DIY-IoT Based Non Invasive Blood Glucose Monitoring System

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Abstract. Diabetes is widely recognized as a ”silent killer” because of its asymptomatic onset behavior and serious long-term health consequences. Continuous high blood glucose level as an indication of the prediabetic phase. Hence, accurate and consistent glucose level monitoring is imperative for living a healthy life. In contrast, unawareness and conventional finger-prick glucose monitoring system discourage individuals from maintaining consistent monitoring practices. Consequently, by 2024 an estimated 589 million adults aged 20–79 years are living with diabetes globally, according to the International Diabetes Federation (IDF) Atlas 11th Edition-2025 report. The proposed solution is focused on mitigating the existing discomfort associated with finger-prick method while leaving the solution cost effective. In this research paper, we developed a non-invasive blood glucose monitoring device by using NIR spectroscopy technology. The device utilizes an ESP-32 microcontroller, 940nm NIR LED, photoconductive monolithic photodiode sensor and a red channel of an RGB LED. The blood glucose level is calculated by incorporating Beer-Lambert Law,which computes concentration based on changes in light intensity and result showed in LCD display. The prototype costs less than $20 and achieves over 90% accuracy, surpassing the average performance of invasive devices. Overall, the device provides modularity; removes finger-pricks disadvantages while upholding affordability.

Keywords: Silent Killer, ESP32, NIR, Non-Invasive, Cost effective

1 Introduction

Recent data indicate that diabetes is highly prevalent in Bangladesh. The International Diabetes federation reports that 13.2% of Bangladeshi adults have diabetes[1]. The 2017-18 Demographic and Health survey found that about 3% of adults had diagnosed diabetes and another 6% were undiagnosed, and one summary cited 8.1% overall manifestation of diabetes, with over 10% of adults being unaware of their condition. These figures underscore a gradually growing epidemic in both rural and urban population[2].

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The healthcare of diabetes patients in Bangladesh is poorly balanced between urban and rural areas. Government, private and non-governmental organizations (NGO) sectors all play a role, but resources are mostly available in cities. However, government hospitals are often understaffed and under-equipped for chronic disease management, and there are specialized diabetes clinics mainly in urban areas such as Dhaka. In practice, most urban diabetic patients seek care in private hospitals or in the Bangladesh Diabetic Association hospital in Dhaka, while rural patients often have to travel far to access qualified providers. Moreover, Gender discrimination means women are less likely than men to be diagnosed or seek specialist care, due to both cultural and social barriers .Against this backdrop, self-monitoring of blood glucose is far from ideal in Bangladesh. Surveys show [3] low awareness and infrequent testing. In one rural study, 75% of the diagnosed were unaware of their condition and, of the diagnosed 78% did not check their glucose levels at least monthly. This poor monitoring is driven by cost: Glucometers range from Tk 400 - Tk 3,500($4 - $33), and a pack of 50 test strips needed for daily monitoring can also be prohibitively expensive for low-income families. As a result, many patients limit their testing to occasional clinic visits.Therefore, routine finger-prick monitoring remains uncommon for most Bangladeshis with diabetes, especially in rural or low income areas. Current monitoring technologies reflect these constraints. The finger-stick Glucometer dominate the market as they are relatively simple and simple to use. However, they require disposable strips and inflict pain and inconvenience. More advanced devices like Continuous Glucose Monitoring(CGM) systems, which use a subcutaneous sensor to provide near-continuous data, are only now entering the Bangladeshi market. Internationally CGMs have proven to be notably effective in improving glucose control, but in Bangladesh their high cost and need for imported sensors make them out of reach of the general public. For example a locally reported prototype costs only Tk 1190($14), whereas commercial products range from Tk 4,000-Tk 121,000($33 - $1000) thus making them far out of reach of low-income families. In practical terms, virtually no government subsidies or insurance covers CGMs in Bangladesh. Cultural boundaries also play a role, as some patients are hesitant to adopt new technologies or perform routine finger-pricks. Altogether, the accessibility of minimally invasive monitoring is extremely limited by cost, supply chains and cultural acceptance.These constraints underscore the urgent need for innovative, affordable, and culturally acceptable solutions.

Recent research has shown promise in non-invasive technologies, such as Near-Infrared (NIR) spectroscopy and photoplethysmorgraphy (PPG). Combining NIR absorption with bio-impedance measurements and Artificial Neural Networks (ANN) with linear regression on the combined data significantly improved performance alongside accuracy. The PPG based system used light sources of multiple wavelength and a random forest algorithm to predict glucose levels. However, these approaches proved to be very costly and complex. We propose a system with a successful integration of a unique sensor combination (940nm NIR + red channel) and a ESP-32 microcontroller to create a non-invasive glucose monitoring device that is both highly accurate and easily affordable, thereby solving the cost-accuracy trade off that has plagued previous solutions. The major contributions of this paper are as follows.

1. An ESP-32 based embedded system for real-time monitoring of blood glucose levels.
2. This study introduces an architecture that enables the integration of all sensor modules into a unified system.
3. The device developed demonstrates full functionality while maintaining a cost under $20, thereby enhancing accessibility through affordability.
4. Implementation of Dual-light penetration approach for improved measurement accuracy.
5. Achievement of accuracy exceeding 90%, while maintaining cost-effectiveness.

This paper is structured into the following sections: Literature Review, Methodology, Results and Conclusion respectively.

2 Literature Review

Though extensive research has been conducted on invasive methods for blood glucose measurement, NIR-based non-invasive monitoring remains a comparatively less-explored domain in diabetes monitoring. S. Udara et al. [6] developed a non-invasive glucose monitoring prototype that built based on NIR spectroscopy technique, integrating Arduino microcontroller , Bluetooth module, custom mobile application along with red channel of an RGB LED. Despite its effective design, the major drawback is the low accuracy rate of glucose level detection. Echoing this approach, A. Kassem et al. [8] introduced Glucotect, a non-invasive system that integrates an Arduino Uno with NIR sensors and a mobile application for real-time glucose monitoring. The device utilized multi-wavelengths for measurement and incorporated Firebase for cloud-based storage of user personal glucose history data. However, the system's accuracy was a concern, with the authors recommending an individual calibration system to improve reliability across different users. S. Hari Krishnan et al. [9] proposed a non-invasive method based on Photoplethysmography (PPG) and machine learning. Their system leveraged multi-wavelength sources (525nm, 660nm, and 950nm) to capture PPG signals,which used to extract statistical features and processed by a Random Forest algorithm to predict blood glucose levels. While technologically advanced, this approach was identified as being costly and complexity hindered its suitability for daily use. Furthermore, N. Nanayakkara et al. [7] proposed a hybrid technique that combined NIR absorption spectroscopy with bio-impedance measurement to estimate glucose concentrations. The system concurrently measured light absorption changes using a 940nm NIR source and variations in the body's electrical impedance, processing the combined data with Artificial Neural Networks (ANN) and linear regression. This convergent approach yielded improved performance along with high clinical accuracy. Expanding on these non-invasive approaches, R. Sulla T. et al. [11] proposed a non-invasive glucose monitor utilizing electric bioimpedance with a tetrapolar arrangement and an AFE4300 System on a Chip (SoC) for measurements on the fingertip. In vivo experiments it has been observed changes on bioimpedance of blood volume, suggesting potential for practical applications, and the system was compared with a commercial glucometer. The researcher are optimistic for future work planned to propose glucose prediction models from calculated parameters. Another approach is shown by S. Sunny and S. Kumar [12] on glucose level monitoring by merging IoT technology and NIR LEDs (650-2500nm) as optical source along with NIR photodiodes to capture reflected light from body parts like the fingertip, applying the Beer-Lambert law for signal processing. The integration of GSM-based IoT facilitates real-time information transmission, providing remote push notifications to the user. Whereas, the proposed solution provides real-time glucose monitoring on the attached display by emerging double channel NIR spectroscopy signal processing. The optimal design and resource efficiency of the device make it more user-friendly and affordable to evaluate glucose level.

3 Methodology

The core objective of this paper was to build a cost effective system to monitor blood glucose in real time. Many research paper used expensive sensor modules whilst the proposed system build based on experimentally reliable, inexpensive sensor technologies and power efficient microcontroller unit.

3.1 Hardware Design

The prototype consist of crucial hardware components such as sensor modules and an embedded controller. Overall hardware implementation of the system is depicted in figure 1. The system comprises the following key components:

- ESP32 Microcontroller - The ESP32 is a low cost, power efficient RISC-V architectural microcontroller. It is introduced by the Espressif Systems as part of their ESP32-C3 series designed to offer Wi-Fi and Bluetooth 5 (LE) connectivity for secure and cost-effective IoT applications. All of the components are connected with this computational IC. The MCU also provides different communication methods to enable seamless interaction with other devices, including UART, SPI, I^2C, CAN, and USB. In the following system the Inter-Integrated Circuit (I^2C) is incorporated with an LCD display to monitor real-time glucose level. The Analog to Digital (ADC) and Digital to Analog (DAC) pins help to diagnose changes among sensors output data for further calculation.

- NIR Emitter and Receiver - Studies suggest that 700nm to 2500nm near-infrared [10] can penetrate the skin and provide valuable insights about cell concentration . The main absorption peak for glucose in the NIR region is located at 1600 nm. However, due to technological scarcity and affordability in concern, the team used a 940nm NIR emitter along with CJMCU-101 OPT-101 photoconductive sensor module which is monolithic photodiode with an on-chip transimpedance amplifier. It provides output voltage that increases linearly with light intensity. Moreover, for better accuracy and light absorption a single red RGB LED being used.

To increase modularity an external power source is used and a step down buck converter helped to distribute power on different peripherals safely.

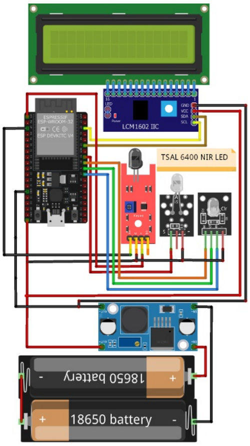

Fig. 1: Hardware circuit diagram of the system

3.2 Logic build-up

The blood glucose concentration is calculated in this study by using the Beer-Lambert Law, which governs the principles of Near-Infrared (NIR) spectroscopy. It states the amount of light absorbed by a substance is directly proportional to its concentration and the distance the light travels through it. The law is mathematically expressed as:

$$A = \epsilon c l \tag{1}$$

In equation (1),

- A = absorbance
- ϵ = molar absorption coefficient
- c = concentration
- l = optical path length

Additionally, absorbance (A) can also be defined in terms of light intensity,

$$A = \log \frac{I_0}{I} \tag{2}$$

Equation (2) shows,

- I_0 = received light intensity
- I = transmitted light intensity

$$\therefore A = \epsilon c l = \log \frac{I_0}{I} \tag{3}$$

A working prototype has been developed by using DIY black plastic bottle shown in figure 2. The black enclosure blocks ambient light and prevent reflections which is necessary for precise calculation.

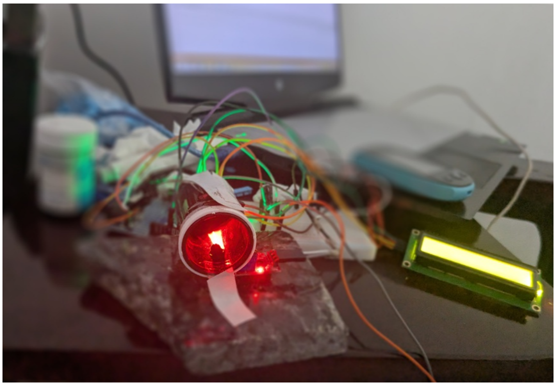

Fig. 2: Non-Invasive Glucose Meter Prototype

3.3 Sensor Calibration

Temporal Signal Averaging (Noise Reduction): To mitigate high-frequency noise and electronic fluctuations in the photodiode response, the system employs a temporal averaging filter. For every measurement instance, the microcontroller acquires N=50 discrete analog samples over a 1-second window ($\mathrm{T}_{samples} = 20ms$) and computes the arithmetic mean to represent a stable signal intensity.

Baseline Calibration: The device utilizes a single-point initial calibration routine during the boot sequence. This phase measures the unobstructed incident light intensity (I_0) passing through the air gap. This baseline value is stored in volatile memory and serves as the reference denominator for subsequent absorbance calculations.

Parametric Constant Definition: The system relies on a semi-empirical model where the effective molar absorptivity and the optical path length (L) are treated as pre-determined constants. L was fixed at 1.4 cm based on the gap between the emitter and receiver sensor module, while ϵ_{eff} was set to 150.0 $\mathrm{L} \cdot \mathrm{mol}^{-1} \cdot \mathrm{cm}^{-1}$ based on preliminary experimental tuning.

4 Results and Discussion

To evaluate the performance of the proposed non-invasive glucose monitoring device, we compared its glucose readings with those obtained from a standard invasive glucose meter.

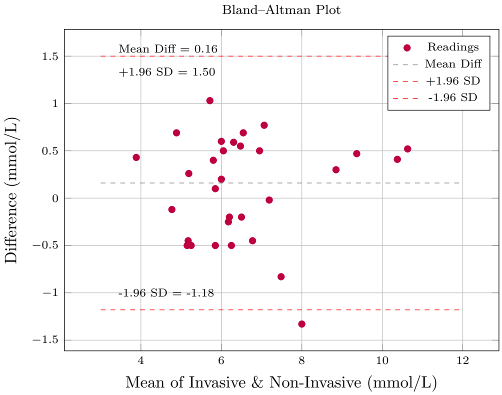

Fig. 3: Bland–Altman plot illustrating the agreement between invasive and non-invasive measurements. The mean difference (bias) is 0.16 mmol/L with limits of agreement from –1.18 to 1.50 mmol/L.

4.1 Analysis and Observations

The non-invasive device showed promising accuracy when compared with the invasive method. From (Table 1) we see that average percentage error across all test cases was approximately **7.65%**, with a standard deviation of 4.39%. Additional error metrics showed a mean absolute error (MAE) of **0.49 mmol/L** and a root mean square error (RMSE) of **0.61 mmol/L**. The coefficient of determination (R^2) was **0.883**, indicating a strong linear relationship between the two measurement methods.

Most readings showed a consistent trend, with the error staying under 10% for the majority of the tests. Test case 6 had the The highest deviation (19.81%), possibly due to sensor misalignment, individual biological variability, or sensor calibration issue such as motion or environmental factors. The lowest error

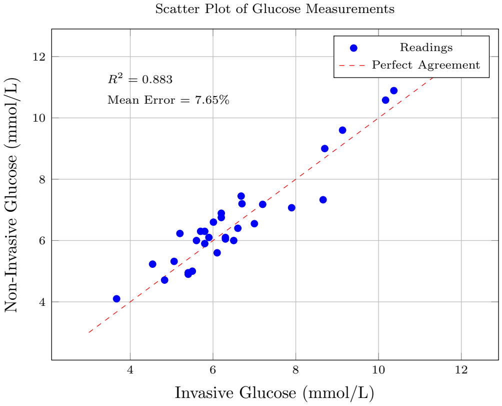

Fig. 4: Scatter plot comparing invasive and non-invasive glucose measurements. A strong correlation is observed ($R^2 = 0.883$) with a mean percentage error of 7.65%.

(0.28%) suggests the device's potential for high accuracy under optimal conditions.

The Bland–Altman plot (Figure 3) indicates a small positive bias of 0.16 mmol/L and limits of agreement ranging from -1.18 to 1.50 mmol/L, demonstrating acceptable agreement between the invasive and non-invasive methods.

The scatter plot (Figure 4) proves the strong linear agreement between invasive and non-invasive glucose measurements, supported by an (R^2) value of 0.883.Minor deviations at higher concentration suggest expected variability due to physiological differences or sensor misalignment.This solidifies observations from from the Blank-Altman analysis.

While the device shows promise, further evaluation against clinical accuracy standards (e.g., ISO 15197:2013) [13] is needed to fully overcoming the clinical reliability.

4.2 Comparative Analysis

We did a through comparative analysis to evaluate the proposed device's performance. cost, and practicality against similar research. The comparison is summarized in (Table 2) which focuses on key aspects such as monitoring approach, accuracy and overall availability. The given analysis highlights the unique advantages of our proposed device, specifically it's low-cost design with high accuracy which address the core limitation of the existing solutions.

Table 1: Comparison of invasive and non-invasive glucose measurements with participant demographics. Values include individual readings, percentage error, and summary statistical metrics.

Test No.	**Invasive (mmol/L)**	**Non-Invasive (mmol/L)**	**Error (%)**	**Age**	**Skin Type**	**Glucose Range**
1	7.20	7.18	0.28	22	Medium Brown	Normal
2	7.90	7.07	10.50	24	Medium Brown	Normal
3	5.50	5.00	9.09	21	Light Brown	Normal
4	6.20	6.89	11.13	25	Medium Brown	Normal
5	5.80	5.90	1.72	20	Medium Brown	Normal
6	5.20	6.23	19.81	23	Light Brown	Low
7	5.40	4.90	9.26	26	Medium Brown	Low
8	6.30	6.05	3.97	22	Medium Brown	Normal
9	5.70	6.30	10.53	21	Dark Brown	Normal
10	6.01	6.60	9.82	23	Medium Brown	Normal
11	6.60	6.40	3.03	24	Medium Brown	Normal
12	5.90	6.10	3.39	25	Light Brown	Normal
13	6.50	6.00	7.69	26	Medium Brown	Normal
14	7.00	6.55	6.43	22	Medium Brown	Normal
15	5.40	4.95	8.33	21	Light Brown	Low
16	6.10	5.60	8.20	23	Medium Brown	Normal
17	5.80	6.30	8.62	24	Dark Brown	Normal
18	6.70	7.20	7.46	26	Medium Brown	Normal
19	5.60	6.00	7.14	20	Medium Brown	Normal
20	6.20	6.75	8.87	25	Light Brown	Normal
21	6.30	6.10	3.17	36	Medium Brown	Normal
22	6.68	7.45	11.51	40	Dark Brown	Normal
23	4.83	4.71	2.58	21	Medium Brown	Low
24	3.67	4.10	11.70	45	Medium Brown	Low
25	5.06	5.32	5.04	23	Medium Brown	Normal
26	8.70	9.00	3.45	24	Medium Brown	High
27	10.17	10.58	4.12	26	Medium Brown	High
28	8.66	7.33	15.37	22	Medium Brown	High
29	10.37	10.89	5.05	20	Dark Brown	High
30	4.54	5.23	15.19	23	Light Brown	Low
31	9.13	9.60	5.12	25	Medium Brown	High
Mean Glucose	**6.49**	**6.59**	**7.65**	–	–	–
SD (Error %)	–	–	**4.39**	–	–	–
MAE (mmol/L)	–	–	**0.49**	–	–	–
RMSE (mmol/L)	–	–	**0.61**	–	–	–
R^2	–	–	**0.883**	–	–	–

4.3 Error Sources

Motion artifacts, sensor misalignment, skin type differences, ambient light leakage, temperature variations, and optical penetration limitations at high glucose levels can all lead to observed deviations.

4.4 Safety and Regulatory Notes

The 940 nm NIR LED operates well within IEC 62471 photobiological safety limits. Similar power LEDs are used in pulse oximeters and wearable sensors. Future regulatory pathway includes ISO 15197:2013 [13] compliance, DGDA approval, and preparation for FDA 510(k) and EU MDR Class IIa certification.

Table 2: Comparative Analysis of Glucose Monitoring Devices

Features	**Udara[6]**	**Kassem[8]**	**Sulla[11]**	**Sunny & Kumar [12]**	**Proposed Device**
Approach	NIR Spectroscopy	NIR Spectroscopy	Bio-impedance	NIR + IoT	NIR Spectroscopy
Real-Time Monitoring	Yes	Yes	Yes	Yes	Yes
Sample Medium	NIR Light	Multi-wavelength NIR	Electrical Signals	NIR Light	Optical NIR Path
Data Collection	Arduino, Bluetooth, Mobile App	Arduino Uno, Firebase Cloud Storage	AFE4300 SoC	GSM, IoT	Dual-channel NIR with ESP32
Cost	Not specified	Not specified	Not specified	Not specified	Prototype $< \$20$
Accuracy	Low	Requires calibration	Compared with commercial devices	Not specified	$> 90\%$
Practicality	Effective design	Real-time with cloud storage	Practical applications	Remote notifications	Portable, user-friendly
Availability	Research stage	Research stage	Research stage	Research stage	Prototype stage

4.5 Challenges

Due to ethical and logistical constraints, the study was limited to 40 test subjects, restricting the statistical power and potential of the findings. Moreover, the range of glucose levels tested was predominantly in the mid-range, and repeated measurements per subject were limited. Environmental and physiological factors such as skin type, temperature variations, and motion artifacts were not systematically controlled or analyzed.

5 Conclusion

This study presents the development of a low-cost, non-invasive blood glucose monitoring device using NIR spectroscopy integrated with an ESP32 microcontroller, the system achieving over 90% accuracy when compared to the standard invasive glucometer, addresses the affordability issue with discomfort and cultural acceptance that limit self-monitoring practices in low-income and rural populations.

5.1 Future Scope

In future works the dataset will be expanded through larger clinical trials that includes a greater and diverse range of test subjects along with a custom web application for historical tracking of glucose levels. The sensor calibration algorithms will be enhanced with AI-based adaptive models that compensate for biological variance and environmental influences to reduce errors. In addition, tests in various physiological states (e.g., exercise, fasting) and environmental conditions will be conducted to further diversify the dataset.

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