

GlucoseBalance: Non-Invasive Blood Glucose Monitoring via Multi-Wavelength Optical Spectroscopy and Machine Learning

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Abstract

Diabetes has become one of the critical health problems globally, with rapidly rising prevalence in developing regions. Nevertheless, many people are still dependent on the finger-pricking method to check blood glucose level. This conventional method is painful and inconvenient for daily use, especially for children and elderly people. To address these limitations, this paper presents GlucoseBalance, a non-invasive glucose monitoring system. It uses multi-wavelength optical spectroscopy and machine learning methods to predict blood glucose level. In this device, a multi-wavelength LED array (White, Red, Green, and Infrared), and an AS7341 spectral sensor are used to detect optical signals from the skin. These signals are sent through Bluetooth Low Energy (BLE) to a Flutter-based mobile app by ESP32-C3, which then forwards the data to the model via backend for glucose prediction. With this motive, we tested two machine learning models: a Multiple Linear Regression model and a Multilayer Perceptron (MLP) Regressor. After evaluation, we observed that the MLP results were much better than the simple linear model, achieving an R^2 of 0.7704 and a Mean Absolute Relative Difference (MARD) of just 5.92%, compared to an R^2 of 0.2763 and MARD of 12.27% for linear regression. This implies that non-linear models would be more appropriate for the capture of this complicated relationship between the optical signal and glucose. Despite the success achieved by this experiment, there are certain limitations to this experiment such as the limited

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data and the hardware computing limit. Hence, this approach reflects that affordable, painless, and accessible glucose monitoring solutions are worth developing further.

Keywords: Non-invasive Glucose Monitoring, Optical Spectroscopy, Near-infrared (NIR), Multilayer Perceptron (MLP), AS7341 Spectral Sensor, Photoplethysmography (PPG), Machine Learning in Healthcare, Embedded Medical Devices.

1. Introduction

According to the World Health Organization (WHO), Diabetes is a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Insulin is a hormone that regulates blood glucose. The global prevalence of diabetes has risen sharply: In 1990, 7% of adults aged 18 and older had diabetes, and by 2022 this figure had doubled to 14%. More than half (59%) of adults aged 30 years and older diagnosed with diabetes were not receiving medication for their condition [1].

Increasing rates of Diabetes patients are being seen in South Asia. A review of the last two decades (2000–2020) of diabetes research conducted in Nepal revealed that approximately 9% of adults in Nepal have type 2 diabetes mellitus, 19.4% have prediabetes, and 11% have impaired glucose tolerance (IGT), a condition where blood sugar levels are higher than normal after eating, but not high enough to be classified as diabetes. Individuals having IGT have a high risk of developing type 2 diabetes mellitus [2]. Despite these figures, awareness and treatment coverage remain inadequate. Approximately half of individuals with diabetes are aware of their condition, a smaller proportion receive antidiabetic medication, and only one-third of those treated achieve adequate glycemic control [3].

The current monitoring strategies are mainly dependent on invasive glucose-monitoring devices, including finger-prick tests and needle insertions. Such techniques are painful and inconvenient, particularly to vulnerable groups of people such as the young and the elderly. The unacceptability and compliance issues associated with existing glucose monitoring techniques hinder the effectiveness of these technologies as far as diagnosis and management of the two forms of diabetes are concerned. Though there have been achievements regarding the management of type 1 diabetes through Continuous Glucose Monitoring (CGM), most existing techniques used in monitoring glucose levels in type 2 diabetes patients are faced with challenges

in sensitivity, specificity, and compliance [4–7].

In this paper, we present GlucoBalance, a non-invasive glucose monitoring system that allows for easy and comfortable glucose level monitoring. In particular, the system relies on near-infrared (NIR) spectroscopy for signal interpretation from the skin and the machine learning models for predicting the concentration of blood glucose. The system employs a multi-wavelength LED array, AS7341 spectral sensor, and ESP32-C3 microcontroller. The various models were trained using the collected data from volunteers to predict the blood glucose level using optical signals in the skin. Besides the system itself, we also designed a useful mobile application that was implemented using Flutter programming language to show the current glucose level, draw a graphical representation of previous measurements, and communicate through the Bluetooth Low Energy (BLE) protocol with the glucose monitoring system. This paper presents the emerging evidence to increase sensitivity, boost accuracy, and enhance the acceptability of developing a painless, cost-effective and accessible glucose monitoring system for diabetes patients. Of relevance are the emerging strategies to deal with the current barriers in using glucose monitors in Nepal and other low-resource settings.

2. Related Works

Non-invasive glucose monitoring is based on the principles of optical spectroscopy, which uses the unique absorption and scattering properties of biological tissues at different wavelengths of different LED lights. In practice, an LED array of various wavelengths, usually including red, green, IR, and white light emitters, is positioned onto the skin to introduce light into the subdermal layer. The penetration depth and behavior of light of each wavelength depends on optical properties of light itself as well as on the molecular absorption spectrum of target media [8,9].

Among these wavelengths, near-infrared (NIR) light is particularly significant. Unlike visible light, NIR penetrates deeper into tissue, reaching vascular structures where glucose is present in the bloodstream. As light interacts with tissue, glucose molecules absorb specific portions of the spectrum, while cellular structures scatter the light, altering both its intensity and spectral composition. These absorption-based changes form the basis for estimating glucose concentration [10].

However, glucose absorption is not the sole factor influencing NIR transmittance. Blood

volume variability in the optical path also influences NIR transmittance. Specifically, an increase in blood volume within the optical path results in decreased light transmittance through the tissue under test. Conversely, as the blood volume in the optical path decreases, the amount of light that can travel through the tissue under test increases. Even when glucose is at the same concentration in the blood, varying blood volumes in the optical path under test can cause varying amounts of NIR light to reach the detector. Thus, another important variable must also be considered for accurate glucose estimation [11,12].

In our system, blood volume was inferred indirectly from sensor-derived signals rather than conventional pulse oximetry. Red light and Infrared (IR) light are used to capture the respective absorption patterns of hemoglobin and oxyhemoglobin in blood. By calculating the attenuation in the respective channels, the presence of vasculature and blood volume locally in the tissue can be estimated, and these can then be included in the glucose estimation model for normalization against blood volume variations [13–15].

Green light plays a critical role in multispectral glucose monitoring. It can only penetrate the superficial layers of the skin; its strong absorption makes it highly effective for detecting heartbeat and local blood volume changes with high signal strength and low power [16]. The high sensitivity of the green LED to skin thickness allows estimation of a path length for NIR glucose measurements that can be used to compensate for inter-user variability in the aforementioned measurements [13]. Additionally, its sharp hemoglobin absorption profile also makes the system robust against motion artifacts, and thus the signal is stable [17].

After these glucose-level influencing factors are captured through optical signals detected by photodetectors, it is possible to extract features associated with glucose concentration. Machine learning techniques further enhance this process, enabling accurate estimation of blood glucose levels without invasive sampling [10].

In our approach, a simple linear regression model was first used to obtain a relation between the sensor output voltage and the corresponding estimated glucose concentration, as suggested by [18]. The authors validated the non-invasive glucose measurement system using statistical techniques such as standard deviation and percentage linearity. The authors obtained a strong linear relation between the sensor output voltage and the corresponding predicted glucose concentration.

The adoption of a linear regression model served as a good starting point; however, linear models fail to capture the complex, non-linear relationship between optical signal features and glucose concentration. To improve the prediction accuracy of our approach over linear models, we used a Multilayer Perceptron (MLP). The work by [10] showed an increase in the correlation coefficient from 0.612 for linear regression to 0.96 with an MLP-based neural network trained with the Levenberg-Marquardt algorithm. This allows for more accurate glucose estimation by capturing additional patterns in the feature space.

2.1 Research Gap and Proposed Approach

Despite recent progress, most non-invasive optical devices still rely on only one or two near-infrared (NIR) wavelengths [10,18]. These limited-channel setups cannot easily distinguish glucose absorption from the overlapping signals of water and hemoglobin [10,11]. They also struggle to correct signal drift caused by differences in skin thickness, light scattering, and changing blood volume [9,11,13]. Additionally, standard linear models cannot capture the complex, non-linear ways light travels through human tissue [10,18].

To address these limitations, the proposed GlucoBalance system uses an 11-channel spectral sensor (AS7341) featuring an integrated White LED with multi-wavelength illumination comprising Green (550 nm), Red (650 nm), and NIR (940 nm) LEDs. This approach allows the system to detect skin blood flow, hemoglobin absorbance, and deep tissue reflection through 50 spectral features [13,15]. By processing the features using the non-linear MLP model, the system is capable of differentiating between the body optical noise and the glucose signals [10].

3. Proposed Work

The proposed system is a non-invasive glucose measurement system employing the Near Infrared (NIR) technology along with machine learning techniques to predict blood glucose level.

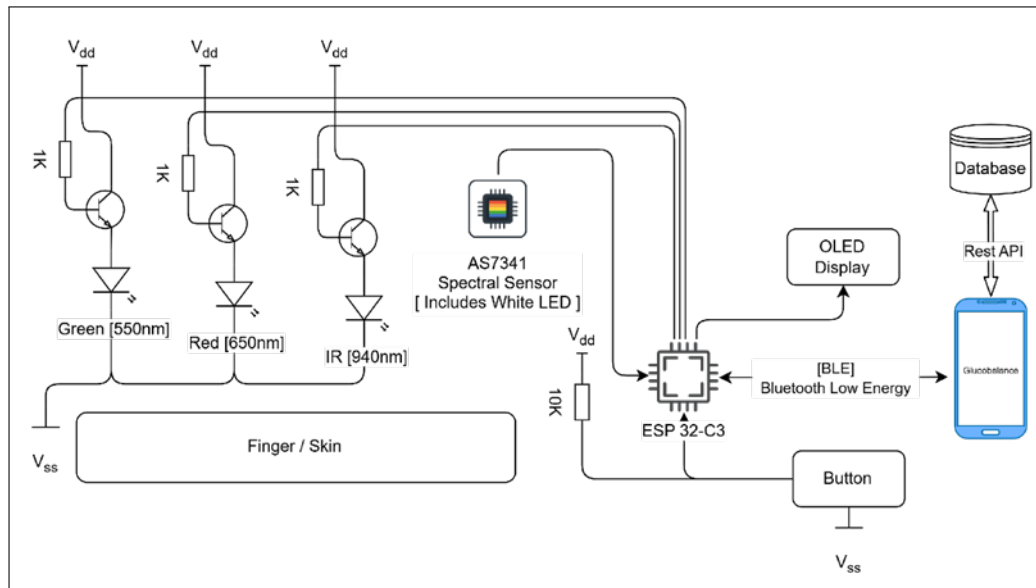


Figure 1. Complete system block diagram showing data acquisition, transmission, processing, and display pipelines.

3.1 Design and Implementation

As illustrated in Figure 1, the whole system can be divided into three main modules; namely the embedded sensor module, the mobile application, and the backend server where the machine learning model resides. The physical prototype is shown in Figure 2.

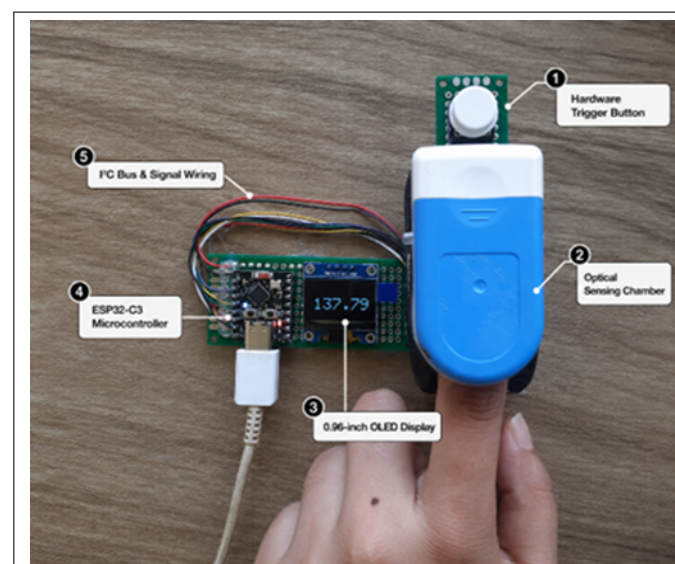


Figure 2. Physical prototype of the GlucoBalance system during testing

3.1.1 Hardware Design

The hardware design is based on ESP32-C3 microcontroller, AS7341 optical sensing module, a push-button, and 0.96 inch OLED screen placed on the customized perfboard (Figure 2). Optical data collection is performed by four illumination sources such as Green (550 nm), Red (650 nm) and Near-Infrared (940 nm) LEDs along with the onboard broadband White LED incorporated into the AS7341 sensor module (Figure 3). AS7341 is used as the main device responsible for acquiring multi-wavelength diffuse reflectance signals both in visible and near-infrared ranges and sending it to the microcontroller via I²C bus. To isolate the optical path from ambient light interference and ensure stable skin contact, AS7341 sensor along with LED array are placed inside modified pulse oximeter housing which was cut and reconfigured.

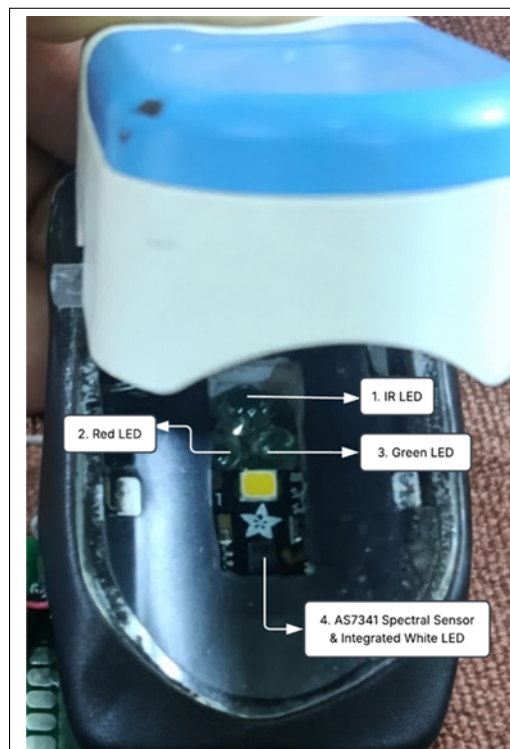


Figure 3. Internal view of the modified optical sensing chamber.

3.1.2 Software Design

The software module in this project is comprised of three interlinked modules, which include the embedded firmware, the mobile app, and the backend service with machine learning models. The ESP32-C3 firmware was programmed using C++ and was responsible for handling button interrupts, controlling the timed LED sequences, sampling the spectral reflectance data at

10 Hz from the AS7341 sensor on the I²C bus, and sending out BLE packets over Bluetooth Low Energy (BLE). The mobile application was programmed in Flutter and served as a BLE central client app that collects the raw data packets, shows the glucose trend analysis chart, and communicates with the backend using REST API endpoints. The backend service was written in Django with a PostgreSQL database, providing secure API endpoints for data persistence and executing pre-trained machine learning models, specifically Multilayer Perceptron (MLP) for real-time glucose estimation.

3.2 System Workflow

The workflow for the system under consideration will be executed within four different modules: user, embedded hardware, mobile app, and backend with the ML model.

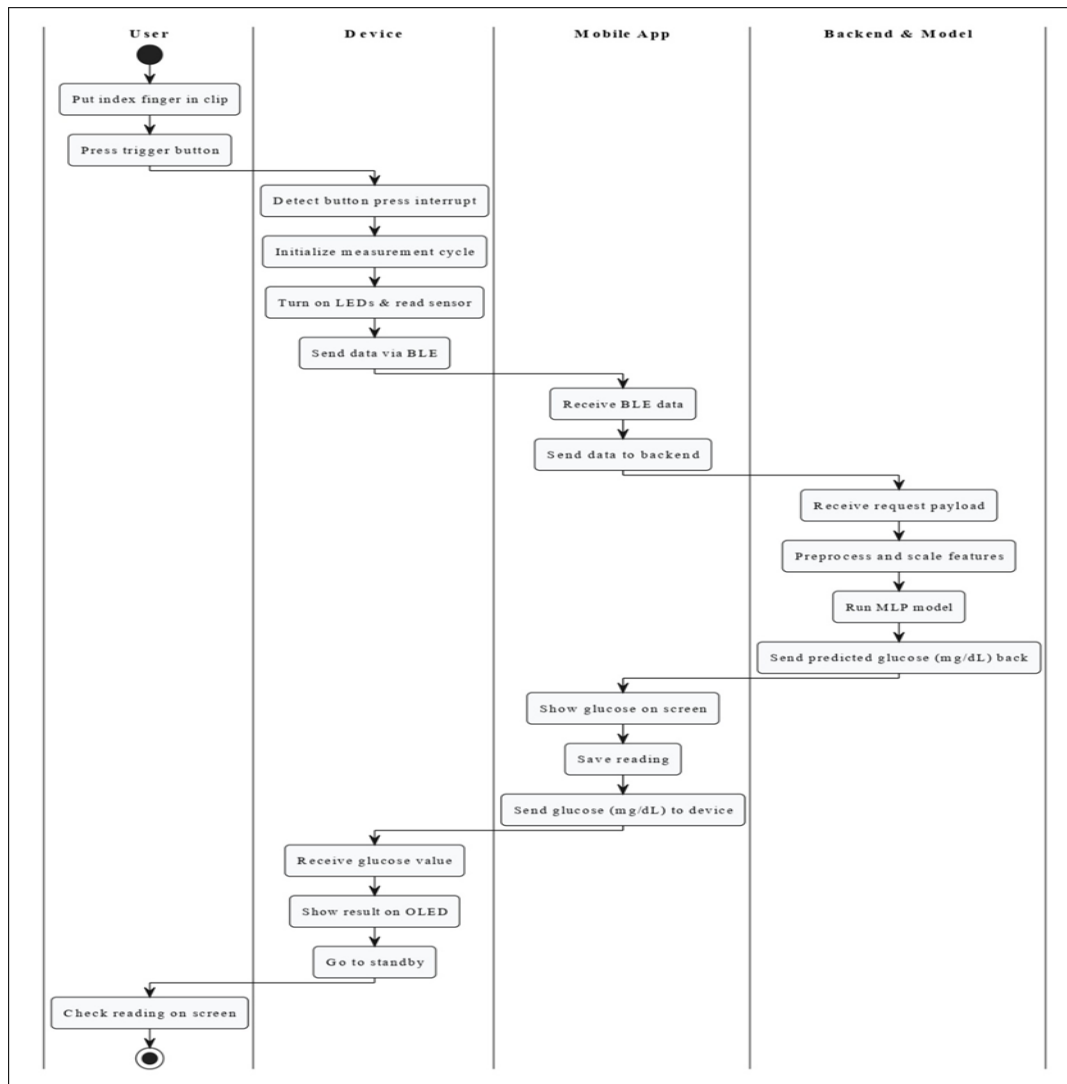


Figure 4. Activity diagram

As illustrated in Figure 4, the workflow starts with placing the index finger in the optical sensing chamber of the hardware unit and pressing the trigger button. ESP32-C3 sequentially switches through the discrete lighting sources: Green (wavelength 550 nm), Red (650 nm), and NIR (940 nm), as well as the White LED that comes with the hardware unit. The generated light propagates into the tissue, being affected by absorption and scattering depending on the blood glucose level, microvascular blood volume, and local properties of the skin.

The multispectral sensor sends the raw optical data to the ESP32-C3 microcontroller through the I²C communication interface. The microcontroller processes the spectral data and sends it to the mobile app using the Bluetooth Low Energy (BLE) technology. The mobile app then passes the spectral data to the machine learning model through the backend in order to estimate the glucose levels. Upon obtaining the estimated glucose level, the mobile app displays the data on the screen and passes the value to the microcontroller using BLE, where it appears on the OLED screen in mg/dL units.

3.3 Machine Learning Model Development

As an implementation of machine learning algorithms, initially, data was collected, preprocessed, a model was generated and then evaluated using metric formulas.

3.3.1 Data collection

In this study, experimental data were taken on a group of $N = 146$ distinct voluntary human subjects whose age ranged from 19 to 55 years old, with different physiological characteristics such as varied skin color, finger morphology, and glycemic history (both normoglycemic as well as subjects with high blood sugar levels).

- **Non-Invasive Optical Sampling:** For each subject, the index finger was placed in the optical sensor chamber that was shielded from any external light. White LED light, Green (550 nm), Red (650 nm), and Near Infrared (940 nm) light sources were cyclically illuminated by the microcontroller. Diffuse tissue reflectance was detected using the AS7341 multispectral sensor with a sample rate of 10 Hz (10 optical frames).
- **Concurrently Tracked Reference Logs:** For the determination of reference values, invasive measurement of capillary blood glucose was made simultaneously with a clinical finger-prick glucometer (Dr. Morepen Gluco One BG-03). The physiological values of

reference blood glucose ranged between 78 to 169 mg/dL during the entire experimental procedure.

- **Varied Physiological States:** Measurements were made during two different metabolic states – fasting and post-prandial states. This yielded a total of 292 valid measurement sessions, corresponding to 2,920 structured optical sample vectors (10 time-series frames per session) paired with clinical reference values. The process of data acquisition followed non-clinical ethical standards and all subjects gave informed verbal consent before data acquisition was done.
- **Data Partitioning Protocol:** The complete dataset of 2,920 sample vectors was split in an 80/20 train-test split ratio. Dataset portion of 2,336 samples (80%) was employed for standardizing features and training the model, while the remaining 584 samples (20%, equivalent to the validation group) were used exclusively for the testing and evaluation of model performance using statistical evaluation criteria (R^2 , MAE, MSE, and MARD).

3.3.2 Data Logging Format

The collected data were recorded in a structured format for each measurement. The recorded fields were:

1. **led label:** Types of LED used for data collection (Green, Red, Infrared, and White).
2. **feature 1 to feature 50:** Spectral readings obtained from AS7341 multispectral sensor.
3. **reference glucose:** Indicates glucose level measured by invasive glucometer.

3.3.3 Data Preprocessing

The high dimensional feature matrix was processed to eliminate unwanted information and enhance prediction stability:

1. **Outlier and Redundancy Filtering:** Datasets were scanned programmatically to verify the absence of duplicate entries or anomalous sensor dropouts.
2. **Multicollinearity Mitigation:** Due to spectral overlap between adjacent visible channels on the AS7341 sensor array, pairwise correlation matrices were generated to identify and drop redundant features.
3. **Normalization Pipeline:** For normalization of the remaining feature columns, Z-score standardization was used through the Standard Scaler package: This step ensures that all

multi-wavelength channels contribute uniformly during the regularization phase.

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

4. Feature Optimization: The most important features were selected using L1 Regularization (Lasso) that resulted in a final set of 40 input features.

3.3.4 Model Evaluation Framework

The predictive engine evaluated two distinct modeling approaches implemented using the scikit-learn scientific computing library:

Multiple Linear Regression: A baseline OLS (Ordinary Least Squares) multivariate linear regression model was trained to provide high model transparency and establish a baseline performance level. The model is formulated as:

$$y = \beta_0 + \sum_{i=1}^k \beta_i X_i + \varepsilon \quad (2)$$

where y denotes the blood glucose level predicted by the model, β_0 is the intercept, X_i represents the 40 standardized multi-wavelength spectral channel features, β_i signifies the calculated regression coefficients, and ε denotes the residual error term.

Multilayer Perceptron (MLP) Regressor: To resolve the complex, non-linear scattering matrices and varying optical penetration depths caused by differences in human skin thickness and blood volume, a deep feedforward artificial neural network architecture was implemented via MLP Regressor. The network contains an optimized two-layer hidden topology containing 64 and 32 hidden neurons, respectively, utilizing the Rectified Linear Unit (ReLU) activation function:

$$f(x) = \max(0, x) \quad (3)$$

The weights were updated for up to 5000 iterations using the Adam optimization solver. To validate prediction accuracy, the models were assessed using identical data splits against the reference finger-prick logs using four distinct performance metrics:

The Mean Squared Error (MSE) is defined as

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4)$$

The Mean Absolute Error (MAE) is given by

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (5)$$

The coefficient of determination, R-squared (R^2), is calculated as

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6)$$

The Mean Absolute Relative Difference (MARD), commonly used in medical prediction tasks, is defined as

$$\text{MARD} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (7)$$

where y_i denotes the reference blood glucose value, $\hat{y}_i$ signifies the value predicted by the model, $\bar{y}$ is the mean value of the real reference dataset, and n denotes the total number of validation samples.

4. Results and Observation

To examine the performance of the non-invasive glucose monitoring system, the predicted glucose values were compared with the reference glucose values acquired from invasive finger prick measurements. The mathematical formulae explained in Eq. (4) – (7) were used to evaluate the prediction accuracy.

4.1 Exploratory Analysis

The multi-wavelength dataset was evaluated before training the models. This evaluation was performed to analyze the correspondence between changing sensor readings and different glucose levels. Each specimen consisted of 50 features that were influenced by blood volume, skin thickness, and glucose concentration. After evaluating the correlation, it was observed that adjacent spectral channels were extremely connected. This correlation was attributed to

the overlapping spectral filters of the AS7341 sensor. Following this, feature selection and data scaling were carried out based on these findings, before training the model. Additionally, data gathered under varying physiological conditions, such as fasting and post-meal, showed that changes in blood volume considerably impacted the raw near-infrared transmittance measurements. Based on this, multi-wavelength signals were integrated to record superficial microvascular changes and establish a localized calibration baseline.

4.2 Model Training and Execution

Both models were trained on the standardized 80% training partition (2,336 samples) using identical random seed initializations to maintain comparative consistency. The Multiple Linear Regression weights were estimated via Ordinary Least Squares, while the MLP Regressor converged within 768 epochs of Adam optimization before triggering the early stopping criterion. After training, both finalized models were evaluated on the held-out validation cohort without any further parameter tuning.

4.3 Evaluation

A quantitative comparison between Multiple Linear Regression and the MLP Regressor evaluated on the held-out validation cohort is presented in Table 1. The evaluation metrics were computed on the independent test set (20% split), which was entirely separate from both the training of the model and the feature selection process. For each test data sample, the model's predicted blood glucose reading ($\hat{y}_i$) was assessed in comparison to the ground truth reading ($y_i \in [78, 169]$ mg/dL) of the patient as measured with the clinical glucometer, as per Eq. (7).

Table 1. Quantitative performance comparison with 95% bootstrap confidence intervals

Metric	Multiple Linear Regression (95% CI)	MLP Regressor (95% CI)
Mean Squared Error (MSE)	288.66 [256.04, 320.63]	91.59 [77.32, 107.69]
Mean Absolute Error (MAE) (mg/dL)	13.74 [12.88, 14.51]	6.56 [6.01, 7.14]
Coefficient of Determination (R^2)	0.2763 [0.2119, 0.3372]	0.7704 [0.7301, 0.8044]
Mean Absolute Relative Difference (MARD)	12.27% [11.50%, 13.01%]	5.92% [5.43%, 6.47%]

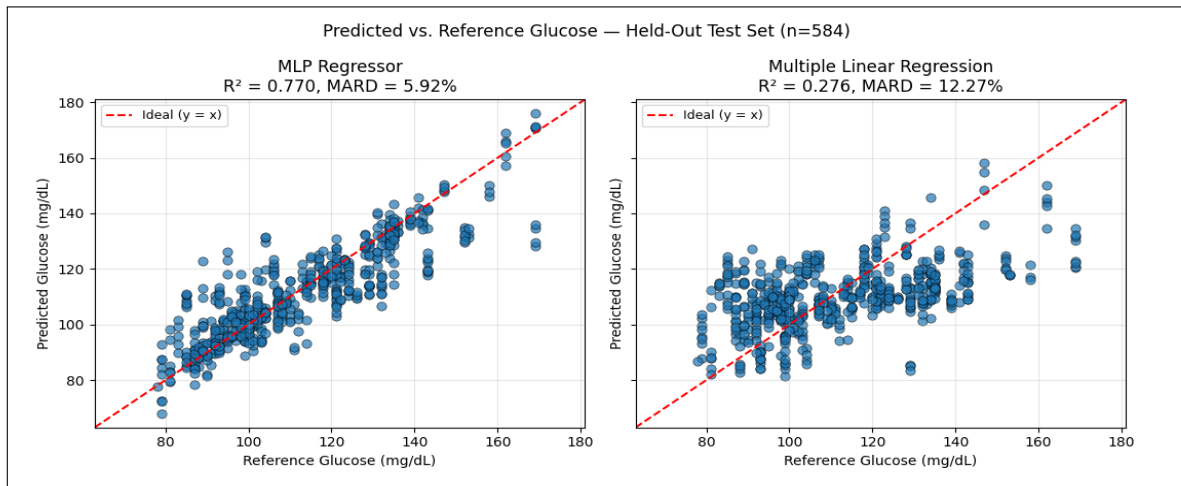


Figure 5. Predicted vs. reference blood glucose concentrations for the MLP regressor and multiple linear regression

Figure 5 visualizes the results of predicted vs. reference blood glucose concentrations on the independent held-out validation cohort (n=584) for the MLP Regressor and Multiple Linear Regression. The red dashed line denotes the ideal line of unity ($y = x$).

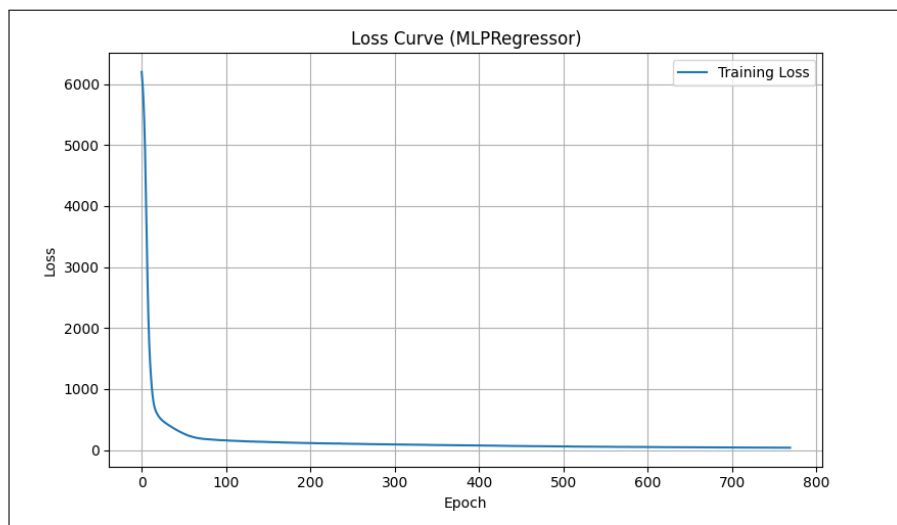


Figure 6. MSE loss curve of the MLP regressor showing training convergence across optimization epochs

As can be seen from Table 1 and Figure 5, the Multiple Linear Regression model showed only moderate prediction capabilities ($R^2 = 0.2763$, $MARD = 12.27\%$). On the other hand, the Multilayer Perceptron (MLP) regressor demonstrated much better performance, decreasing the Mean Absolute Error to 6.56 mg/dL, improving the R^2 value up to 0.7704 and obtaining a total MARD of 5.92% (95% CI: [5.43%, 6.47%]). A paired t-test confirmed that this error reduction

over the baseline linear model was statistically significant ($t = 18.98$, $p < 0.001$), demonstrating the network's capacity to resolve non-linear optical attenuation in human tissue across both fasting and post-prandial glycemic states.

The training loss curve in Figure 6 demonstrates steady numerical convergence of the MLP architecture during optimization. These comparative findings confirm that the non-linear MLP regressor is substantially better suited than baseline linear regression for capturing multi-wavelength optical absorption dynamics for non-invasive blood glucose estimation.

5. Conclusion

This research shows that it is possible to estimate blood glucose level non-invasively through multi-wavelength spectroscopy and machine learning. As for the models analyzed, MLP was more effective than the simple linear regression model, because it provided lower MARD and better represented the non-linear relationships between optical measurements and physiological responses of glucose. Blood volume measurement obtained from Red and NIR absorption showed slight improvements, which suggests that blood volume might be considered a confounding factor when estimating glucose using optical sensors. Nevertheless, this improvement needs confirmation with a bigger dataset. There were a number of factors which influenced negatively the efficiency and generalization ability of the system, including skin properties, finger pressure, lighting conditions, movements and electrical noise. The sample size and demographic diversity present generalizability constraints, where constrained datasets increase the risk of overfitting during hyperparameter optimization. Moreover, the ESP32-C3 limitations do not allow using more sophisticated models and real-time measurements. Future studies may be conducted on large and diversified sets of data collected in clinical settings, along with improvements in processing algorithms and sophisticated learning architectures. The connection to cloud services may also help in the secure storage of longitudinal data and trend analysis, as well as making the data clinically available. The results suggest the possibility of optical measurements based on MLP modeling in non-invasive glucose detection.

References

- [1] World Health Organization. "Diabetes." WHO Fact Sheets (2024). Available <https://www.who.int/news-room/fact-sheets/detail/diabetes>
- [2] Shrestha, Dhan Bahadur, Pravash Budhathoki, Yub Raj Sedhai, Achyut Marahatta, Samit Lamichhane, Sarbin Nepal, Anurag Adhikari, Ayusha Poudel, Samata Nepal, and Alok Atreya. "Type 2 Diabetes Mellitus in Nepal from 2000 to 2020: a systematic review and meta-analysis." *F1000Research* 2021, vol. 10, 543.
- [3] Shrestha, Nipun, Shiva Raj Mishra, Saruna Ghimire, Bishal Gyawali, and Suresh Mehata. "Burden of Diabetes and Prediabetes in Nepal: a Systematic Review and Meta-Analysis." *Diabetes Therapy* 2020, vol. 11, no. 9, 1935-1946.
- [4] Battelino, Tadej, Thomas Danne, Richard M. Bergenstal, Stephanie A. Amiel, Roy Beck, Torben Biester, Emanuele Bosi "Clinical Targets for Continuous Glucose Monitoring Data Interpretation: Recommendations from the International Consensus on Time in Range." *Diabetes Care* 2019, vol. 42, no. 8, 1593-1603.
- [5] Ferreira, Rafael Oliva Morgado, Talita Trevisan, Eric Pasqualotto, Matheus Pedrotti Chavez, Beatriz Friedrichsen Marques, Rodrigo Nunes Lamounier, and Simone van de Sande-Lee. "Continuous Glucose Monitoring Systems in Noninsulin-Treated People with Type 2 Diabetes: A Systematic Review and Meta-Analysis of Randomized Controlled Trials." *Diabetes Technology & Therapeutics* 2024, vol. 26, no. 4, 252–262.
- [6] Heinemann, Lutz, and Guido Freckmann. "CGM versus FGM; or, continuous Glucose Monitoring is Not Flash Glucose Monitoring." *Journal of Diabetes Science and Technology* 2015, vol. 9, no. 5, 947-950.
- [7] Barchiesi, Maria Assunta, Armando Calabrese, Roberta Costa, Francesca Di Pillo, Antonio D’Uffizi, Luigi Tiburzi, and Erum Zahid. "Continuous Glucose Monitoring in Type 2 Diabetes: a Systematic Review of Barriers and Opportunities for Care Improvement." *International Journal for Quality in Health Care* 2025, vol. 37, no. 3, mzaf046.
- [8] Anderson, R. R., J. Hu, and J. A. Parrish. "Optical Radiation Transfer in the Human Skin and Applications in Vivo Remittance Spectroscopy." In *Bioengineering and the Skin: Based on the Proceedings of the European Society for Dermatological Research Symposium, held at the Welsh National School of Medicine, Cardiff, 19–21 July 1979*, 253-265.
- [9] Payne, Peter A. "Measurement of Properties and Function of Skin." *Clinical Physics and Physiological Measurement* 1991, vol. 12, no. 2, 105-129.
- [10] Hina, Aminah, and Wala Saadeh. "Noninvasive Blood Glucose Monitoring Systems using

- Near-Infrared Technology—A review." *Sensors* 2022, vol. 22, no. 13, 4855.
- [11] Saptari, Vidi Alfandi. "A spectroscopic System for Near Infrared Glucose Measurement." PhD diss., Massachusetts Institute of Technology, 2004.
- [12] Smith, John L. "The Pursuit of Noninvasive Glucose: Hunting the Deceitful Turkey." Revised and Expanded, copyright (2015).
- [13] Ahmad, M., A. M. Kamboh, and A. Khan. "Non-Invasive Blood Glucose Monitoring Using Near-Infrared Spectroscopy." *EDN Magazine* 2013, 1–6. <https://www.edn.com/non-invasive-blood-glucose-monitoring-using-near-infrared-spectroscopy/>
- [14] Aoyagi, Takuo. "Improvement of the Ear-Piece Oximeter." In 13th Annual Meeting of Japanese Soc. Med. Electronics and Biomed. Engr., 1974, 90-91.
- [15] Leppänen, Timo, Samu Kainulainen, Henri Korkalainen, Saara Sillanmäki, Antti Kulkas, Juha Töyräs, and Sami Nikkonen. "Pulse Oximetry: the Working Principle, Signal Formation, and Applications." In *Advances in the Diagnosis and Treatment of Sleep Apnea: Filling the Gap Between Physicians and Engineers*, Cham: Springer International Publishing, 2022, 205-218.
- [16] Maeda, Yuka, Masaki Sekine, and Toshiyo Tamura. "The Advantages of Wearable Green Reflected Photoplethysmography." *Journal of medical systems* 2011, vol. 35, no. 5, 829-834.
- [17] Matsumura, Kenta, Peter Rolfe, Jihyoung Lee, and Takehiro Yamakoshi. "iPhone 4s Photoplethysmography: Which Light Color Yields the Most Accurate Heart Rate and Normalized Pulse Volume Using the iPhysioMeter Application in the Presence of Motion Artifact?" *PLoS ONE* 2014, vol. 9, no. 3, e91205.
- [18] Lawand, Komal, Mahesh Parihar, and Shital N. Patil. "Design and Development of Infrared LED based Non Invasive Blood Glucometer." In 2015 Annual IEEE India conference (INDICON), IEEE, 2015, 1-6.