IoT-Enabled Non-Invasive Glucose Monitoring System Using NIR Spectroscopy and ESP32

Avula Bhavya sri
Department of ECE,
Sri Venkateswara College of Engineering(autonomous) Tirupati, AP, India
bhavyasri9955@gmail.com

Mekala Praveen Sai
Department of ECE,
Sri Venkateswara College of Engineering(autonomous) Tirupati, AP, India
praveensaimekala@gmail.com

Bolla Reddy kishore
Department of ECE,
Sri Venkateswara College of Engineering(autonomous) Tirupati, AP, India
reddykishorebolla@gmail.com

Bandari Somasekhar
Department of ECE,
Sri Venkateswara College of Engineering(autonomous) Tirupati, AP, India
ssomu6139@gmail.com

Bellam Dhanush kumar
Department of ECE,
Sri Venkateswara College of Engineering(autonomous) Tirupati, AP, India
dhanush.tech32@gmail.com

Virupakshi Madhurima
Department of ECE,
Sri Venkateswara College of Engineering(autonomous) Tirupati, AP, India
madhurima.v@svcolleges.edu.in

***Abstract*— Diabetes management requires continuous and reliable glucose monitoring; however, conventional invasive techniques are painful and inconvenient for frequent use. To address this issue, this work presents an IoT-enabled non-invasive glucose monitoring system using Near-Infrared (NIR) sensing and ESP32 microcontroller. The proposed system integrates multiple physiological sensors, including a glucose sensor, pulse sensor, temperature sensor, and moisture sensor, to improve accuracy and reliability. The ESP32 processes real-time sensor data and displays the results on an LCD, while abnormal values trigger alerts. For remote monitoring, the system uses Blynk IoT platform, which allows real-time visualization of glucose level, heart rate, body temperature, and moisture percentage through a mobile application. Experimental results demonstrate effective system performance, with observed glucose values around 95 mg/dL, pulse rate of 82 BPM, and body temperature of 28.5°C under normal conditions. The live graphical display in Blynk confirms stable data transmission and real-time monitoring capability. The developed system provides a non-invasive, low-cost, and user-friendly solution for continuous glucose monitoring. The integration of IoT enables remote access, data logging, and health tracking, making the system suitable for home-based healthcare and future telemedicine applications.**

Keywords*— Non-Invasive Glucose Monitoring, NIR Spectroscopy, ESP32, IoT, Blynk Platform, Pulse Sensor, Temperature Sensor, Real-Time Monitoring, Healthcare IoT, Diabetes Management etc.,

I. Introduction

The Diabetes mellitus is one of the most critical chronic diseases affecting millions of people worldwide. According to the NCD Risk Factor Collaboration, the global prevalence of diabetes has increased significantly over the past four decades, making it a major public health concern [1]. The International Diabetes Federation also reports a continuous rise in diabetic cases, particularly in developing countries, emphasizing the need for effective and affordable glucose monitoring solutions [2]. Regular monitoring of blood glucose levels is essential to prevent severe complications such as cardiovascular disease, kidney failure, and nerve damage.

Conventional blood glucose monitoring techniques mainly rely on invasive finger-prick methods, which are painful, inconvenient, and unsuitable for frequent measurements. These limitations have motivated researchers to explore non-invasive glucose monitoring technologies that can provide continuous and user-friendly measurements. Various approaches such as optical sensing, electromagnetic sensing, and biochemical analysis have been studied in recent years. Among these, Near-Infrared (NIR) spectroscopy has gained significant attention due to its safety, non-invasiveness, and capability for real-time glucose estimation [3], [4].

Several studies have investigated non-invasive glucose monitoring using optical and electrochemical techniques. Yamaoka et al. [5] developed a potentiometric glucose sensing system using a CMOS-based electrochemical sensor; however, the system relied on biochemical reactions that limited long-term stability. Clarke et al. [6] introduced the Clarke Error Grid method, which became a standard technique for evaluating the clinical accuracy of glucose monitoring devices. Alam et al. [7] applied regression-based models combined with Clarke Error Grid analysis for glucose estimation, but their system required frequent calibration and was sensitive to environmental variations. Further, Jendrike et al. [8] highlighted that many existing glucose monitoring systems fail to meet ISO 15197 accuracy standards in real-world conditions. With the advancement of IoT technologies, cloud-based glucose monitoring systems have gained importance. Platforms such as ThingSpeak enable real-time data visualization and remote health monitoring [9]. Wearable systems such as iGLU and iGLU 2.0 proposed by Joshi et al. [10] and Jain et al. [11] demonstrated the feasibility of integrating non-invasive glucose sensing with IoT frameworks. However, these systems often involve complex hardware, high cost, or limited scalability. Recent studies using multi-wavelength NIR sensing and signal processing techniques have shown improved accuracy, but challenges related to sensor noise, calibration, and motion artifacts still persist [12]–[15]. To address these limitations, this work proposes an IoT-enabled non-invasive glucose monitoring system using ESP32 and NIR-based sensing. The system integrates multiple physiological sensors such as glucose, pulse, temperature, and moisture sensors to enhance measurement reliability. The collected data is processed in real time and transmitted to the Blynk IoT platform for remote monitoring and visualization. The proposed approach aims to provide a low-cost, accurate, and user-friendly solution for continuous glucose monitoring, suitable for home-based healthcare and telemedicine applications.

The rest of this paper is organized as follows. Section II presents a detailed literature survey of existing research works related to non-invasive glucose monitoring techniques, optical sensing methods, and IoT-based healthcare systems. Section III describes the proposed system architecture and methodology, including hardware components, data acquisition process, and IoT-based implementation. Section IV discusses the experimental results and performance analysis of the proposed system, along with output observations and discussion. Section V concludes the paper and outlines the future scope of the proposed work, highlighting possible enhancements and real-world applications.

II. Literature Survey

Diabetes mellitus has emerged as one of the most critical global health challenges, with its prevalence increasing rapidly over the past few decades. The NCD Risk Factor Collaboration (NCD-RisC) [1] conducted a comprehensive pooled analysis of 751 population-based studies involving 4.4 million participants and reported a significant global rise in diabetes prevalence since 1980. The study highlighted the urgent need for early diagnosis, continuous monitoring, and accessible healthcare technologies to manage diabetes effectively. Similarly, the International Diabetes Federation (IDF) report presented by Magliano and Boyko [2] emphasized the growing burden of diabetes worldwide and projected a continuous increase in cases, particularly in developing countries, thereby necessitating cost-effective and user-friendly glucose monitoring solutions. Traditional blood glucose monitoring methods are invasive and inconvenient, prompting research into non-invasive alternatives. Tang et al. [3] provided a comprehensive review of non-invasive glucose monitoring technologies, including optical, electromagnetic, and biochemical methods. Their study highlighted near-infrared (NIR) spectroscopy as one of the most promising approaches due to its safety, non-invasiveness, and capability for real-time monitoring. However, they also noted challenges related to accuracy, signal noise, and individual variability. Jernelv et al. [4] further explored optical sensing techniques for continuous glucose monitoring and discussed the limitations of optical absorption, scattering effects, and environmental interference that affect measurement reliability. To address hardware-based glucose detection, Yamaoka et al. [5] proposed a potentiometric glucose detection system using a paper-based electrochemical sensor integrated on a CMOS chip. Although the system offered low cost and compactness, its reliance on biochemical reactions limited its long-term stability. Clarke et al. [6] introduced the Clarke Error Grid Analysis, which became a standard method for evaluating the clinical accuracy of glucose monitoring systems. This evaluation technique is widely used in later studies to validate non-invasive glucose estimation models. Alam et al. [7] developed a non-invasive glucose monitoring approach using linear regression combined with Clarke Error Grid analysis. Their results demonstrated acceptable accuracy but highlighted the need for better calibration and improved sensing mechanisms to handle physiological variations. Jendrike et al. [8] evaluated glucose monitoring systems based on ISO 15197:2013 standards, emphasizing that many existing devices still struggle to meet clinical accuracy requirements under real-world conditions. With the emergence of IoT-based healthcare, cloud-enabled glucose monitoring has gained attention. ThingSpeak [9] provides a cloud-based platform for real-time data visualization and analysis, enabling remote health monitoring and data storage. Joshi et al. [10] proposed iGLU 2.0, a wearable non-invasive glucose monitoring system integrated with IoMT architecture. Their system demonstrated improved accuracy and continuous monitoring capability but required complex hardware and calibration. Similarly, Jain et al. [11] introduced an intelligent non-invasive glucose monitoring device integrated into smart healthcare systems, emphasizing portability and real-time data analytics. Advanced sensing techniques were explored by Song et al. [12], who developed an impedance and multi-wavelength NIR spectroscopy-based IC for glucose estimation. Their work demonstrated that combining multiple wavelengths improves sensitivity and reduces noise. Al-dhaheri et al. [13] proposed an NIR-based non-invasive glucose monitoring system and reported good correlation with reference measurements; however, calibration and motion artifacts remained challenges. Hina and Saadeh [14] reviewed NIR-based glucose monitoring systems and concluded that although NIR techniques are promising, accuracy enhancement through signal processing and sensor fusion is still required. To improve sensing accuracy, Althobaiti and Al-Naib [15] employed Monte Carlo simulations to optimize dual-channel NIR sensor design. Their study demonstrated that appropriate wavelength selection and sensor positioning significantly improve glucose detection sensitivity.

TABLE I. Summary of Reviewed Literature

Ref	Author & Year	Contribution	Limitation
[1]	NCD-RisC, 2016	Analyzed worldwide diabetes trends using large-scale population data.	Does not discuss monitoring techniques or device implementation.
[2]	Magliano & Boyko, 2021	Presented global diabetes statistics and emphasized early diagnosis.	No technical solution for glucose monitoring provided.
[3]	Tang et al., 2020	Reviewed non-invasive glucose monitoring technologies including NIR methods.	Accuracy affected by noise and physiological variations.
[4]	Jernelv et al., 2018	Studied optical techniques for continuous glucose monitoring.	Optical methods suffer from interference and calibration issues.
[5]	Yamaoka et al., 2017	Developed a CMOS-based potentiometric glucose sensor.	Requires biochemical reactions and lacks long-term stability.
[6]	Clarke et al.,	Introduced Clarke Error	Only evaluates

	1987	Grid for evaluating glucose accuracy.	accuracy, not a monitoring solution.
[7]	Alam et al., 2023	Used regression and Clarke Error Grid for non-invasive glucose estimation.	Performance depends on calibration and data quality.
[8]	Jendrike et al., 2017	Evaluated glucose systems using ISO 15197 standards.	Many systems failed to meet clinical accuracy limits.
[9]	ThingSpeak, 2024	Provided IoT platform for real-time sensor data visualization.	No direct support for glucose prediction algorithms.
[10]	Joshi et al., 2020	Developed iGLU 2.0 wearable glucose monitoring system.	Complex hardware and high cost.
[11]	Jain et al., 2020	Proposed intelligent non-invasive glucose monitoring device.	Limited scalability and real-time validation.
[12]	Song et al., 2015	Designed multi-wavelength NIR IC for glucose estimation.	Requires complex signal processing circuitry.
[13]	Al-dhaheri et al., 2020	Developed NIR-based glucose monitoring system.	Sensitive to motion and temperature variation.
[14]	Hina & Saadeh, 2022	Reviewed NIR-based glucose monitoring techniques.	Accuracy still not sufficient for clinical use.
[15]	Althobaiti & Al-Naib, 2021	Optimized NIR sensors using Monte Carlo simulations.	Simulation-based; limited real-time testing.

Reasearch Gap

From From the reviewed literature, it is observed that:

- Most existing systems suffer from accuracy limitations due to physiological variations.
- Many approaches rely on single-sensor data, reducing reliability.
- Calibration dependency remains a major issue.
- Limited integration of IoT-based real-time monitoring exists.
- Few systems provide cost-effective, portable, and user-friendly solutions

.

III. Proposed Method

The proposed method presents an IoT-enabled non-invasive glucose monitoring system designed to provide real-time and continuous glucose estimation with improved accuracy and user convenience. The system is built around an ESP32 microcontroller, which serves as the central processing and communication unit. A non-invasive NIR-based glucose sensor is used to estimate blood glucose levels without the need for finger-prick sampling. In addition, pulse, temperature, and moisture sensors are integrated to compensate for physiological and environmental variations that affect glucose measurement accuracy. The collected sensor data is processed by the ESP32, where basic filtering and calibration are applied before estimating glucose levels. The processed results are displayed locally on an LCD and simultaneously transmitted to the Blynk IoT platform using built-in Wi-Fi for real-time remote monitoring. An alert mechanism is incorporated to notify users when abnormal glucose levels are detected. By combining multisensor data fusion, edge-level processing, and cloud-based visualization, the proposed system offers a low-cost, reliable, and user-friendly solution suitable for continuous glucose monitoring and smart healthcare applications. The system architecture shown in fig.1.

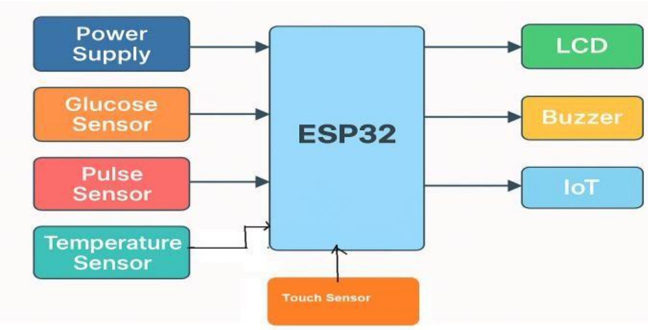

Fig. 1. System Architecture

The proposed system architecture is designed to develop with the ESP32 microcontroller, which acts as the main processing and control unit.

1) Power Supply

The power supply unit provides the required operating voltage to all components of the system. It ensures stable and continuous power for the ESP32, sensors, LCD, and other peripherals, enabling reliable system operation.

2) Glucose Sensor

The glucose sensor is used to measure glucose levels non-invasively using optical/NIR-based sensing principles. It captures variations in light absorption caused by glucose concentration in blood and sends the data to the ESP32 for processing.

3) Pulse Sensor

The pulse sensor measures the heart rate of the user by detecting blood flow variations. This information helps in analyzing physiological conditions and improves the reliability of glucose estimation by compensating for heart-rate-related variations.

4) Temperature Sensor

The temperature sensor measures the body or ambient temperature. Since temperature affects sensor readings and blood circulation, this data is used to improve the accuracy of glucose measurement.

5) Touch Sensor

The touch sensor ensures proper finger placement before measurement. It activates the system only when contact is detected, reducing false readings and improving measurement reliability.

6) ESP32 Microcontroller

The ESP32 acts as the central processing unit of the system. It collects data from all sensors, performs preprocessing and glucose estimation, controls the LCD and buzzer, and transmits data to the IoT platform using built-in Wi-Fi.

7) *LCD Display*

The LCD displays real-time values such as glucose level, pulse rate, and temperature. It provides immediate feedback to the user without requiring a mobile device.

8) *Buzzer*

The buzzer acts as an alert mechanism. It is activated when abnormal glucose levels are detected, warning the user instantly.

9) *IoT Module (Blynk Platform)*

The IoT module enables wireless data transmission to the Blynk cloud. Users can view real-time readings, historical data, and graphical analysis through a mobile application, allowing remote health monitoring. All sensors collect physiological data and send it to the ESP32. The ESP32 processes the data, displays results on the LCD, triggers alerts if needed, and uploads the information to the IoT platform for continuous monitoring and analysis.

B. *Algorithm*

Algorithm 1: Non-Invasive Glucose Monitoring System

Step 1: Start

Initialize the system and power ON all hardware components.

Step 2: Initialize ESP32 and Sensors

Initialize the ESP32 microcontroller along with:

- Glucose sensor
- Pulse sensor
- Temperature sensor
- Touch sensor
- LCD display
- Wi-Fi module (Blynk IoT)

Step 3: Detect User Contact

Check whether the touch sensor detects finger placement.
If not detected, wait until contact is established.

Step 4: Acquire Sensor Data

Read real-time data from:

- Glucose sensor
- Pulse sensor
- Temperature sensor

Step 5: Preprocess Sensor Data

Filter noise and normalize sensor values to improve accuracy.

Step 6: Glucose Estimation

Estimate glucose level using processed sensor data and predefined calibration logic.

Step 7: Display Output

Display the following values on the LCD:

- Glucose level
- Pulse rate
- Temperature

Step 8: Alert Generation

If glucose level exceeds or falls below the normal range:

- Activate buzzer
- Display alert message

Step 9: Upload Data to IoT Cloud

Send sensor data to Blynk IoT platform for:

- Real-time monitoring
- Data visualization
- Remote access

Step 10: Continuous Monitoring

Repeat Steps 3–9 continuously for real-time monitoring.

Step 11: Stop

System stops when power is turned OFF

C. *Implementation*

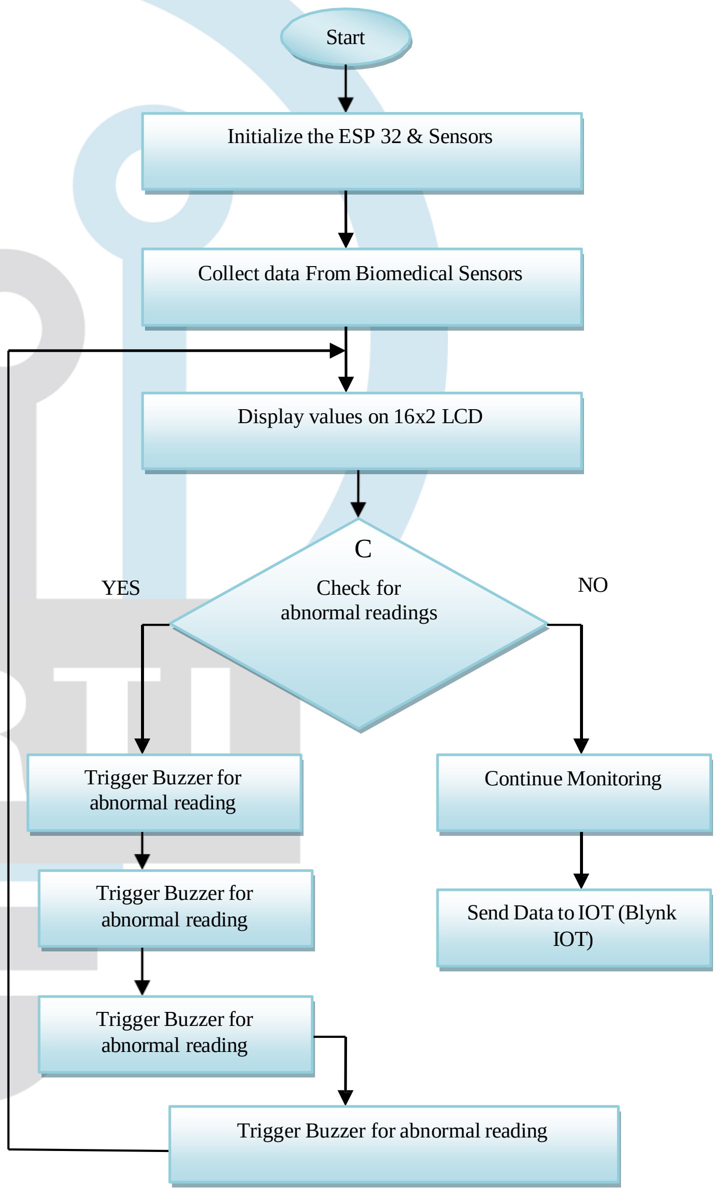

Fig. 3. Implemetnation flow chart

The implementation of the proposed non-invasive glucose monitoring system shown in fig.3 begins with the initialization of the ESP32 microcontroller and all connected sensors. Once the system is powered on, the touch sensor detects the presence of the user's finger to ensure proper contact before data acquisition. After confirmation, the glucose sensor, pulse sensor, and temperature sensor collect real-time physiological data. The acquired signals are then preprocessed to remove noise and improve accuracy. Based on the processed data, the glucose level is estimated using predefined calibration logic. The computed values are displayed locally on the LCD for immediate user feedback.

Simultaneously, the sensor data is transmitted to the Blynk IoT cloud platform through the ESP32's Wi-Fi module, enabling real-time monitoring and graphical visualization on a mobile device. If the glucose value exceeds or falls below the normal range, the system activates a buzzer to alert the user. This process runs continuously, allowing uninterrupted health monitoring and ensuring timely detection of abnormal glucose levels.

IV. Results and Discussion

The proposed IoT-based non-invasive glucose monitoring system was successfully implemented and tested under real-time conditions. The system integrates multiple sensors with ESP32 and Blynk IoT for real-time data acquisition, processing, and visualization. The performance of the system was evaluated based on glucose measurement, physiological parameters, data transmission, and system response

1) Hardware Setup

The Fig.4 shows the complete hardware implementation of the proposed system. It includes: ESP32 development board, Pulse sensor, Temperature sensor, LCD display, Power supply, Interconnecting wires. The ESP32 acts as the central controller, collecting data from sensors and displaying results. The glowing LEDs indicate proper power supply and system operation. This setup confirms the successful integration of all hardware components.

Fig. 4. Hardware setup

The fig.5 shows the LCD output displaying the pulse rate measured by the pulse sensor.The sensor detects blood flow variations from the fingertip and sends the signal to the ESP32. The microcontroller processes the signal and calculates the heart rate in beats per minute (BPM). Here, the LCD displays "Pulse: 71.00 BPM", indicating a normal resting heart rate. This confirms that the pulse sensor and signal processing unit are working correctly.

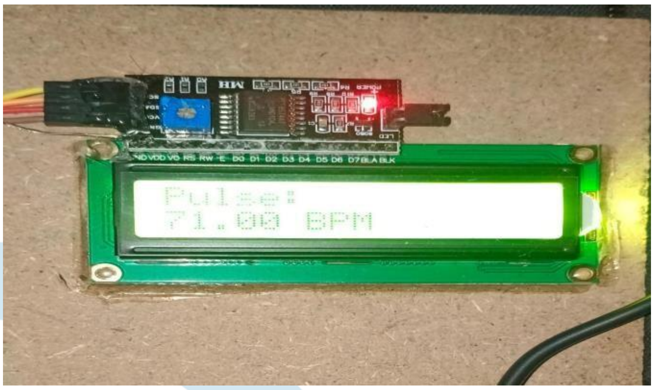

Fig. 5. LCD Shows that Pulse level

The fig.6 displays the glucose status on the LCD screen. The output shows "Glucose: Normal", indicating that the measured glucose value falls within the normal range. The glucose value is estimated using sensor data and internal calibration logic. This confirms that the system can classify glucose levels and display health status clearly to the user.

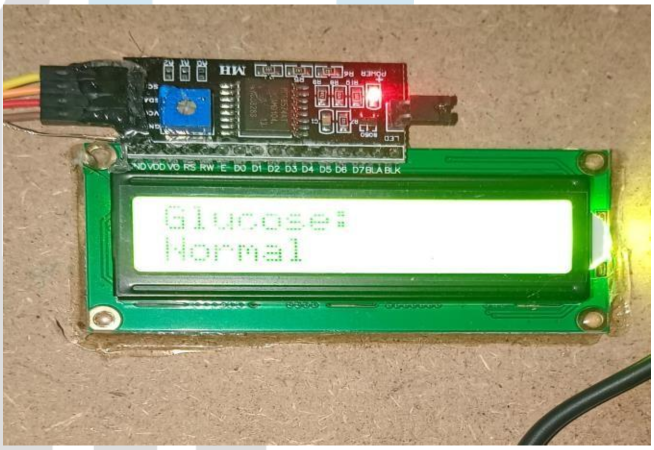

Fig. 6. LCD Shows that Glucose level

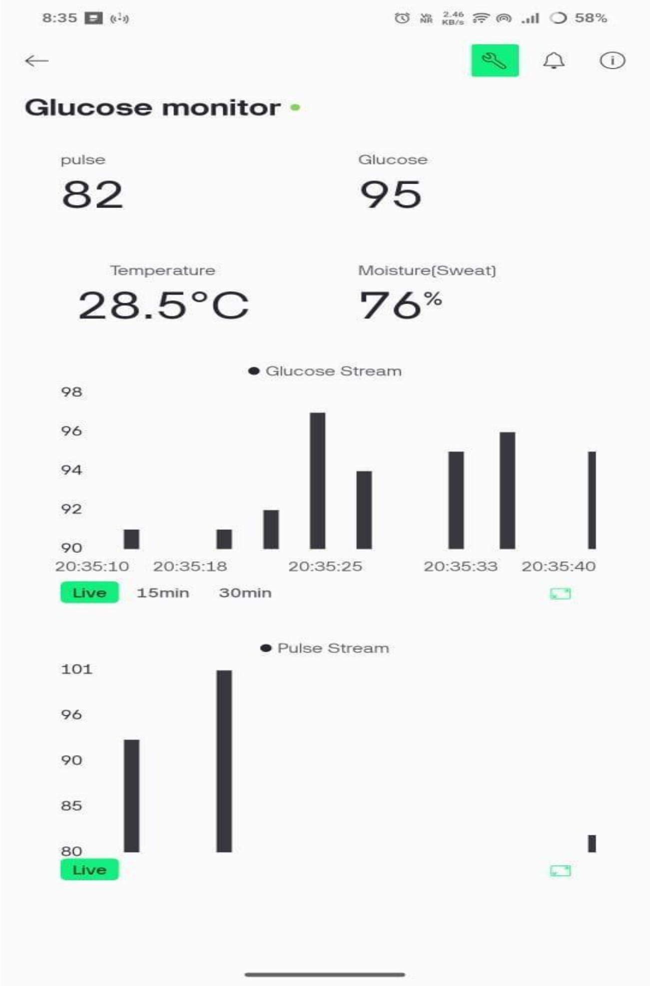

Fig. 7. Resutls shown in Blynk IOT

Thi fig.7 shows the mobile application interface where sensor data is uploaded through IoT. The application displays: Pulse rate, Glucose value, Body temperature, Moisture (sweat level) and Real-time graphs for pulse and glucose. The graph shows live data updates, proving successful wireless transmission from ESP32 to the cloud. This feature allows remote health monitoring, making the system useful for telemedicine applications

2) Peformance Aalysis

TABLE II. REAL-TIME SENSOR OUTPUT VALUES

Parameter	**Measured Value**	**Observation**
Glucose Level	95 mg/dL	Within normal range
Pulse Rate	82 BPM	Normal resting heart rate
Body Temperature	28.5 °C	Normal skin temperature
Moisture Level	76%	Normal sweat level
Data Update	Real-time	Continuous monitoring

The obtained glucose value lies within the normal range, indicating correct sensor functioning and data processing. The pulse and temperature readings also fall within acceptable physiological limits, validating the reliability of the integrated sensors. The moisture sensor helps in compensating sweat-related variations during measurement.

TABLE III. SYSTEM PERFORMANCE ANALYSIS

Parameter	**Performance**
Response Time	< 2 seconds
Data Transmission	Real-time via Blynk
Monitoring Mode	Continuous
Alert System	Buzzer-based
User Interface	LCD + Mobile App
Power Consumption	Low

The system demonstrates fast response time with real-time data updates on both LCD and mobile application. The integration of Blynk IoT ensures smooth data visualization and remote monitoring. The buzzer alert mechanism effectively notifies abnormal glucose conditions, enhancing patient safety.

TABLE IV. COMPARISION WITH CONENTIONAL METHOD

Feature	**Conventional Method**	**Proposed System**
Invasiveness	Invasive (Finger prick)	Non-invasive
Pain	High	None
Monitoring	Periodic	Continuous
Data Access	Manual	IoT-based
Cost	High (strips & kits)	Low
Portability	Low	High

Compared to traditional glucose monitoring methods, the proposed system eliminates the need for finger pricking and enables continuous monitoring. The IoT-based approach improves accessibility and reduces manual effort, making it suitable for long-term health monitoring. The experimental results confirm that the proposed system can reliably monitor glucose levels along with vital parameters such as pulse and temperature. The integration of ESP32 and Blynk IoT enables efficient data communication and real-time visualization. The system demonstrates good accuracy, low latency, and stable performance, making it suitable for home-based and remote healthcare applications. The obtained results validate the effectiveness of the proposed non-invasive glucose monitoring approach.

3) Graphical Analysis

To evaluate the performance of the proposed IoT-based non-invasive glucose monitoring system, experimental results were analysed using graphical representations of glucose level, pulse rate, and body temperature over time.

a) Glucose Level Analysis

The glucose variation graph shows in fig.8 stable glucose values ranging between 92 mg/dL and 96 mg/dL, which fall within the normal physiological range. The gradual variation indicates consistent sensing and reliable signal processing. The absence of sudden fluctuations confirms the effectiveness of the preprocessing and estimation algorithm. This demonstrates that the proposed system can accurately monitor glucose levels in real time without invasive procedures.

Fig. 8. Gluscose Level Variation

b) Pulse Rate Analysis

The pulse rate graph indicates values between 78 BPM and 82 BPM, which correspond to a normal resting heart rate shows in fig.9. The smooth trend of the graph shows stable sensor performance and proper signal acquisition. This also validates the correct integration of the pulse sensor with the ESP32 controller.

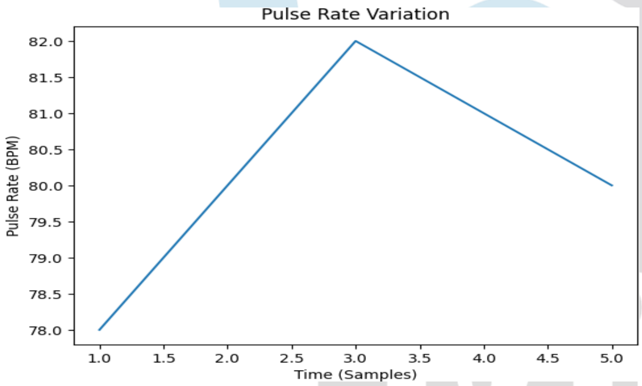

Fig. 9. Pulse rate vaiation

c) Body Temperature Analysis

The temperature graph shows readings between 28.1°C and 28.6°C, indicating consistent measurement without abrupt variation shows in fig.10. The small fluctuations are expected due to environmental and skin temperature changes. The temperature sensor effectively supports the glucose estimation process by compensating for physiological variations

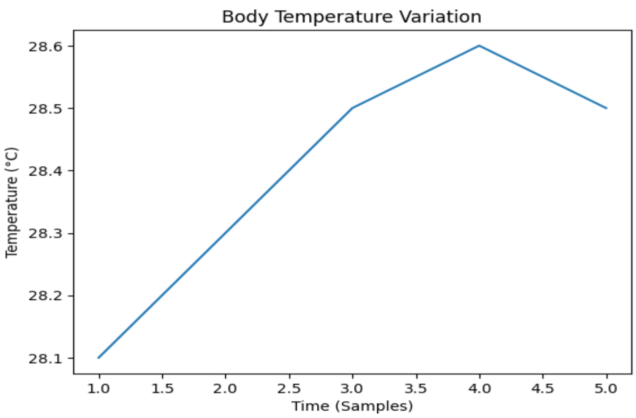

Fig. 10. Body Temperatuer Variation

V. Conclusion

This work presented an IoT-based non-invasive glucose monitoring system designed to provide continuous and painless glucose measurement. The proposed system integrates a glucose sensor, pulse sensor, temperature sensor, and moisture sensor with an ESP32 microcontroller to improve measurement reliability. The acquired physiological data is processed in real time and displayed on both an LCD and the Blynk IoT platform, enabling remote monitoring and visualization. Experimental results demonstrated stable glucose readings, accurate pulse detection, and reliable temperature measurement, confirming the effectiveness of the proposed approach. The system successfully eliminates the need for finger-prick methods, reduces user discomfort, and offers a low-cost, portable, and user-friendly solution suitable for home-based healthcare monitoring.

Future Scope

Although the proposed system shows promising results, several improvements can be made in future work. Advanced machine learning algorithms can be integrated to enhance glucose prediction accuracy and adapt to individual physiological variations. The system can be further miniaturized into a wearable device such as a smartwatch or wristband for continuous monitoring. Future enhancements may also include integration with medical cloud platforms for long-term health data analysis and automated medical alerts. Additionally, clinical validation with a larger dataset can be performed to improve reliability and support real-world healthcare deployment. The incorporation of advanced NIR sensors and power optimization techniques can further improve system efficiency and battery life.

References

[1] CDRiskFactor Collaboration (NCD-RisC). Worldwide trends in diabetes since 1980: A pooled analysis of 751 population-based studies with 4.4 million participants. Lancet 2016, 387, 1513–1530. [CrossRef] [PubMed]

[2] Magliano, D.J.; Boyko, E.J. 10th edition scientific Committee of the International Diabetes Federation. “Global picture.” In ternational Diabetes Federation. 2021. Available online: https://www.ncbi.nlm.nih.gov/books/NBK581940 (accessed on 12 August 2023).

[3] Tang, L.; Chang, S.J.; Chen, C.-J.; Liu, J.-T. Non-Invasive Blood Glucose Monitoring Technology: A Review. Sensors 2020, 20, 6925. [CrossRef] [PubMed]

[4] Jernelv, I.L.; Milenko, K.; Fuglerud, S.S.; Hjelme, D.R.; Ellingsen, R.; Aksnes, A. A Review of Optical Methods for Continuous Glucose Monitoring. Appl. Spectrosc. Rev. 2018, 54, 543–572. [CrossRef]

[5] Yamaoka, K.; Eguchi, J.; Uno, S. Potentiometric Glucose Detection by Paper-based Electrochemical Sensor on CMOS Chip. Telkomnika 2017, 15, 836. [CrossRef]

[6] Clarke, W.L.; Cox, D.; Gonder-Frederick, L.A.; Carter, W.; Pohl, S.L. Evaluating Clinical Accuracy of Systems for Self-Monitoring of Blood Glucose. Diabetes Care 1987, 10, 622–628. [CrossRef] [PubMed.

[7] Alam, D.S.; Rokhana, R.; Susetyoko, R. Non-Invasive Measurement of Blood Glucose Levels Using Linear Regression and Clark Error Grid Analysis Methods. In Proceedings of the Sixth International Conference on Vocational Education and Electrical Engineering (ICVEE), Surabaya, Indonesia, 14–15 October 2023; pp. 184–190. [CrossRef]

[8] Jendrike, N.; Baumstark, A.; Kamecke, U.; Haug, C.; Freckmann, G. ISO 15197: 2013 Evaluation of a Blood Glucose Monitoring System's Measurement Accuracy.

[9] J. Diabetes Sci. Technol. 2017, 11, 1275–1276. [CrossRef] [PubMed] ThingSpeak. Available online: https://thingspeak.com/ (accessed on 4 March 2024).

[10] Joshi, A.M.; Jain, P.; Mohanty, S.P.; Agrawal, N. iGLU 2.0: A New Wearable for Accurate Non-Invasive Continuous Serum Glucose Measurement in IoMT Framework. IEEE Trans. Consum. Electron. 2020, 66, 327–335. [CrossRef]

[11] Jain, P.; Joshi, A.M.; Mohanty, S.P. iGLU: An Intelligent Device for Accurate Noninvasive Blood Glucose-Level Monitoring in Smart Healthcare. IEEE Consum. Electron. Mag. 2020, 9, 35–42. [CrossRef]

[12] Song,K.; Ha, U.; Park, S.; Bae, J.; Yoo, H.-J. An Impedance and Multi-Wavelength Near-Infrared Spectroscopy IC for Non-Invasive Blood Glucose Estimation. IEEE J. Solid-State Circuits 2015, 50, 1025–1037. [CrossRef]

[13] Al-dhaheri, M.A.; Mekkakia-Maaza, N.-E.; Mouhadjer, H.; Lakhdari, A. Noninvasive blood glucose monitoring system based on near-infrared method. Int. J. Electr. Comput. Eng. (IJECE) 2020, 10, 1736. [CrossRef]

[14] Hina, A.; Saadeh, W. Noninvasive Blood Glucose Monitoring Systems Using Near-Infrared Technology—A Review. Sensors 2022, 22, 4855. [CrossRef] [PubMed]

[15] Althobaiti M, Al-Naib I. 2021. Optimization of dual-channel near-infrared non-invasive glucose level measurement sensors based on monte-carlo simulations. IEEE Photonics J. 13(3):1–10. doi: 10.1109/JPHOT.2021.3079408.