

Estimation of Blood Glucose Levels Using A Non-Invasive Infrared-Based Optical Sensor: A Pilot Study

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Abstract—Blood glucose measurement is critical to diabetes management and prevents chronic complications such as neuropathy, nephropathy, and retinopathy. However, current methods are invasive, uncomfortable, and costly. Although several non-invasive approaches have been explored, no commercially available device offers a simple, affordable, and user-friendly solution for non-invasive blood glucose estimation, particularly one suitable for self-measurement outside clinical settings. This underscores the need for practical and inclusive alternatives. This study aimed to develop and evaluate a blood glucose estimation device using infrared LEDs to measure light transmittance through the fingertip. The research was conducted in two stages: initial testing using glucose solutions with varying concentrations (0.02, 0.06, 0.10, and 0.20 g/ml) and added red dye (0.05, 0.10, and 0.15 ml) to validate the sensor's response, followed by direct validation on human fingers against commercial blood glucose test strip readings. The results showed a strong positive correlation between sensor output and glucose levels, with a Pearson correlation coefficient of $r = 0.995$. Using a regression-based calibration model, the system achieved a mean absolute error (MAE) of 1.63 mg/dL, and a root mean square error (RMSE) of 1.72 mg/dL. Cross-validation, such as Bland-Altman analysis and Clarke Error Grid, was conducted to verify model robustness. These preliminary results suggest that the developed system holds strong potential as a simple, affordable, and non-invasive tool for blood glucose self-monitoring, especially in resource-limited settings. However, further validation on larger, more diverse populations is necessary.

Keywords—Non-invasive Glucose Monitoring, Infrared Sensor, Pilot Testing, Photodetector, Device Validation

I. INTRODUCTION

Blood glucose monitoring is critical in managing diabetes and preventing associated complications. For individuals living with diabetes, the ability to measure glucose levels accurately, painlessly, and independently at home is essential for maintaining optimal glycemic control. Traditional blood glucose measurement relies heavily on invasive methods, which, although highly accurate, are often painful, inconvenient, and impractical for frequent daily use. Therefore, the development of non-invasive, user-friendly, and affordable glucose monitoring technologies has become

increasingly urgent to promote adherence and enhance the quality of care.

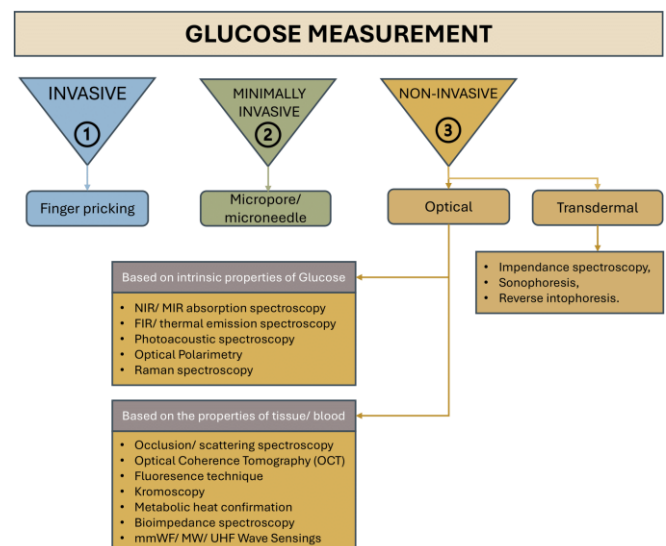


Fig. 1. An overview and classification of blood glucose measurement techniques [1][2].

As illustrated in Fig. 1, blood glucose monitoring technologies can be broadly classified into invasive, semi-invasive, and non-invasive approaches. Invasive methods involve directly extracting blood samples, typically through finger-pricking or needles, and provide high accuracy and reliability. However, these techniques are often painful, carry the risk of infection, and are unsuitable for continuous monitoring. Semi-invasive methods, including minimally penetrating sensors or skin-surface electrodes, offer more comfort and allow continuous measurements. Still, long-term use may raise concerns regarding skin irritation and signal stability [1][2].

While several non-invasive glucose monitoring systems have been introduced, many struggle with environmental or physiological interference, device complexity, or cost. The novelty of our approach lies in its dual-stage validation (phantom and fingertip), low-cost modular design, and

clinically oriented evaluation through Clarke Error Grid Analysis (CEGA) to show the quantitative performance of the device [3], [4], which is rarely addressed in comparable low-budget prototypes. Furthermore, recent works, including *GlucoWatch*, *Diasensors*, *Aspire*, *Gluco-band*, *GlucoTrack*, *Orsense*, *SugarTrac*, [5], [6] and other developed devices [7]–[9] have explored near-infrared (NIR) spectroscopy, but often without testing under realistic constraints or consideration of confounding factors.

This study addresses this gap by integrating design benchmarking, phantom calibration, and repeatability analysis in physical and biological models by developing a pilot version of a non-invasive glucose monitoring device that is low-cost, easy to use, and reasonably accurate for independent use. The system is designed to estimate glucose levels based on an optical technique using 880 nm IR LED light transmission through the bloodstream of the fingertip and captured by a photodetector. Further accuracy improvements are achieved by improving the developed device's reading performance and comparing the results of reference blood sugar measurements.

To guide this development, the study seeks to answer the following research question: Can a simple and affordable non-invasive device be designed to estimate blood glucose levels with a target mean absolute error (MAE) of < 5 mg/dL, suitable for personal, at-home screening use?

II. MATERIALS AND METHODS

A brief overview of the methodology (see Fig. 2) follows: the developed design system, system testing using a phantom solution, validation with a fingertip, error correction, and evaluation. The study began with designing and developing a non-invasive glucose monitoring system, employing an infrared LED and a photodiode in a transmission configuration, integrated into a fixed-position housing to ensure consistent finger alignment and minimize external interference. The device was then subjected to system testing using phantom solutions, including glucose solutions with known concentrations to examine the sensor's response to varying glucose levels, and glycerin solutions to simulate the viscosity of human blood and evaluate signal behavior in a blood-like medium. Phantom solutions consisting of distilled water and glycerol (95%) were also used to simulate blood-like fluids in terms of optical and viscosity properties. These mixtures were enriched with various concentrations of glucose to mimic physiological ranges. Using phantom models enables safe, cost-effective, and repeatable testing in a controlled environment before human subject trials. This approach is widely accepted in biomedical optics research for preliminary sensor evaluation [14], [15], [16].

Subsequently, the system underwent validation using real fingertip measurements, where optical signals were collected and compared against reference values from a commercial strip-based glucometer to assess baseline accuracy. An error correction and modelling step followed, where deviations between the optical estimates and reference measurements were analyzed and adjusted using a predictive correction approach. Finally, a comprehensive evaluation was conducted to determine the system's overall performance in accuracy, repeatability, and usability for non-invasive, self-administered glucose monitoring.

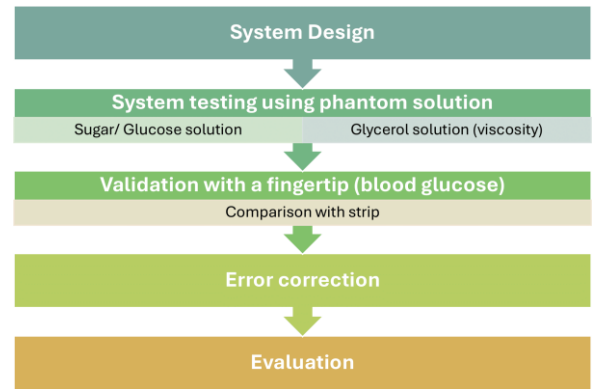


Fig. 2. Research design process.

A. Material

The designed system was tested using several types of solutions to determine the developed system's measurement performance on the following phantom fluids.

- 1) Variation of sugar concentration from pure sugar dissolved in distilled water.
- 2) Solution 1 was then added with red dye to resemble the color of blood.
- 3) Variation of pure sugar liquid concentration dissolved in glycerin.

The reason for using glycerin is that its viscosity resembles blood.

B. Optical Glucose Measurement Method Using Transmission Technique

The developed device estimates blood glucose levels using an optical transmission technique based on glucose's specific properties. This method uses the principle that glucose changes biological fluids or tissues' optical characteristics, such as absorbance, scattering, and refractive index. When a beam of infrared light passes through a fingertip, variations in glucose concentration affect the intensity and propagation of the transmitted light [10].

The system employs a direct transmission configuration. The light source and photodetector are aligned on opposite sides of the fingertip, ensuring light travels through the vascular network before reaching the sensor. The light signal captured by the photodetector is then converted into a voltage signal proportional to the amount of transmitted light. As the glucose concentration increases, it causes measurable changes in the transmitted light due to absorption and scattering effects, which reduce the detected intensity. This optical signal is recorded and further analyzed to extract patterns or features correlating with glucose levels.

The transmission-based approach's main advantage is its sensitivity to optical changes along the light path, potentially allowing accurate glucose concentration estimation when anatomical and optical conditions are stable. This method requires precise alignment, control of confounding physiological variables (such as tissue heterogeneity and hydration), and a robust calibration model to ensure reliable and reproducible performance.

This optical transmission technique has been widely investigated for noninvasive glucose sensing, particularly in

the near-infrared spectrum, as it allows painless monitoring and avoids the discomfort associated with blood sampling [10].

C. Developed System Design

The optical sensing circuit for the non-invasive blood glucose measurement device, as illustrated in Fig. 3b, consists of a transmission-mode configuration comprising a near-infrared (NIR) LED and a photodiode-based photodetector. The system uses an NIR LED with a peak emission wavelength of 940 nm, aligned with the sensitivity range of the BPW34 photodiode, which detects light from 430 to 1100 nm and has a peak sensitivity at 900 nm. This silicon PIN photodiode features a $\pm 65^\circ$ angle of half sensitivity and is housed to detect transmitted light passing through either phantom fluids or fingertip tissue. The photodiode converts received light into a small photocurrent, which is then amplified using an OpAmp UA741 signal amplifier. A parallel 100 k Ω feedback resistor and a 100 nF capacitor are used to achieve high sensitivity and minimize noise. The resulting analogue voltage signal is digitized using an ESP32 with a 12-bit SAR ADC. The microcontroller handles data acquisition, processing, and transmission, which sends data to display.

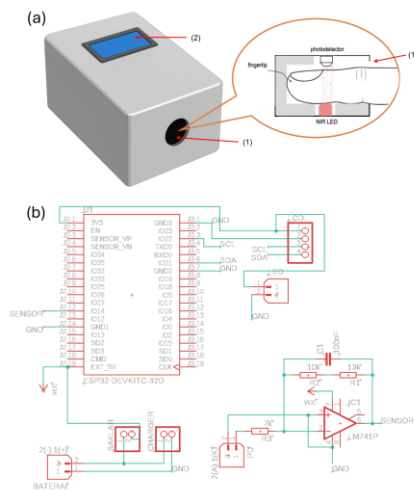


Fig. 3. (a) Design of the non-invasive blood glucose measurement device, where the fingertip is inserted into (1) a hole on the side of the device, and the glucose estimation result is displayed on (2) the top-mounted OLED screen. (b) Schematic representation of the printed circuit board (PCB) used in the developed system.

The custom housing ensures consistent alignment between the infrared LED and the BPW34 photodiode in a direct transmission configuration by allowing the fingertip to be inserted into a designated hole on one side of the device (as illustrated in Fig. 3a). The hand is positioned so the fingertip is directly aligned with the LED and the photodetector, maintaining a stable optical path with an incidence angle of approximately 0° . This working method is called the transmissive type. Additionally, the enclosure helps to eliminate ambient light interference, thereby enhancing signal stability and improving the reproducibility of measurements.

Table 1 compares selected previous research that applied NIR techniques for non-invasive blood glucose estimation. The table highlights the LED wavelength configuration, sensor placement, and reported accuracy metrics. As seen in Table 1, Jongdeog Kim et al. utilized multimodal diffused NIR sources at high wavelengths (1310/1370/1625 nm) with sensors placed on the earlobe, achieving high CECA accuracy

(97.0%) but with only three subjects [11]. Prakteeek Jain et al. employed dual-wavelength NIR (940 nm and 1300 nm) in transmission and reflectance modes, reporting an R^2 of 0.9084 and MAE of 3.87 mg/dL for five subjects, [12]. Chowdury A. Haque et al. applied Monte Carlo-based modelling using 660 nm and 940 nm reflectance LEDs on the finger, with a moderate Pearson correlation ($r = 0.85$) and $R^2 = 0.68$ across 35 subjects. This comparison supports our assertion that effective glucose prediction does not strictly require complex hardware or large participant numbers. With appropriate sensor design, stable testing conditions, and repeated trials per subject, a simplified system such as ours can achieve competitive accuracy in early-stage evaluations.

TABLE I. COMPARISON OF NIR TECHNIQUES IN PREDICTING THE BLOOD GLUCOSE

Previous Research	Hardware Setup		Result
	LED Configuration	Sensor Location	
Jongdeog Kim et. al [11]	Multimodal diffused NIR at wavelengths of 1310/ 1370/ 1625 nm	Earlobe	97.0% CECA for three subjects
Prakteeek Jain et. al. [12]	Dual wave absorption NIR at wavelengths of 940 nm and 1300 nm and a 940 nm reflectance NIR	Finger or earlobe	$R^2 = 0.9084$ MAE = 3.87 mg/dl for five healthy subjects
Chowdury A Haque et. al [13]	Reflectance mode of 660 nm and 940 nm PPG via Monte Carlo photon propagation	Finger	Pearson's $r = 0.85$; $R^2 = 0.68$ using 35 healthy subjects

While these studies used advanced techniques, many involved more complex optical setups, higher component costs, and thermally sensitive sensor locations (e.g., earlobe). In contrast, our system employs a single 880 nm IR LED—well aligned with glucose absorption characteristics—and a BPW34 photodiode sensitive in the 430–1100 nm range. This setup is embedded in a 3D-printed enclosure stabilizing finger alignment and shielding ambient light.

The ESP32 microcontroller has a built-in ADC and BLE, enabling low-power, wireless data acquisition without needing external modules. Compared to the studies listed, our device prioritizes cost-efficiency, simplicity, and portability yet achieves high performance ($R^2 = 0.9894$; MAE = 1.63 mg/dL; 100% Zone A CECA).

D. System Testing Procedure

System testing was conducted to evaluate the initial performance of the non-invasive blood glucose meter based on infrared light transmission. The testing was conducted in three stages:

- 1) Lighting condition testing
- 2) Testing on glucose solutions and reference fluids
- 3) Testing on human fingertips

For lighting condition testing, the device was tested under two different lighting conditions, namely (i) exposure to room light and/ or direct sunlight and (ii) dark conditions (in a closed box). The reading results from the photodetector were compared to determine the most stable and least-interfering conditions. Based on these results, the best environmental conditions will be used for further testing.

This experiment compares the results of photodetector readings on several types of solutions with specific sugar concentrations, namely distilled water and 95% glycerol. Both solutions were chosen because they ease preparation and availability, and allow comparative analysis against human blood based on viscosity. It is known that the viscosity of distilled water (20 °C) is around 1.002 mPas, while the effective viscosity of blood plasma at 37 °C is approximately 1.0 mPas. The effective viscosity of blood with 10% to 38% sample is in the range of 1.4–3.3 mPas [14], and 95% glycerol has a viscosity of 1.4663 mPas [15], [16].

Although these fluids provide controllable and stable environments for testing the optical response of the sensor, it must be noted that their optical and chemical properties do not fully replicate those of real blood or interstitial fluids. Specifically, biological tissues exhibit complex scattering, absorption, and refractive behaviors, especially under physiological temperature and dynamic tissue conditions, which are not captured by water- or glycerol-based phantoms. Therefore, these surrogate media serve only as preliminary models to simulate general optical behavior before moving toward biological validation.

The testing on glucose solutions and reference fluids is carried out after determining the optimal conditions. The photodetector was tested to read the intensity of light passing through several types of fluids:

- 1) Clear glucose solutions with different concentrations,
- 2) Red glucose solutions, and
- 3) Glycerin solution (comparing viscosity and refractive index).

This stage aims to observe the effect of optical properties on the system's reading results. Meanwhile, a closed test design with glass tubes, illustrated in Fig. 4, was used to isolate measurements from external light interference.

The 3D-printed design for housing the test tube in each tube features rectangular mounting slots that hold an LED emitter on one side and a photodetector on the opposite side. These slots ensure proper light path alignment through the solution inside the tube while blocking ambient light interference. The disassembled components are shown at the bottom of Fig. 4a: the cylindrical object represents the test tube, and the green and orange rectangular modules are the LED and photodetector units, respectively. A zoomed-in view in Fig. 4b shows the final configuration, where each sensor module is inserted into a bracket and becomes part of the assembled sensor assembly. This structural design allows for precise and repeatable placement of the optical components while minimizing the influence of external lighting, creating a controlled dark environment essential for reliable optical glucose measurements.

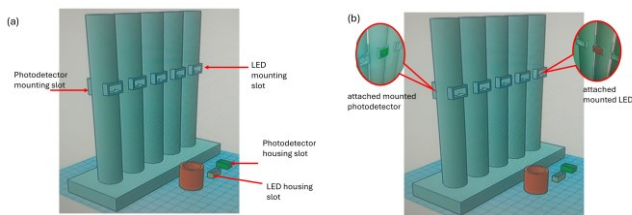


Fig. 4. (a) The testing setup for phantom solutions is enclosed. (b) The illustration highlights the installation process, where the LED and photodetector units are inserted into their mounting slots to align with the optical path through the test tube.

E. Blood Glucose Testing Procedure

After the system testing, the human fingertips were tested by placing the participant's fingertips in the device's hole. The signal reading from the photodetector is recorded. Blood glucose levels are simultaneously measured using a commercial glucometer, *GlucoDr*, with a gold-plated test strip (model AGM-2100, electrochemical method, and 11 seconds of measurement time) as reference data. The finger position is kept constant and perpendicular to the direction of light transmission.

Data were collected from five participants during different physiological states, specifically in fasting conditions (before meals) and after food intake (postprandial conditions). Given the small sample size, this study is categorized as an exploratory pilot trial to demonstrate technical feasibility rather than clinical validation. Each participant underwent repeated measurements (at least three times) to increase validity. The data collected includes i) Light intensity value from the photodetector (analogue voltage) and ii) Blood glucose measurement results from the glucometer strip.

After data collection, a mapping was carried out between the photodetector signal and the reference glucose value using the linear regression method. The data was processed to perform i) Initial calibration, ii) Formation of a glucose prediction model based on optical signals, and iii) Evaluation of correlation and deviation of results.

F. Accuracy Analysis

The developed system's accuracy and analysis are improved through a comparative approach to reference data and model validation using the following statistical parameters.

1. Linear Regression [9]

Used to form a glucose prediction model from optical signals. The model results are compared with reference data, and the coefficient of determination (r^2) value is used to measure the closeness of the relationship between the predicted value and the reference value.

A leave-one-out cross-validation (LOOCV) procedure assesses the regression model's generalisation ability. In each iteration, the regression line was fitted using 9 out of the 10 available data points, and the remaining point was used to evaluate the model prediction [17], [18].

2. Statistical Evaluation of Errors [19]

Calculated to measure how much the system deviates, namely, by MAE and Root Mean Square Error (RMSE) from the reference value, see (1) and (2).

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

3. Bland-Altman Analysis [20][21]

Used to assess the level of agreement between the non-invasive device and the reference glucometer. This plot presents the difference in values from the mean and shows the upper and lower limits (± 1.96 SD) to identify potential systematic bias.

4. Clarke Error Grid Analysis (CEGA) [22][12] [23]

CEGA can be used to assess the safety of the predicted results based on clinical zones A–E (see Fig. 5). This

evaluation shows the extent to which measurement errors are still clinically tolerable. This method classifies each predicted-reference glucose pair into zones (A to E) based on their clinical impact:

- Zone A: Clinically accurate measurements (within $\pm 20\%$ of reference values for glucose > 70 mg/dL, or within ± 20 mg/dL for glucose ≤ 70 mg/dL).
- Zone B: Benign errors that would not lead to inappropriate treatment.
- Zone C: Errors that could lead to incorrect clinical decisions, resulting in unnecessary treatment
- Zone D: Errors that indicate a dangerous failure to detect and treat, including unnecessary or missed treatments.
- Zone E: Errors that confuse the treatment of hypoglycemia for hyperglycemia and vice versa.

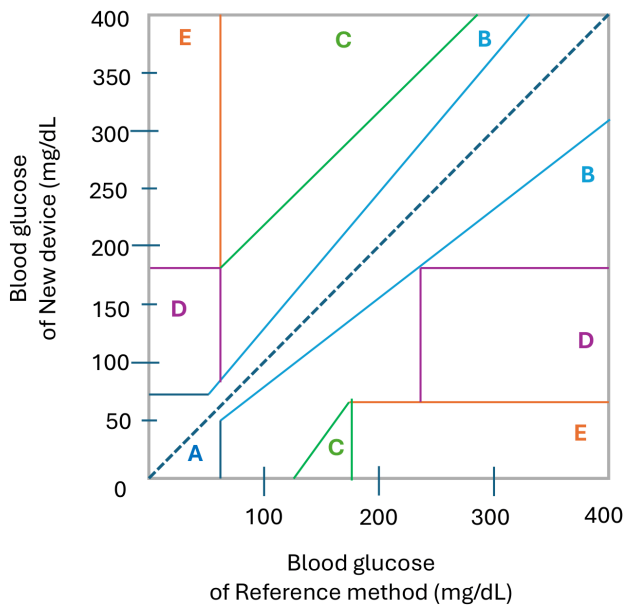


Fig. 5. Five zones of Clarke's grid diagram, a visual representation of the potential impact of the device's measurement error on clinical decision-making, are used to evaluate the clinical accuracy of blood glucose measurements.

III. RESULTS AND DISCUSSION

This section discusses the results of the System Testing Procedure, Data Processing, Accuracy Improvement, and Performance described in the Materials and Methods Section.

A. System Testing Result

Photodiode BPW34 performance tests the reliability of a stable photodetector sensor reading unaffected by other inferences, such as external light and lamps. Measurements were performed under three lighting scenarios. Ambient lighting condition: normal room illumination, combining overhead lamps and incoming sunlight; Augmented lighting condition: it is the same as the ambient lighting, but with an additional point-source flashlight directed at the fingertip; Controlled dark condition: measurements inside an opaque dark box, ensuring zero external light (see Fig. 6).

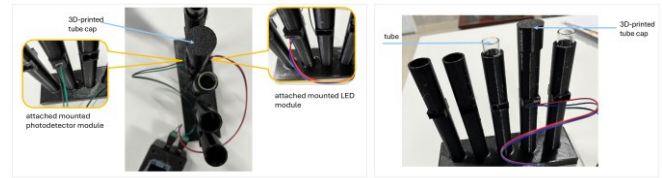


Fig. 6. Illustration of photodetector testing in controlled-dark conditions.

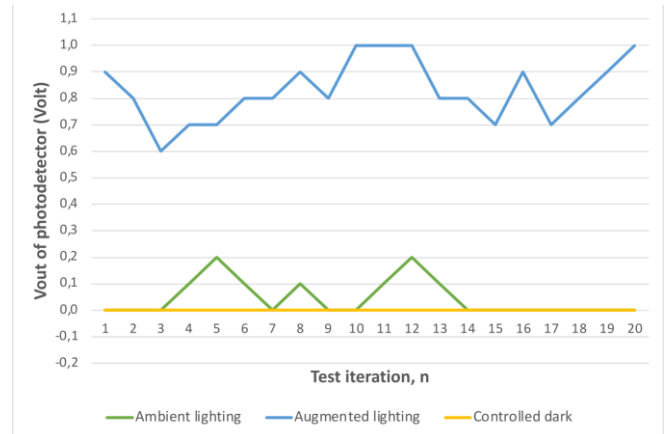


Fig. 7. Comparison of sensor voltage measurements in varying light environments.

Fig. 7 compares photodetector sensor testing under three different conditions, showing the system's photodetector output voltage (V_{out}) measured repeatedly under three lighting conditions. In the augmented lighting condition, the photodetector output voltage is in the highest range, between 0.7 and 1.1 Volts. This value tends to be stable and high in almost all samples. This shows that adding an external light source (flashlight) significantly increases the light intensity the photodetector receives. However, it can create interference or excessive signals to the infrared originating from the main LED. In the ambient lighting, the output voltage is 0 to 0.3 Volts, and fluctuates between samples. This indicates uncontrolled exposure to environmental light, such as sunlight and room lights, which causes variations in the light intensity received by the sensor. This fluctuation reflects inconsistency in readings and can interfere with the accuracy of glucose level estimation. In contrast, the photodetector voltage in the controlled dark condition is close to zero and constant, indicating no external light interference and low background noise. This condition provides the cleanest environment to observe the pure response of infrared light passing through body tissues.

In other words, the data in Graph Fig. 7 shows that the controlled dark condition provides an ideal baseline with minimal noise. In contrast, the augmented lighting condition produces a high signal but is likely to contain external interference components. Meanwhile, the ambient lighting condition shows signal instability, indicating that ordinary room light is inconsistent enough for reliable measurements. Thus, external light shielding or barriers are essential to ensure the accuracy of IR-based optical sensor systems, especially in non-invasive applications such as blood glucose estimation.

B. Glucose Solution Measurement Results

To test the performance of the photodetector reading, as explained in the section III materials and methods, subsection D, Table 2 and Table 3 show the types and variations in the concentration of sugar solutions used in distilled water and glycerin. Fig. 8 presents the performance evaluation of the BPW34 photodetector-based system under various glucose concentrations and optical interference from red dye, as part of a preliminary study for potential blood glucose detection applications.

TABLE II. TEST CONDITIONS FOR SUGAR CONCENTRATION IN 500 ML OF DISTILLED WATER WITH VARYING CONCENTRATIONS (0% TO 20%) AND ADDITION OF RED DYE (0.00 TO 0.15 ML)

Types of Test Conditions	Sugar Concentration in 500 ml Distilled Water		Addition of Red Dye (ml)
	in (g/ml) unit	in percentage unit	
1	0.00	0%	0.00
2	0.02	2%	0.00
3	0.06	6%	0.00
4	0.10	10%	0.00
5	0.20	20%	0.00
6	0.20	20%	0.05
7	0.20	20%	0.10
8	0.20	20%	0.15

TABLE III. TEST CONDITIONS FOR EVALUATING THE EFFECT OF RED DYE ADDITION ON SENSOR RESPONSE IN GLYCEROL-BASED SUGAR SOLUTIONS

Types of Test Conditions	Addition of Red Dye (ml)	
	4% sugar concentration in glycerol 94%	7% sugar concentration in glycerol 90%
1	0.00	0.00
2	0.15	0.15
3	0.35	0.35

In Fig. 8a, the measurements were repeated 10 times for each test condition. The blue curve shows a consistent decrease in output voltage as the sugar concentration increases from 0% to 20%, with the average reading dropping from 1.38 V to 1.29 V. This trend reflects the reduced transmittance of infrared light through the denser and more optically absorbent glucose solution. Additionally, when red dye was added to the 20% glucose solution (simulating increased turbidity like blood), the output voltage dropped sharply to 1.16 V (0.05 ml dye), 0.71 V (0.10 ml dye), and 0.55 V (0.15 ml dye) (see Table 4). Increasing color saturation significantly attenuates the photodetector signal, indicating potential interference if the system is used in optically complex fluids such as human blood. Fig. 8b shows the average output voltage of this repeated test in 2 minutes, which confirms the inverse relationship between sugar concentration and sensor voltage and the sharp decrease associated with the addition of red dye. This validates the sensor's consistency while highlighting the need for optical calibration or compensation techniques in real biological applications.

Although the LED's emission peak (880 nm) does not precisely match the photodiode's peak sensitivity (900 nm), the BPW34 still exhibits high responsivity at 880 nm. Therefore, the mismatch minimally affects signal acquisition

and is acceptable for the intended application. This spectral compatibility contributes to the sensor's reliable performance across the tested conditions, even under optical interference.

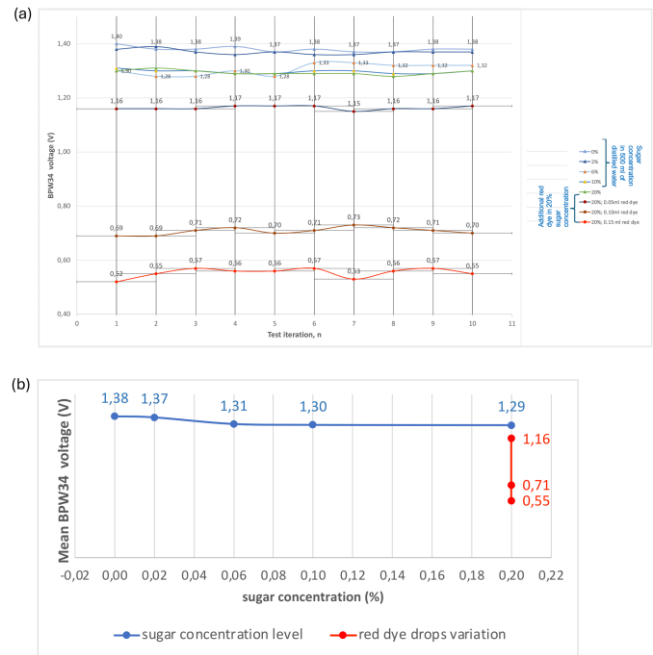


Fig. 8. (a) Sensor voltage from 10 repeated measurements across glucose concentrations with and without red dye. (b) Averaged voltage trend showing signal reduction with increasing glucose and dye content.

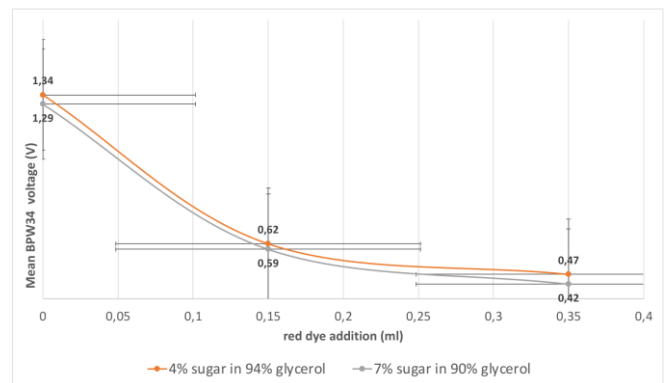


Fig. 9. Mean output voltage of the BPW34 photodetector for two glycerol-based sugar solutions (4% sugar in 94% glycerol and 7% sugar in 90% glycerol) as increasing volumes of red dye were added (0.15 and 0.35 ml). The results show a decreasing trend in sensor voltage with higher dye concentration, demonstrating the system's sensitivity to changes in optical absorption and simulating the attenuation effect of haemoglobin-like compounds in biological tissues.

Further testing was carried out on a medium that more closely resembles the physical characteristics of blood, namely a glycerol solution with a low sugar content. Glycerol was chosen because its viscosity and optical properties are closer to biological fluids than pure water. Fig. 9 presents the photodetector response to two glycerol-based sugar solutions with varying red dye concentrations. It shows the average output voltage of the BPW34 photodetector with red dye (0.15 ml and 0.35 ml) in two test solutions: 4% sugar in 94% glycerol and 7% sugar in 90% glycerol. The results show that the sensor voltage decreased sharply and consistently with the increasing red dye concentration in both solutions. For example, in a 4% sugar solution, the voltage dropped from 1.34 V (without dye) to 0.62 V (0.15 ml dye) and finally 0.47 V (0.35 ml dye). A similar pattern was observed in the 7%

sugar solution, with the voltage dropping from 1.29 V to 0.42 V. The graph shows the observed trend of decreasing voltage with increased dye volume, demonstrating the sensor's capability to detect incremental optical absorption. This finding supports the suitability of these phantom fluids as simplified models for simulating tissue-like attenuation.

TABLE IV. TEST CONDITIONS FOR SUGAR CONCENTRATION IN 500 ML OF DISTILLED WATER WITH VARYING CONCENTRATIONS (0% TO 20%) AND ADDITION OF RED DYE (0.00 TO 0.15 ML)

Types of Test Conditions	Sugar Concentration in 500 ml Distilled Water		Addition of Red Dye (ml)
	in (g/ml) unit	in percentage unit	
1	0.00	0%	0.00
2	0.02	2%	0.00
3	0.06	6%	0.00
4	0.10	10%	0.00
5	0.20	20%	0.00
6	0.20	20%	0.05
7	0.20	20%	0.10
8	0.20	20%	0.15

Thus, it can be concluded that the sensor remains responsive to variations in sugar levels and red dye in distilled water and glycerol media, which have higher viscosity than water. Thus, it can be concluded that the system effectively and responsively detects changes in glucose concentration through optical transmission to variations in sugar levels and red dye, both in distilled water and glycerol media with higher viscosity than water. Likewise, the addition of red color in the solution system responds to a decrease in sensor voltage. This aligns with the concept that infrared light absorbs red color so that its impact drastically reduces signal intensity. For this reason, further testing is needed using human blood for comparative testing to adjust the accuracy of the sensor reading.

TABLE V. TEST CONDITIONS FOR EVALUATING THE EFFECT OF RED DYE ADDITION ON SENSOR RESPONSE IN GLYCEROL-BASED SUGAR SOLUTIONS

Types of Test Conditions	Addition of Red Dye (ml)	
	4% sugar concentration in glycerol 94%	7% sugar concentration in glycerol 90%
1	0.00	0.00
2	0.15	0.15
3	0.35	0.35

C. Blood Sugar Measurement Results on Finger

Furthermore, blood sugar measurements using the *GlucoDr* reference device and the developed system were carried out simultaneously (Fig. 10). This measurement involved five participants, each with measurements before and after meals. Table 6 shows the results of measurements using the device alternately. It presents the detailed measurements collected from five participants using both the commercial reference device (*GlucoDr*) and the developed non-invasive system. Each subject was measured under two physiological states—fasting (before meal) and postprandial (after meal)—resulting in 10 total datapoints. The

corresponding mean sensor voltages show a clear increasing trend in response to higher blood glucose levels, suggesting that the system is sensitive to changes in glucose concentration across physiological conditions. This consistency across multiple individuals and states provides preliminary validation of the sensor's responsiveness and its potential for real-time glucose monitoring.

TABLE VI. PAIRED MEASUREMENTS OF BLOOD GLUCOSE LEVELS (FROM COMMERCIAL GLUCOMETER) AND MEAN OUTPUT VOLTAGE OF THE OPTICAL SENSOR FOR EACH SUBJECT (N = 10). THESE VALUES WERE USED IN THE REGRESSION MODEL AND LOOCV VALIDATION

No	Measured Blood Glucose using Reference Device (<i>GlucoDr</i>)		Mean Sensor Voltage (Volt)
	in mmol/l unit	in mg/dl unit	
1	4.0	72	0.41
2	4.6	83	0.48
3	4.7	86	0.55
4	5.1	92	0.58
5	5.3	95	0.60
6	5.5	99	0.66
7	5.7	104	0.73
8	6.1	110	0.79
9	6.4	115	0.81
10	6.9	124	0.90

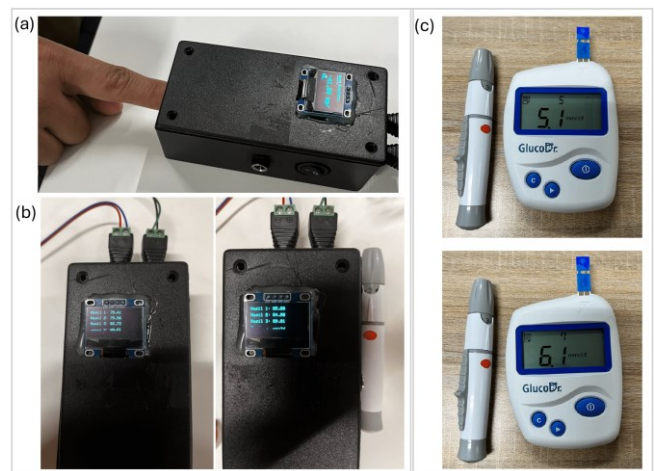


Fig. 10. (a) Illustration of output voltage measurement using a developed system to test BPW34 sensor readings against blood flow in the fingertip, (b) examples of measurement results, and (c) comparison of blood sugar using the BBB device.

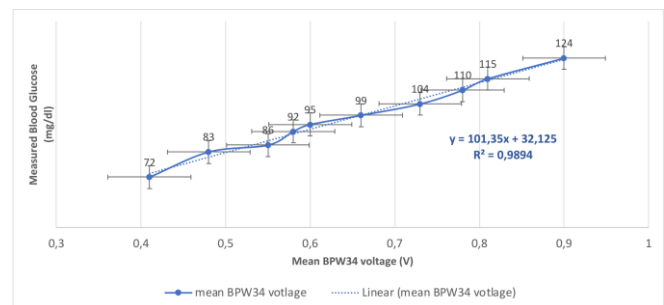


Fig. 11. Linear correlation between the measured blood glucose values (mg/dL) obtained from *GlucoDr* and the mean voltage output from the developed BPW34-based optical sensing system.

Fig. 11 shows the linear relationship between the average voltage generated by the BPW34-based optical sensor system and the blood glucose value (in mg/dL) measured using a commercial glucometer as a reference. Each data point on the graph represents one simultaneous measurement from both systems. The regression results show a linear equation of (3) with a coefficient of determination of $R^2 = 0.9894$.

$$y = 101.35x + 32.125 \quad (3)$$

The value of R^2 approaching 1 indicates a robust correlation between the voltage signal from the sensor and the reference blood glucose value. This proves that the developed system has strong potential to estimate glucose levels non-invasively, based on the optical signal generated by the BPW34 detector. This result is better than the research of Prateek Jain et al using NIR spectroscopy and Huber's regression model, where the coefficient of determination (R^2) value was 0.9084 using the regression model [12]. Furthermore, the developed system can produce blood sugar estimation results using the correction from (3).

D. Performance Validation of the Developed System

Several statistical analyses evaluated the predictive performance and agreement between the developed optical sensing system and a commercial glucometer, including Pearson correlation, Bland-Altman analysis, as well as MAE and RMSE calculations.

The Pearson correlation coefficient was $r=0.995$, indicating a strong positive linear relationship between the predicted glucose values from the developed system and the reference values obtained from the commercial glucometer. This strong correlation demonstrates that the system output closely tracks changes in blood glucose levels.

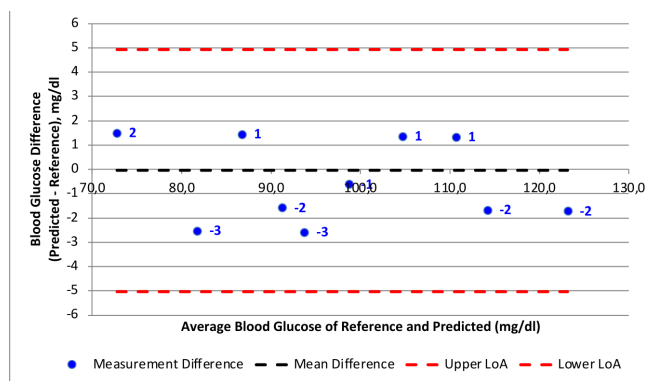


Fig. 12. Bland-Altman plot comparing the predicted blood glucose values from the developed optical sensor system with those from a commercial glucometer.

A Bland-Altman plot, shown in Fig. 12, was constructed to further assess the agreement between the developed optical glucose sensing system and the reference commercial glucometer. This method visualizes the agreement by plotting the difference between predicted and reference glucose values against their mean. In this analysis, the mean difference (bias) between predicted and reference measurements was approximately 0 mg/dL, indicating that the developed system does not exhibit systematic overestimation or underestimation. This lack of bias strongly shows consistency between the two methods.

The limits of agreement (LoA) were calculated as Upper LoA: +4.93 mg/dL and Lower LoA: -5.03 mg/dL. These boundaries represent the range within which 95% of the differences between the two measurement methods are expected to fall. The plot shows that all data points lie within this interval, with no apparent trends or outliers. This suggests that the differences are randomly distributed and not dependent on the magnitude of glucose concentration, supporting the assumption of homoscedasticity. The narrow range between the upper and lower agreements further indicates that the measurement variability between the developed system and the reference device is minimal and acceptable for practical use. Thus, the Bland-Altman plot confirms that the developed system achieves a high level of agreement with the reference method, with minimal bias and acceptable variation, making it a promising candidate for further development in non-invasive blood glucose monitoring. Furthermore, the error metrics calculated were MAE = 1.63 mg/dL and RMSE = 1.72 mg/dL. These low error values further validate the accuracy and reliability of the developed system under the test conditions. The relatively small gap between RMSE and MAE indicates low variance in prediction errors, and the near-zero bias confirms no systemic deviation.

A LOOCV procedure was applied to the ten fingertip measurement data points to assess the model's generalization ability. The regression model was trained on nine data points in each iteration and tested on the remaining one. The averaged prediction errors across the folds yielded a MAE of 1.91 mg/dL and RMSE of 2.07 mg/dL. This slight increase compared to the original regression error (MAE = 1.63 mg/dL, RMSE = 1.72 mg/dL) suggests the model maintains consistent predictive accuracy and robustness, despite the small sample size. These results also indicate that the model does not overly rely on specific data points and is thus unlikely to suffer from overfitting.

While our system demonstrated high correlation under controlled conditions, it is important to note that factors such as skin pigmentation, hydration level, and tissue thickness can significantly influence optical readings. These confounders were not varied in this pilot test but will be explored in future trials to strengthen clinical reliability. Notably, the increase in prediction error from in-sample regression (RMSE = 1.72 mg/dL) to cross-validation (RMSE = 1.91 mg/dL) is minimal, suggesting the model maintains consistent performance even when tested on unseen data. This consistency reflects low sensitivity to individual data points and supports the system's generalization potential. Interestingly, the identical values of MAE and RMSE (both 1.91 mg/dL) during cross-validation indicate that the magnitude of errors was both small and uniformly distributed across folds.

To evaluate the clinical relevance and safety of the predicted glucose values generated by the developed optical system, a CEGA was performed. As stated in Fig. 5, all predicted glucose values fell within Zone A of the Clarke Error Grid, indicating that the developed system's readings were clinically accurate with no risk of incorrect treatment decisions and safe, as shown in Fig. 13. This result further confirms that the system demonstrates strong statistical accuracy (valued by R^2 , RMSE, and MAE) and meets the clinical standards for safety and reliability in blood glucose monitoring applications.

In addition, these results turned out to be much better than the research of Vandana et al., who used the decision tree algorithm and only obtained the highest accuracy of 89.97%

and used CEGA for as many as 94.27% of data points in clinically accepted regions (Region A and Region B) [24], or the results of Oscar Reyes et al., who used linear, quadratic, and cubic regressions, where only 77.78% of data were in zone A and 22.22% in zone B [25]. By ensuring all predicted values fall within the acceptable clinical zone, the CEGA reinforces the potential usability of the developed system in real-world health monitoring, especially as a non-invasive or low-invasive alternative to conventional blood glucose testing.

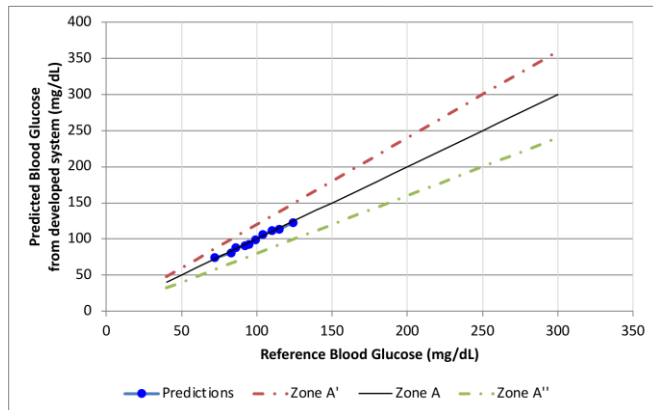


Fig. 13. Clarke Error Grid Analysis (CEGA) compares predicted blood glucose values from the developed system against reference measurements from a commercial glucometer. All prediction points fall within Zone A, indicating the developed system's high clinical accuracy and safety.

IV. CONCLUSION

This study successfully developed and evaluated a non-invasive blood glucose estimation system using an infrared-based optical transmission technique. The system demonstrated strong linear correlation ($R^2 = 0.9894$) with reference glucometer measurements, with low error margins (MAE = 1.63 mg/dL; RMSE = 1.72 mg/dL). Validation through Bland-Altman analysis showed minimal bias and acceptable limits of agreement, while Clarke Error Grid Analysis confirmed that all predictions fall within clinically accurate Zone A. These results confirm that the proposed system has high potential as a simple, affordable, and non-invasive alternative for self-monitoring of blood glucose levels. Technologically, the device provides a promising approach for continuous, painless glucose monitoring, especially in resource-limited or home-based settings. However, further development is needed to enhance robustness, including expanding the participant pool, conducting clinical trials across diverse populations, and integrating advanced machine learning algorithms to improve prediction accuracy and generalization. Future work will also include longitudinal testing to evaluate intra-individual consistency across multiple days and validation under real-world conditions—such as skin pigmentation and hydration levels—to improve clinical reliability. Thus, while the system demonstrates promising results under controlled settings, we acknowledge that larger clinical studies and real-life testing are essential before any claims of continuous monitoring can be made. These preliminary findings should be viewed as proof-of-concept demonstrating feasibility under pilot study conditions rather than clinically validated outcomes.

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