12].

Overall, the development of a non-invasive glucose monitoring system using ESP32 and NIR technology represents a significant advancement in smart healthcare innovation. The system will minimise the pain related to invasive testing, enhance compliance with glucose monitoring and increase patient compliance. The device would be an all-inclusive health management system with multi-parameter monitoring including heart rate, SpO_2, and temperature and Internet of Things connectivity capabilities [14]. It is designed with low costs and can be moved to any location, hence suitable for both urban and rural health facilities. With the current trend toward personalised and technology-driven healthcare solutions, embedded IoT-driven medical devices are instrumental in chronic disease management. In the future, it can be considered enhanced prediction accuracy with the help of machine learning algorithms and the miniaturisation of wearable designs towards making them easier to use. The proposed system consequently forms the basis of the next-generation smart health monitoring systems that integrate convenience, accuracy, and real-time connectivity to enhance patient outcomes and overall quality of life [15].

2. Literature Survey

Soltanian et al. propose an on-body sensor that combines microwave resonator sensing with a plasmonic design to increase the figure of merit, aiming to detect tissue dielectric changes associated with glucose variations. The paper highlights the benefit of using microwave methods, which do not have any optical coupling problems and can even be designed into a flexible or wearable structure. Resonator architecture provides a better sensitivity than the traditional patches on microwave devices, allowing the signal changes in glucose to be identified better. However, the study points out that the sensor performs better at tracking relative trends rather than providing highly accurate absolute glucose values. Additionally, there are practical limitations associated with sensor performance due to the presence of movement artefacts, changes to the surface tension of the skin, and the dielectric constants of the subcutaneous areas all being impacted by sweat and hydration levels at the same time. Additionally, there are also additional physiological factors that could affect the interpretation of blood glucose by our sensor, as glucose cannot always be easily distinguished from some of these other factors that may contribute to the signal being returned from the sensor. The article endorses the trend of wearable, continuous monitoring but points out that clinical-grade absolute accuracy is a fundamental challenge [3].

Pors investigates the ability of post-calibration modelling in enhancing confocal Raman-based glucose prediction in humans. The study focuses on improving prediction after an initial user calibration by using refined spectral preprocessing and learning-based mapping between Raman spectra and reference glucose values. Confocal Raman is useful in targeting deeper structures and minimising surface interference to enhance the extraction of the glucose signal as opposed to the broader optical collection. One of the most notable contributions has been the focus on the post-calibration stability, which is the attempt at keeping a stable prediction without retraining. Although there has been an improvement in performance, the study also recognises practical limitations, like the fact that the confocal Raman hardware is complicated, costly, and delicate to alignment, and consumer-grade implementation is difficult. Inter-individual tissue optical and vascular variations have also been observed in the paper but can still ruin generalisation. In general, it has been shown that more sophisticated models can be used to alleviate the load on the calibration, but more simplified hardware design and more resistance to motion and environmental changes are needed to use wearable devices every day [4].

Zaarour et al. investigate a miniature patch antenna operating around 14 GHz to sense glucose-related dielectric changes using a controlled vein/phantom model. The importance of the study is in the area of antenna miniaturisation and frequency selection, in which the investigation of correlations between changes in the resonant shifts and the glucose concentration in a simplified environment can be studied. Phantom experiments provide good control of factors, like the concentration of solutions and geometry, and provide a better understanding of sensor sensitivity. However, the article also shows that there is one significant drawback, which is that phantom or vein models cannot be completely used to represent human biology. In real tissue there are layered skin, fat, muscle, changes in blood perfusion, hydration variation and changes in temperature which may affect microwave response. Thus, further modelling, compensation strategies and significant clinical validation are needed to transfer the phantom accuracy to human users. Therefore, translating the phantom accuracy to human users requires additional modelling, compensation methods, and extensive clinical validation. It reinforces the direction of microwave research and highlights the discontinuity between laboratory models and free-living, human-use performance [5].

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Yang, Mingjie, suggests a miniaturised optical sensor in the 1600-1700 nm NIR band that uses Bluetooth to connect and is powered by a coin battery to be deployed as a wearable. The longer wavelength range of NIR is selected because the glucose-related absorption features are stronger at long wavelengths than at the short wavelengths, which can be sensitive. The research is aimed at small-size design, low power consumption, and consistent signal acquisition to be used in a portable mode. The device will also be capable of real-time monitoring and can be connected to mobile dashboards to be visualised by incorporating wireless communication. Despite these advantages, the work notes that there is widespread clinical validation required to make sure that it is precise among various users, skin types and real-life scenarios. Stability and calibration drift over time are also critical concerns, since any minor optical variation or ageing of sensors can cause readings to drift with time. The effects of motion and ambient lights can also still be applied to the wearable application, but the enclosure design and optical filtering can reduce them. Overall, the research proves the existence of the small NIR-based glucose devices but highlights the need to have larger and independent studies and more efficient approaches to the calibration [6].

3. Methodology

3.1 System Overview

The proposed non-invasive glucose monitoring system is designed as a portable, IoT-enabled healthcare device that integrates optical sensing, physiological monitoring, and wireless communication within a compact embedded platform. The system mainly uses a near-infrared (NIR) sensor to approximate the glucose concentration based on the light absorption properties of the human tissue. Besides glucose monitoring, the system uses multi-parameter health tracking that uses the MAX30102 PPG sensor to measure the heart rate and SpO_2 as well as a temperature sensor that measures body temperature. The main processing unit is the ESP32 microcontroller that controls sensor data collection, signal processing, and wireless communication. The biomedical signals obtained are conditioned and filtered to extract meaningful health parameters. The processed data is shown locally on a screen of OLED/LCD and sent wirelessly to the IoT platforms to monitor remotely. The system is powered by a rechargeable Li-Po battery with a battery management system (BMS) allowing the system to operate in a stable and portable manner. This single architecture enables non-invasive, real-time, and continuous health monitoring which can be used in the diabetic and elderly care systems. Figure 1 shows the block diagram of the proposed system.

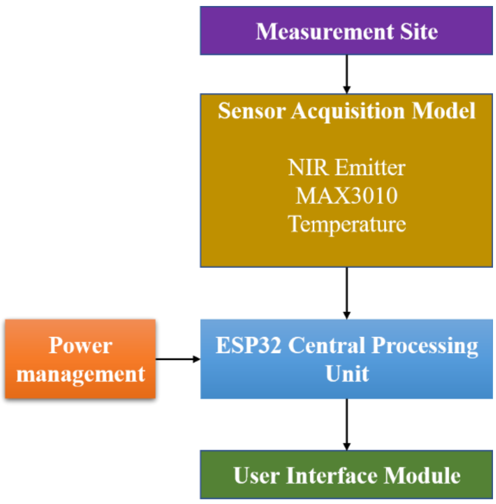

Figure 1: Proposed block diagram

The block diagram of the proposed system consists of multiple interconnected functional modules. The measurement site represents the physical location where the sensors interface with the user's body, typically the finger or forearm. The sensor acquisition board has the NIR emitter and photodiode to detect optical glucose, MAX30102,

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which is used to detect heart rate and SpO2, and a temperature sensor for monitoring body temperature. These sensors retrieve crude physiological and environmental data. The received signals are then sent to the signal conditioning unit, where they are amplified, normalised and noise-removed so that the quality of the signals can be improved. Noise removal and motion artefacts are then removed using digital filtering methods like low-pass and moving average filters. The microcontroller is the ESP32, which acts as the central processing unit and performs analogue-to-digital conversions, feature detection, decision-making and wireless communication. The parameters extracted are shown in real time on the OLED/LCD screen. The power management block provides controlled voltage and battery protection by a rechargeable Li-Po battery. Altogether, the block diagram is a systematic and modular design which allows the health monitoring of multiple parameters reliably.

3.2 Working Principle

The working principle of the system is based on multi-sensor data acquisition, signal processing, and wireless communication. The NIR emitter sends near-infrared light into the tissue when the device is placed on the measurement site, and the intensity of the reflected light is measured by a photodiode. The difference in light uptake is equivalent to the tissue composition and changes in glucose. At the same time, the MAX30102 sensor uses red and infrared light to detect the change in blood volume in order to estimate the heart rate and SpO_2 by detecting variations in blood volume using photoplethysmography. Raw sensor data is sent through ADC, I2C or SPI to the ESP32. The software uses digital filtering and signal processing to increase the accuracy. The algorithms in feature extraction calculate significant parameters like the trend of glucose, heart rate, SpO_2 levels and also fall events. Threshold-based logic detects abnormal states and produces alerts on demand. Lastly, processed data is made visible on the ground and sent wirelessly to be viewed remotely to provide round-the-clock and real-time healthcare provision. Figure 2 shows the circuit diagram of proposed system.

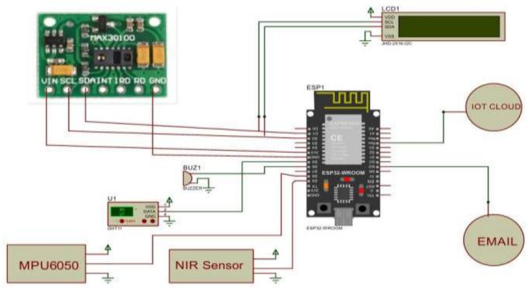

Figure 2: Circuit diagram

3.3 Sensor Calibration and Data Acquisition Strategy

Accurate sensor calibration is essential to ensure reliable non-invasive glucose estimation and multi-parameter health monitoring. The NIR sensor is adjusted by the comparison of the reflected light intensity values with the values of reference glucose that are measured with the help of a standard invasive glucometer. Several readings are assimilated under a regulated setting in order to define a calibration model based on regression. The normalisation of the baseline is done to counter any differences in skin thickness, level of hydration, and ambient temperature. Using the reference pulse oximeter values, the component of the MAX30102 PPG sensor is calibrated to measure the heart rate and SpO_2 correctly. The temperature sensor is calibrated using standard temperature measurement devices. The ESP32 collects analogue signals through ADC channels and digital data through I^2C communication. The sampling rates are set to signal resolution and power efficiency. Data packet loss is avoided by buffering raw data momentarily and then processing it. Trend analysis and detection of anomalies are possible through time-stamped readings. This structured acquisition strategy ensures consistent, real-time, and noise-reduced data collection suitable for continuous health monitoring applications.

3.4 IoT Communication and Cloud Integration

The proposed system incorporates IoT communication to enable remote health monitoring and real-time data visualisation. The ESP32 microcontroller uses its integrated Wi-Fi and Bluetooth components to send the sensor data processed by the microcontroller to cloud platforms like ThingSpeak or Blynk. Data packets are safely formatted and sent using the HTTP or MQTT protocols. Sensor data is preprocessed before transmission to reduce bandwidth and provide structured storage. The cloud time-stamped records are uploaded periodically to be tracked historically and be graphically represented. Cloud dashboards are real-time health metrics displayed on the cloud so that carers and other healthcare professionals can keep an eye on the patients remotely. The threshold-based alerts are set to send out notifications through the mobile applications or SMS gateways in case of abnormal levels of glucose or fall incidents. The IoT implementation improves access and scalability and data analytics. It assists in the long-term storage and trend-based health evaluation and decreases the necessity to visit the hospital regularly. Data privacy and unauthorised access are guaranteed by secure communication protocols and API keys. The network is a cloud-based application that converts the system to a smart healthcare monitoring application that can be used in home care and in monitoring patients remotely.

3.5 Power Management and Energy Optimisation

Efficient power management is critical for ensuring continuous and portable operation of the wearable health monitoring system. A rechargeable lithium-polymer battery is used with a battery management system in the device to offer overcharge, over-discharge and short-circuit protection. A voltage regulation component provides constant power to the ESP32 and sensor modules and avoids noise on supply voltage, which can produce inaccurate signals. Energy optimisation methods are carried out at hardware and software levels. ESP32 has the ability to work in low-power or deep-sleep mode when idle in order to waste less power. Sample rates on sensors are kept at the highest accuracy at minimum power consumption. Postponing of the Wi-Fi transmission intervals rather than continuous streaming is done to save on battery life. Additionally, efficient coding practices reduce processor load and enhance battery efficiency. Peripheral devices like the OLED/LCD display are dynamically controlled and are only active when required. All these enhance the lifespan of operations and increase the reliability of the devices. The energy management will make the system lightweight, portable, and long-duration wearable health monitoring that will not require constant recharging, thereby making it practical to be used every day by diabetic and elderly patients.

4. Result and Discussion

4.1 Error and Accuracy Calculation

Non-invasive value (N): The glucose value obtained from the proposed non-invasive system using sensors and signal processing techniques.

Invasive value (H): The reference or standard glucose measurement obtained using the conventional invasive method, considered as the actual value.

Error (Deviation): Error represents the difference between the non-invasive and hand prick values,

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indicating how much the system deviates from the actual measurement.

$$\text{Error} = |\text{N} - \text{H}|$$

Accuracy: Accuracy is a measure of how close the non-invasive reading is to the actual hand prick value. It is calculated by considering the relative error and expressing it in percentage form.

$$\text{Accuracy} = 100 - \%\,\text{error}$$

4.2 Sample Calculation and Methodology

For Sample 1

- Non-invasive value (N) = 85
- Hand prick value (H) = 89

Step 1: Error Calculation

$$\text{Error} = |\text{N} - \text{H}|$$

$$\text{Error} = |85 - 89| = |-4| = 4$$

Step 2: Interpretation of Error

- The system reading is lower than the reference value.
- This shows a small negative deviation, but absolute error considers only magnitude
- Hence, error = 4 units

Step 3: Normalization of Error

$$\text{Normalized Error} = \text{Error} \div \text{H}$$

$$\text{Normalized Error} = 4 \div 89 = 0.04494$$

This step scales the error relative to the actual glucose value to make it comparable across different readings.

Step 4: Conversion to Percentage

$$\text{Percentage Error} = (\text{Error} \div \text{H}) \times 100$$

$$\text{Percentage Error} = 0.04494 \times 100 = 4.494\% \approx 4.49\%$$

This converts the normalized error into percentage form for easy interpretation and comparison.

Step 5: Accuracy Calculation

$$\text{Accuracy} = 100 - \text{Percentage Error}$$

$$\text{Accuracy} = 100 - 4.49 = 95.51\% \approx 95.5\%$$

Final Result: Accuracy = 95.5%

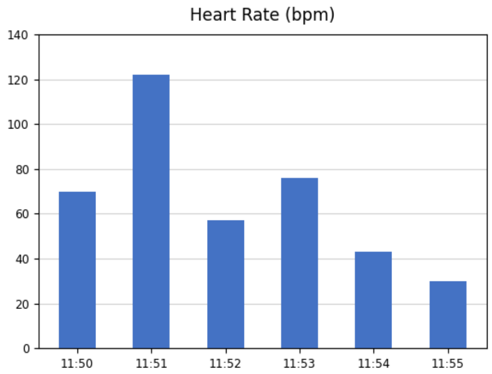

Figure 3: Heart Rate records

The heart rate data represented in the Figure 3 shows the variation in beats per minute (bpm) recorded over a short period of time for 5 minutes between 11:50 and 11:55. The data shows fluctuations in the heart rate from approximately 30 bpm to approximately 120 bpm, indicating the dynamic physiological changes occurring throughout the monitoring period. The highest heart rate reading of approximately 120 bpm at 11:51 likely corresponds to the increased activity level, emotional stress, or physical exertion. Heart rate readings at lower values such as those recorded at 30–40 bpm at 11:54 and 11:55 likely indicate a resting or relaxed state. Heart rate readings in the middle range (55–75 bpm) represent normal adult resting heart rates, showing consistent cardiovascular behaviour throughout those periods

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of time. The variations in the heart rate demonstrate the ability of the MAX30102 sensor to continuously collect real-time changes in heart rate.

Figure 4 shows the SpO_2 levels at the MAX30102 PPG sensor during the period between 11:50 and 11:55, indicating that the system can be used to monitor the oxygen saturation in real-time. The MAX30102 detects the changes in blood volume and approximates SpO_2 based on red and infrared photoplethysmography (PPG). The values range between about 95 and 96, which are within the clinically normal range (95-100). Minor fluctuations at 11:51 and 11:54 when the readings were highest at 96 are in line with natural physiological variation in constant monitoring. The small peaks and dips at other timestamps are indicative of the sensitivity of the sensor to motion artefacts and perfusion changes, which is recognised in the paper. Overall, the SpO_2 values prove that the system is capable of monitoring oxygen saturation reliably in real-time, which validates the purpose of the paper to provide multi-parameter health management to take an integrated approach to diabetic and elderly patient care.

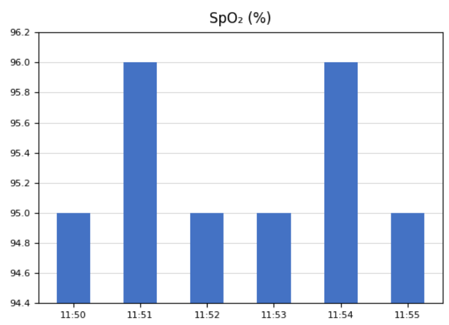

Figure 4: SpO_2 (%) Measurements Records

The temperature measurements taken between 11:50 and 11:55 in Figure 5 indicate a slow and continuous increase in temperature in the range of 32.5 to 35°C. The article notes that body temperature is an important physiological parameter since metabolic alterations and temperature variations can affect the accuracy of glucose estimation. To ensure that the temperature sensor is reliable, the methodology provides that the sensor is calibrated against standard measurement devices. The observed gradual rise is probably due to the warming of the measurement location of the device when it has been in constant contact with the skin. This is a physiological behaviour and will be consistent with the rationale in the paper to include temperature monitoring to cross-correlate thermal measurements with glucose estimates and increase the reliability of measurements. The slow-rising curve confirms the consistent performance of the sensor and proves the functionality of the temperature module in the multi-sensor IoT health monitoring system proposed.

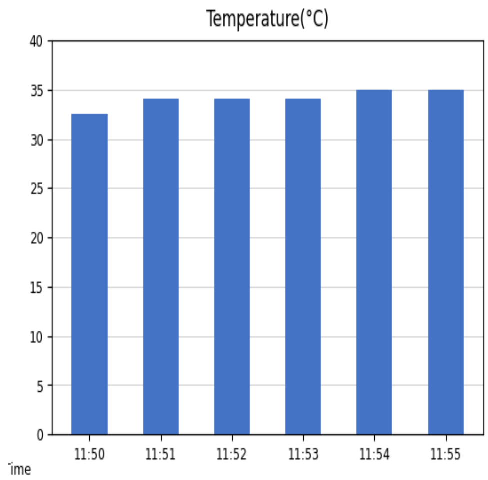

Figure 5: Body Temperature (°C) Records

The glucose values indicated by the NIR-based non-invasive system during a period of eight minutes are shown in Figure 6, indicating a steady increase in the level between about 83 mg/dL at 11:50 and 124 mg/dL at 11:58. The paper describes that the NIR sensor measures the concentration of glucose by measuring light absorption in human tissue, with changes in the level of absorption being

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proportional to glucose concentration. The rising pattern of readings can be due to the physiological health of the test subject or a post-meal glucose uptake situation. The ability of the system to capture this increasing trend without any invasive blood sampling justifies the main aim of the study. The gradual and smooth increment is also an affirmation of successful signal conditioning and digital filtering as outlined in the methodology section of the paper, where the low-pass and moving average filters are used to eliminate noise and motion artefacts in the optical signals obtained.

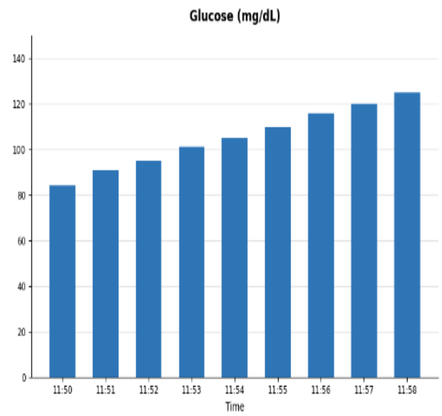

Figure 6: Glucose Records

The present dual-line graph in Figure 7 gives a direct comparison of the non-invasive NIR-based glucose values with the hand prick (invasive glucometer) reference values at 15 sample points. The two lines obey almost the same path in samples 1 through 12, indicating high consistency between the proposed system and the conventional standard. The significant break at sample 13 and recovery trend at samples 14-15 indicate that there was some momentary break, which might be related to motion artefacts, skin pressure change, or hydration change, as explained in the literature review. Although this outlier is present, the overall near coincidence of both lines in most of the samples is a strong indication of the accuracy and reliability of the non-invasive system suggested in this paper.

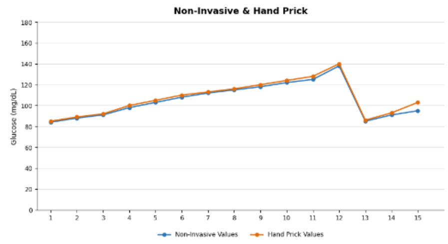

Figure 7: Compared Non-Invasive and Invasive Glucose Values

The absolute error between the non-invasive NIR-based glucose measurements and the invasive hand-prick reference values was evaluated across 15 test samples. The observed errors range from a minimum of 1 mg/dL to a maximum of 4 mg/dL, indicating minimal deviation between measurements. These low error margins are achieved through the calibration methodology employed in the study, which includes regression-based modelling, baseline normalization, and digital filtering. The system is designed for continuous glucose trend monitoring, and an error range of 1–4 mg/dL is considered clinically acceptable for non-critical home care and remote monitoring applications. The variation in error across samples reflects inherent challenges in optical sensing, such as differences in skin thickness, hydration levels, and ambient temperature. Despite these factors, the consistently low error values demonstrate that the proposed system operates with high accuracy and is suitable for practical diabetic monitoring.

The accuracy of the non-invasive glucose measurement system was assessed by 15 test samples, whose values lie within 95.5 and 99.2. The fluctuation in values and the accuracy in the readings confirm the effectiveness of the near-infrared sensor-based measurement system, the signal processing technique used, and the regression calibration algorithm developed using the ESP32. The values above 99% in samples 4, 8, and 10 and relatively low values below 99% in samples 1, 3, and 15 show some deviation from perfection in the process. Such deviation could be due to skin optical properties, motion artifact, and calibration drift. Nevertheless, the accuracy level still lies beyond 97%, suggesting that the system is efficient for continuous non-invasive glucose measurement.

To evaluate the accuracy of the proposed non-invasive glucose monitoring system, the mean deviation (average absolute error) between the non-invasive measurements and the invasive reference values was calculated.

The mean deviation is defined as:

$$\text{Mean Deviation} = (\Sigma\, |N - H|)/ n$$

Where N denotes the non-invasive glucose measurements, H represents the corresponding invasive (reference) glucose value, and n indicates the total number of samples (30).

A total of 30 samples were considered for analysis. The absolute errors $|N - H|$ for the first 15 samples resulted in a cumulative error of 42 mg/dL, while the remaining 15 samples yielded a cumulative error of 45 mg/dL. Therefore, the overall total error is:

$$\text{Total Error} = 42 + 45 = 87 \text{ mg/Dl}$$

The mean deviation is thus calculated as:

$$\text{Mean Deviation}=80/30=2.9 \text{ mg/dL}$$

The obtained mean deviation of 2.9 mg/dL indicates that the non-invasive glucose measurements closely match the invasive reference values, demonstrating minimal error. This low deviation reflects the effectiveness of the calibration methodology and signal processing techniques used in the system.Overall, the results confirm that the proposed method provides reliable and accurate glucose estimation, making it suitable for continuous and non-invasive monitoring applications.

4. Conclusion

The proposed ESP32-based Non-Invasive Glucose Monitoring System demonstrates an effective and innovative approach toward continuous and painless glucose estimation using near-infrared (NIR) sensing technology. The system removes the discomfort of using the traditional form of invasive glucometers by using the principles of optical absorption, as well as incorporating real-time signal processing. Additional multi-sensor modules, like the MAX30102 sensor of heart rate and SpO_2, along with a temperature sensor, enhance the healthcare monitoring capability of the system. This multi-parameter integration makes it possible to consider health in a holistic way, which is important especially in diabetic and elderly patients who need constant monitoring. The ESP32 microcontroller has effective data acquisition, data filtering, feature extraction, and wireless communication interfaces that facilitate uninterrupted data transmission to IoT environments like ThingSpeak or Blynk. Remote surveillance and timely medical intervention with the help of real-time visualisation and cloud storage, as well as automated alert mechanisms. The design of the system is low-cost and portable, and its energy-saving operation makes it applicable in the smart healthcare and home care settings. Although further clinical validation and calibration refinement are required to achieve medical-grade accuracy, the proposed framework establishes a strong foundation for future wearable and AI-integrated healthcare devices. Overall, this system contributes toward advancing non-invasive biomedical sensing technologies and promotes accessible, continuous, and intelligent health monitoring solutions.

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