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Development and Evaluation of a Sensor-Based Non-Invasive Blood Glucose Monitoring System Using Near-Infrared Spectroscopy †

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Abstract: Diabetes Mellitus is a significant global health issue, affecting over half a billion people worldwide. Current glucose monitoring methods are invasive, painful, and require skilled application, highlighting the need for development of effective, non-invasive, and easy to use methods. This paper presents our work on the design, development, and evaluation of a non-invasive blood glucose monitoring system, utilizing Near-Infrared Spectroscopy technique for glucose monitoring. The proposed system comprises of MAX30102 biosensor connected to an ESP32 microcontroller. The biosensor captures the photoplethysmogram signals, which are then processed by a microcontroller to evaluate blood glucose level. In order to increase the accuracy of the results, we have incorporated linear regression with Clarke error grid analysis to calibrate our system. The linear regression model is trained by comparing the results obtained through the developed system with that of commercial-off-the-self invasive device. The glucose levels obtained through the developed system are displayed in real-time on an Organic LED (OLED) screen and simultaneously uploaded to a cloud server via Internet of Things for remote monitoring. To validate the performance of the proposed system, we have compared the performance metrics of our system against existing solutions published in the literature. Performance comparison show that our system achieves a reasonably good accuracy with a root mean square error of 13.8 mg/dL and a mean absolute relative difference of 12%. The proposed system offers a painless and convenient solution, potentially improving glucose monitoring for patients.

Keywords: near infrared spectroscopy; non-invasive; blood glucose monitoring; linear regression; Internet of Things (IoT)

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1. Introduction

Diabetes Mellitus is a prevalent and serious metabolic condition affecting millions worldwide, with a projected rise in cases to 783 million by 2045 according to the International Diabetes Federation [1]. Effective management and monitoring of blood glucose levels (BGL) are essential to prevent severe complications such as heart disease, kidney failure, and stroke. Traditional glucose monitoring methods, which require invasive finger-prick blood tests multiple times daily, are not only painful and inconvenient but also limited in providing continuous glucose monitoring, a necessity for optimizing diabetes management. This has spurred significant research interest in the development of non-

invasive BGL monitoring techniques, which promise greater comfort, convenience, and cost-effectiveness.

Non-invasive glucose monitoring techniques are being explored in recent years [2], with optical methods like Near-Infrared (NIR) spectroscopy showing significant promise. NIR spectroscopy, which operates within the 750–2500 nm wavelength range, offers deep skin penetration and has been identified as a cost-effective solution for glucose monitoring [3]. The effectiveness of these systems hinges on selecting an appropriate NIR wavelength. At 880 nm, light balances deep tissue penetration with moderate water absorption [4], ensuring it reaches the capillaries where glucose levels are representative of BGL concentrations. This wavelength minimizes interference from other tissues and benefits from the availability and affordability of 880 nm components, making it ideal for research and real-world applications. By leveraging the "therapeutic window," 880 nm optimizes accuracy and reliability in non-invasive glucose monitoring. These methods provide a framework for developing devices that can replace invasive glucometers and offer continuous monitoring, improving patient outcomes.

The use of Photoplethysmography (PPG) signals in glucose monitoring is another area of research gaining traction. PPG is an optical technique that measures changes in blood volume in the microvascular bed of tissue [5], typically using a light source like an LED and a photodetector. The PPG signal, when processed and interpreted correctly, can provide valuable insights into heart rate, blood flow, and oxygen saturation, which are indirectly related to glucose levels. This optical technique, combined with the application of Machine Learning (ML) models, allows for the correlation between PPG signals and BGLs. Such advancements suggest the potential for continuous, non-invasive glucose monitoring, which could significantly enhance diabetes management. Despite the advancements in non-invasive glucose monitoring technologies, there remains a need for a comprehensive solution that integrates these technologies into a user-friendly, real-time monitoring system.

In this paper, we have presented the work undertaken to design, develop, and evaluate a sensor-based non-invasive BGL monitoring system. The aim of this research is to address the need for easy-to-use and painless methods of BGL monitoring by developing an Internet of Things (IoT) enabled, prick-free BGL monitoring system that utilizes NIR spectroscopy and PPG signals to gauge glucose level in the body. We have increased the accuracy of the results obtained through this system by incorporating linear regression with Clarke error grid analysis [6] for calibration. We have validated the performance of our developed system by comparing its performance against existing solutions published in the existing literature, which show a reasonably accuracy, meeting the standards of currently available methods of BGL monitoring. The BGL obtained through the developed system are displayed in real-time and also uploaded to a cloud server via IoT for remote monitoring.

Rest of the paper is organized as follow: In Section 2 we have discussed the system design elaborating the hardware implementation, data collection, and calibration of the systems. Results are discussed in Section 3 along with comparative analysis to validate the accuracy. Concluding remarks are provided in Section 4.

2. System Design and Development

In this section we have presented the system design components and their interconnectivity to obtain an IoT enabled device for BGL monitoring. There are three aspects to the system design, first being the hardware involved in device prototyping, secondly the linear regression to calibrate the sensor to detect accurate BGL reading and thirdly the cloud connectivity of the controller using ThingSpeak for data storage and visualization. These aspects are discussed in detail in subsequent subsections.

2.1. Hardware System Design and Implementation

In order to acquire BGL reading, we have utilized the infrared (IR) component of the MAX30102 biosensor by Analog Devices (United States) to develop a non-invasive BGL monitoring system. The sensor emits 880 nm IR light, a wavelength carefully selected for its ability to penetrate tissue and interact with glucose molecules in the blood. By analyzing the reflected IR light, our system detects changes in absorption that correspond to glucose concentrations, allowing us to estimate BGL without invasive procedures. We have fine-tuned the sensor's performance through software adjustments, ensuring it meets the specific demands of BGL. The MAX30102's compact design and effective ambient light rejection capability makes it suitable for wearable applications as well, enabling reliable monitoring in various conditions. In our system, the ESP32 microcontroller plays a pivotal role in sensor integration, acquisition of data and it's processing and communication to the cloud. Leveraging its dual-core architecture, we program the ESP32 using the Arduino IDE to handle real-time data from the biosensor, ensuring accurate and timely BGL estimations. Using its Wi-Fi connectivity capabilities for seamless data transfer, we have programmed the controller to upload BGL readings against each patient to the IoT cloud. The final system integrates the MAX30102 biosensor with the ESP32 microcontroller, enabling real-time, non-invasive blood glucose monitoring and seamless data communication within the IoT ecosystem. The BGL reading along with patient ID is also displayed on the OLED display interfaced with the ESP32 controller. Figure 1 depicts the system design showing interworking of ESP32, MAX30102 biosensor and the OLED display. The figure also shows stage of ML model analysis for accurate BGL prediction. Figure 2 shows the hardware implementation of the design proposed in Figure 1.

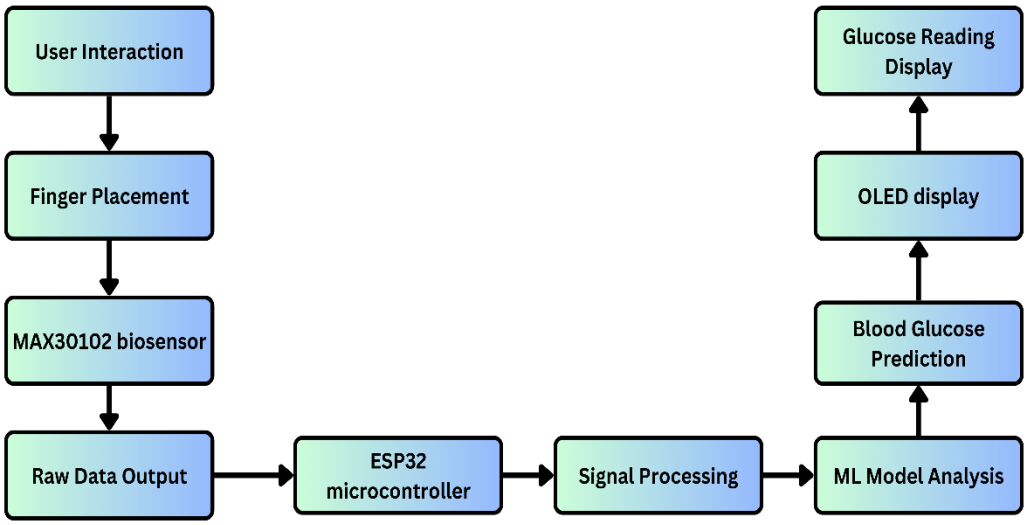

Figure 1. System design showing connectivity and interworking of ESP32, MAX30102 sensor and real-time OLED display.

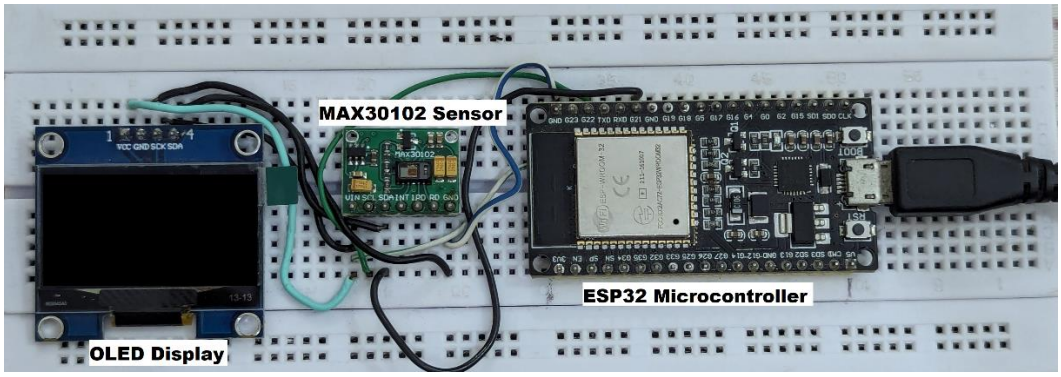

Figure 2. Hardware Implementation of the system design.

2.2. Data Collection and Linear Regression

To enhance the accessibility of our system and reduce the dependency on individual calibration, we developed generalized models. These models enable glucose measurement without requiring each user to perform multiple invasive readings for calibration. Considering the variations in body composition and glucose metabolism, we categorized the models based on Body Mass Index (BMI) into three groups: underweight (BMI < 19), moderate weight (19 < BMI < 25), and overweight (BME > 25). Different weight categories exhibit distinct characteristics, such as varying levels of body fat and typically higher glucose levels in overweight individuals compared to those with moderate or underweight. By categorizing the models into underweight, moderate-weight, and overweight groups, we can better account for these variations and improve the accuracy of the models, ensuring that users from different BMI categories can obtain reliable glucose readings. For the underweight category, data was collected from 12 individuals. The data was collected anonymously and each participant provided data points, including age, gender, BMI, PPG voltage (X), and invasive blood glucose levels (Y). These data points were tabulated and used to compute the coefficients for the linear regression model. Coefficients were derived from the collected data, forming the regression model for predicting blood glucose concentrations for underweight individuals based on their PPG readings. Same procedure was followed for data collection from 14 individuals in the moderate weight category and for 8 individuals in the overweight category. Table 1 shows the consolidated data from the three categories.

Table 1. Data Collection for development of underweight, moderate weight and overweight model.

Underweight Data					Moderate Weight Data					Overweight Data				
Age	**Gender**	**BMI**	**PPG Voltage (X)**	**BGL (Y)**	**Age**	**Gender**	**BMI**	**PPG Voltage (X)**	**BGL (Y)**	**Age**	**Gender**	**BMI**	**PPG Voltage (X)**	**BGL (Y)**
21	Male	14.75	1.24	118	21	Male	19.08	1.27	79	22	Male	25.21	1.16	100
21	Male	16.13	1.2	60	21	Female	19.29	1.4	99	40	Male	25.39	1.23	92
21	Male	16.13	1.35	77	21	Female	19.38	1.33	94	23	Female	25.68	1.05	109
19	Female	16.67	1.47	89	21	Female	19.58	1.39	125	45	Male	26.68	1.21	155
22	Male	17.04	1.25	84	22	Female	20.18	1.36	117	37	Female	29.02	1.25	118
22	Male	17.23	1.3	98	23	Female	20.80	1.33	109	29	Male	30.60	1.34	84
43	Male	17.77	1.16	118	21	Male	21.02	1.33	82	47	Male	31.24	1.03	121
22	Female	18.14	1.42	84	22	Male	21.65	1.01	102	21	Female	34.67	1.28	94
21	Female	18.16	1.3	66	21	Female	22.27	1.47	89					
22	Male	18.25	1.28	86	42	Male	23.10	0.75	87					
22	Male	18.11	1.25	82	29	Female	23.44	1.12	99					
21	Female	18.45	1.39	91	24	Male	24.21	1.43	80					
					45	Male	24.81	1.1	103					
					32	Male	24.97	0.86	63					

Assume $X = \{X1, X2, \ldots, Xn\}$ represents the set of PPG readings obtained through the developed systems and $Y = \{Y1, Y2, \ldots, Yn\}$ represents the set of the BGL readings obtained through the invasive method. Using the data set a linear regression model to relate the PPG reading to the BGL reading can be developed in the following form

$$Y = mX + b \quad (1)$$

where, the coefficients slope m and intercept b are calculated using the linear regression model as given in Equations (2) and (3).

$$m = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sum(X_i - \bar{X})^2} \quad (2)$$

where X_i and Y_i are individual data points of PPG Reading and Invasive BGL Reading respectively and $\bar{X}$ and $\bar{Y}$ are the mean values of X and Y data points respectively.

$$b = \bar{Y} - m\bar{X} \quad (3)$$

The regression model presented in Equation (1) was formed for the three categories for predicting blood glucose concentrations based on their PPG readings.

2.3. Clarke Error Grid Analysis

Non-invasive glucose measuring devices have gained significant attention due to their potential to improve patient compliance and quality of life. Evaluating the performance of these devices is essential to ensure their reliability and effectiveness. One of the most widely used methods for assessing the clinical reliability of glucose measurement systems is the Clarke Error Grid Analysis (CEGA) [7]. The CEGA is designed to categorize the clinical significance of discrepancies between a reference method (usually a laboratory glucose measurement) and the device under test. It divides the possible range of glucose values into five zones (A to E) [7], each representing different levels of clinical accuracy and potential risk to the patient. The current international standard that regulates the precision of glucose measurement systems is ISO 15197:2015 [8] (The International Organization for Standardization (ISO), 2013). According to this standard, for Clarke Error Grid Analysis, measurement systems must meet the criteria that 99% of the individual measured glucose values must fall within Zones A or zone B of the Clarke Error Grid. This stringent requirement ensures that glucose monitoring devices provide clinically accurate readings that are safe for patient use.

2.4. Data Visualization Using ThingSpeak

ThingSpeak [9] is an Internet of Things (IoT) analytics platform service that allows users to aggregate, visualize, and analyze live data streams in the cloud. By leveraging ThingSpeak, we can upload glucose readings in real-time, store them against individual patient channels, and visualize this data to facilitate better monitoring and management of glucose levels. Setting up ThingSpeak channels was crucial in organizing and managing the glucose data for individual patients. Ensuring that the glucose data is accessible to the right individuals while maintaining privacy is paramount. For this purpose, our system provides secure login credentials for each user, as well as flexible data access and sharing options to accommodate different needs. These include private, public, and shared access channels that restrict data access on three different levels.

3. Results and Comparative Analysis of the Developed System

In this section, we have presented the results obtained after developing the system and apply CEGA to compute BGL through PPG signal. The results have been analyzed in relation to the underweight, moderate weight, and overweight model. Moreover, we have also presented comparison of the developed prototype performance with existing systems which use non-invasive methods for BGL monitoring.

3.1. Performance of Generalized Calibration Models

To validate the predictive accuracy of our non-invasive blood glucose monitoring system, we employ Root Mean Square Error (RMSE) and Mean Absolute Relative Difference (MARD) metrics. These assessments provide crucial quantitative measures of the system's performance in predicting blood glucose levels based on optical sensor data. The accuracy of generalized models, segmented by BMI ranges, provides insights into how effectively these models predict blood glucose levels across varying body mass index categories. This segmentation allows for tailored predictions that account for the physiological differences associated with different BMI levels, enhancing the precision of non-inva-

sive blood glucose monitoring. Table 2 provides few samples for the comparison of underweight, moderate weight, and overweight models calculated values using the system and blood glucose level using invasive method.

Table 2. Comparison of underweight, moderate weight, and overweight models calculated values through our non-invasive system and invasive glucose values.

Underweight		Moderate Weight		Overweight	
BGL (Invasive)	**BGL (Non-Invasive)**	**BGL (Invasive)**	**BGL (Non-Invasive)**	**BGL (Invasive)**	**BGL (Non-Invasive)**
84	86.7	107	101	97	107
82	86.84	96	89.64	81	103
77	83.32	83	94.34	134	108.21
96	89.7	88	100.33	109	113.2
83	85.8	81	97.46	87	92.07

All three models have been tailored to accurately predict blood glucose levels specifically for individuals with BMI values indicating the conditions defined under each category. It incorporates adjusted coefficients to accommodate unique physiological characteristics such as reduced subcutaneous fat and potential variations in blood flow dynamics typical of this BMI range, ensuring precise and reliable glucose level predictions. Table 3 summarizes the performance metrics evaluated for each of the category

Table 3. Summary of evaluated performance metrics.

Model	RMSE (mg/dL)	MARD (%)
Underweight model	14.5365	10.85761%
Moderate weight model	11.20719	12.04549%
Overweight model	16.077	13.27936%

Clarke Error Grid Analysis

One of the most widely used methods for assessing the clinical reliability of glucose measurement systems is the Clarke Error Grid Analysis (CEGA). As can be seen in Figure 3, the results show that for the proposed linear regression models, 76.5% of the points fell into Zone A, 23.5% of the points fell into Zone B, and 0% of the points fell into Zones C, D, and E. These results indicate that 100% of the measurements fall within the clinically acceptable range (Zones A and B), demonstrating the device's high accuracy and reliability, also meeting the ISO 15197:2015 requirement that 99% of measurements must be within Zones A and B.

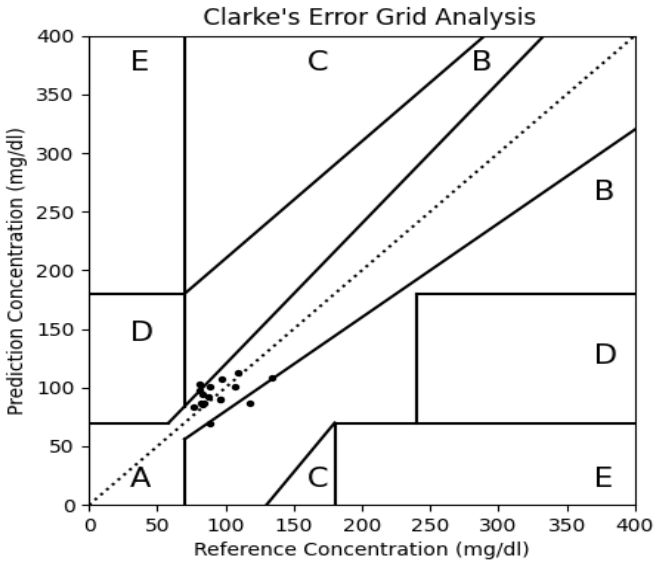

Figure 3. Clarke Error Grid Analysis of the Estimated Glucose Values using proposed model.

3.2. Comparative Analysis Against Existing Non-Invasive BGL Systems

In the comparative analysis, the accuracy of the non-invasive blood glucose monitoring system have been evaluated against existing solutions found in published literature. This assessment is based on metrics RMSE and MARD to gauge the system's efficacy in predicting blood glucose levels without invasive procedures. For the selection of comparable solutions shown in Table 4, we identified relevant studies [10-14] that focus on non-invasive methods for measuring BGL. These solutions were chosen based on their use of similar methodologies involving optical sensors, PPG, and comparable metrics for accuracy assessment identified in the literature review, RMSE and MARD. The selected studies represent a diverse range of approaches and technologies aimed at achieving reliable and precise non-invasive blood glucose monitoring, providing a comprehensive basis for comparison with our proposed system. Our developed system demonstrates reasonably accurate performance, achieving an RMSE of approximately 13.84 and a MARD of 12.08%. These values indicate that our developed system performs competitively, even when compared to established research. For instance, while Joshi et al. [10] present RMSE values of 13.57 and 11.5 with MARD values of 4.86% and 7.30% respectively, our model maintains a strong standing with its balanced error rates. In [11] despite having the highest MARD value of 19%, shows a lower RMSE of 8.3, indicating lower magnitude errors but higher relative errors compared to our model. Overall, while there is room for improvement in terms of reducing both RMSE and MARD to achieve more accurate and reliable predictions, the proposed model displays a reasonable performance, proving to be an accurate predictor.

Table 4. Comparison of Proposed System with previous work based on RMSE and MARD values.

Research Work	Wavelength Used	RMSE	MARD
A. M. Joshi, et al. [10]	940 nm & 1300 nm	13.57 mg/dL	4.86%
P. Jain, et al. [11]	940 nm & 1300 nm	11.5 mg/dL	7.30%
K. Song, et al. [12]	850 nm, 950 nm, & 1300 nm	8.3 mg/dL	19%
M. A. Al-dhaheri, et al. [13]	940 nm	10.44 mg/dL	7.25%
A. Hina and W. Saadeh [14]	940 nm	10.20 mg/dL	6.90%
Developed prototype	880 nm	13.94 mg/dL	12.06%

4. Conclusions

This paper encapsulates the principal findings of our research work, detailing the journey from conceptualization to the realization of a non-invasive blood glucose monitoring system. Contributions discussed include the development of predictive models, where the authors have successfully developed both personalized and generalized predictive models for non-invasive blood glucose monitoring using PPG signals. The personalized models addressed individual variations, while the generalized models, categorized by BMI, enhanced the accessibility and accuracy of glucose readings for a diverse user base. Secondly, the authors have successfully integrated the developed system with ThingSpeak, which functions as a database for real-time glucose monitoring, ensuring secure data management and dynamic monitoring capabilities. Lastly, the key accuracy metrics for gauging reliability and effectiveness of the predictive models for BGL monitoring were evaluated, which include RMSE and MARD. The system developed by the authors achieved an RMSE of 13.84 and a MARD of 12.08%, performing better compared to most of the developed systems in the existing literature. Moreover, the Clarke Error Grid Analysis showed 100% of measurements within clinically acceptable zones, underscoring the system's high accuracy and reliability.

To this stage we have developed a proof-of-concept (POC) for a non-invasive system. However, the results presented in the paper are based on the linear regression developed using limited data set. As future work on this system, we expect to increase the accuracy of the system by collecting more data using the system and developing the regression models based on larger datasets. Moreover, the effect of non-linear regression models is yet to be evaluated aiming to further increase the accuracy of the system.

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