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NON- INVASIVE GLUCOSE MONITORING DEVICE USING PHOTOPLETHYSMOGRAPHY SIGNAL AND MACHINE LEARNING MODEL

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Abstract
Diabetes mellitus is a metabolic condition that is permanent and that is why the blood sugar level is under constant monitoring. Conventional surveillance is based on invasive finger-prick tests that may be painful and may decrease patient compliance. In order to deal with this problem, this paper suggests an estimation system of glucose that will be non-invasive and work with photoplethysmography (PPG) signals and machine learning. The system employs a MAX30105 optical sensor to record PPG signals through the fingertip and ESP32 microcontroller to take data, process it, and analyze it in real-time. The synchronized PPG signals along with reference glucose values of a standard glucometer were acquired as a dataset. The PPG waveform was processed to obtain relevant features and was sent through a machine learning model to predict glucose. It has been demonstrated that a low-cost, portable, and non-invasive glucose monitoring system can be developed using PPG signal analysis and machine learning together and be used in wearable healthcare systems.

I. Introduction

Diabetes mellitus is a long-term systemic malfunction disorder that relates to the deficiency to regulate the blood sugar level in the body [1][2]. It arises at the times that the pancreas fails to produce insulin adequately or when the body becomes insulin-resistant. Consequently, glucose is deposited in the blood creating hyperglycemia [3]. Severe complications include cardiovascular diseases, kidney failure, blindness and nerve damage which are caused by prolonged high levels of blood glucose. As such, effective management of diabetes requires that the level of blood glucose be monitored regularly. The current situation is that most diabetic patients use traditional glucometers where they have to take blood samples by finger pricking. Even though these devices are accurate, they are invasive and they can lead to pain, discomfort and low levels of patient compliance particularly when continuous measurements are needed. These restrictions have encouraged scientists to consider non-invasive and more convenient ways of glucose monitoring [4].

Among such promising techniques, there is photoplethysmography (PPG), which is an optical technology that can be utilized to measure changes in blood volume in peripheral tissues. PPG sensors measure alterations in absorption of light due to pulsatile blood circulation which is useful in physiological measures of blood circulation and tissue properties [5]. As these physiological properties may be affected by metabolic changes, PPG signals may have indirect measures of blood glucose levels.

New advancements in machine learning have also enhanced the prospects of non-invasive glucose monitoring [6][7]. Machine learning algorithms can process multifaceted physiological signals and detect trends that are related to glucose changes. With the help of machine learning models and PPG signal analysis, one can estimate glucose levels without having to perform invasive blood sampling.

This paper suggests a non-invasive glucose monitoring device using PPG signals and machine learning algorithms. The aim is to create a safe and low-cost and portable solution that will enhance the comfort of patients and assist them in easier glucose tracking.

II. Methodology

The research will present a non-invasive glucose monitoring device that works on photoplethysmography (PPG) signal and machine learning [8]. The implementation methodology can be described as hardware implementation, data collection, signal processing, feature extraction, and developing a machine learning model.

Hardware Components

It is based on the MAX30102, ESP32-S3 microcontroller and ILI9341. The sensor named MAX30102 records the red and infrared PPG signals on the fingertip via the sensor detecting the differences in the light absorption due to pulsatile blood flow [9][10]. the ESP32-S3 microcontroller serves as the main processing unit that receives data on the sensors, preprocesses the signals and runs the machine learning model. The system is displayed on an ILI9341 TFT LCD. The ESP32 communicates with the sensor by using the I2C protocol which allows effective transfer of data. Figure 1 shows the hardware and internal design of the proposed system.

Figure 1 Hardware design of the proposed system showing the integration and connections of the main components used in the prototype.

Data Collection

The max30102 sensor was used to gather PPG records at the fingertip whereas a standard glucometer was used to record the reference glucose values. The measurements took about 15 seconds and sampled at a rate of 50 Hz yielding an approximate of 750 values per sample. First, there were 91 samples with glucose level of 53 mg to 373mg/dl. The extreme values were eliminated to enhance the stability of the dataset, which left 72 samples on which the model was developed.

Signal Processing

Butterworth filter is used for the processing of PPG signals. It provides the baseline drift and high-frequency noise of the recorded PPG signals [10][11][12]. Analysis of the filtered signals was done to extract the physiological parameters of the

AC and DC components, heart rate and perfusion index. Whereas, power spectral density was also used in frequency-domain examination to determine the physiological patterns that dominated in the signal [13].

Feature Extraction

The number of statistical and physiological characteristics were obtained from the processed PPG signals. These are the average and the standard deviation of the infrared signal, AC/DC ratio, PSD aspects, R-ratio, and the estimated oxygen saturation (SpO_2). The obtained features were the input variables of the machine learning model.

Machine Learning Model

After completing the data collection, signal processing, feature engineering and data augmentation, the following process in this project was to train a machine learning model that can predict glucose. The primary aim of the model was to acquire the correlation between the programmed PPG parameters and the reference blood glucose levels. Blood glucose level cannot be read directly through PPG, the model needed to determine the latent behaviour of the optical signal characteristics vis-a-vis the actual glucose readings.

A number of regression models were tested, among them being the Random Forest, Gaussian Process Regression, Gradient Boosting, and the ensemble. The highest performance with the data was demonstrated by the ExtraTrees regression algorithm. The model is also a combination of several randomized decision trees the predictions of which are averaged to come up with the final glucose estimate [13][15][16]. This model had a Mean Absolute Error (MAE) of about 19.5mg/dL.

Validation, Testing and Training.

The model was trained on the augmented dataset where the inputs were the PPG features extracted and the target labels were the glucometer readings. Model stability and overfitting were checked with the help of Leave-One-Out Cross Validation (LOO-CV) and K-Fold validation. Lastly, the system was tested with an 80/20 train-test split, and mean absolute error (MAE) and +-20 mg/dL accuracy was used to assess the performance.

III. Results and Discussion

The proposed glucose non-invasive monitoring system demonstrated a consistent performance in the 70-220mg/dL glucose range. ExtraTrees regression model, which was trained on 12 PPG features, was tested on 80/20 train-test split and Leave-One-Out Cross Validation (LOO-CV). The findings gave a MAE of approximately 19.5-21.3 mg/dL and +-20mg/dL accuracy of 66-73 implying that most of the predictions lie within a clinically acceptable range. The comparison of predicted values and true values indicates that the predicted values are usually near to actual glucometer readings and majority of the residual values fall within +-20mg/dl indicating that there is no significant bias in prediction. Normal glucose levels also performed well with classification analysis as compared to Elevated levels since it had few samples. Figure 2 shows the comparison between the models predicted output and actual measured value.

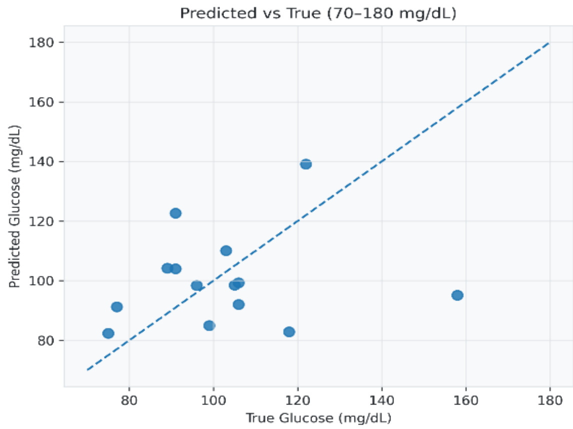

Figure 2 Predicted vs. true values

Real-Time Monitoring

Once the model training and offline assessment was done, the system was implemented on the ESP32 device to monitor glucose real time. The ExtraTrees model that was trained was translated into C++ and implanted into the microcontroller. In real time tests, the device recorded 750 PPG resolutions in a 15 second time window with a 50 Hz sampling rate. Based on these readings, the 12 features were computed within the machine itself. Normalization of these features was then done using the stored mean and standard deviation values, and forwarded through the five decision trees in the ExtraTrees model.

The last glucose was calculated as the average prediction of all trees and it was presented on the screen. Figure 3 shows the real time monitoring interface displaying the result comparison of non invasive PPG prototype and blood glucose monitor. It shows that non-invasive glucometer shows approximately same result as invasive glucometer.

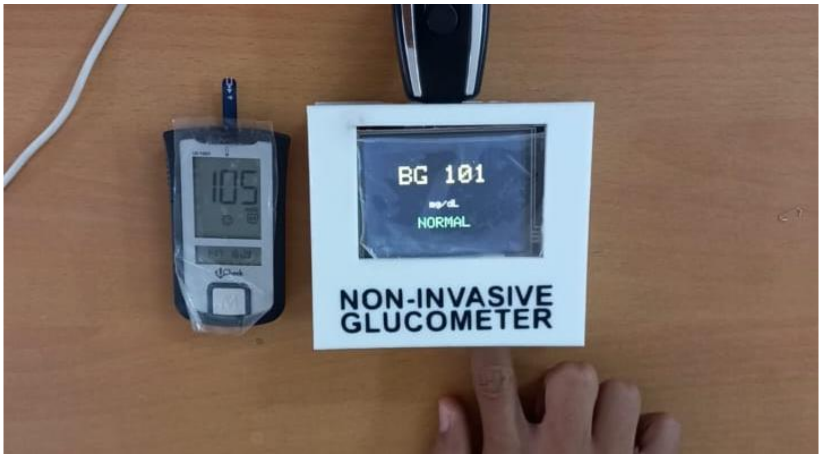

Figure 3 Real-time monitoring interface displaying the measurement from the prototype.

Prototype Validation

The testing of the created device was conducted to check the accuracy and reliability of the glucose results.

To this end, glucose values produced by the proposed device were compared

with the glucose values produced by a normal invasive glucometer. In the validation, the subjects had glucose readings which were taken using both of the methods. Firstly, the participant place the tip of their finger on the optical sensor of the developed device capturing the PPG signal. The signal was then processed on the ESP32 microcontroller, the features that were needed were extracted and the trained machine learning model was used to estimate the glucose level. This value was the estimate of non-invasive glucose produced by the proposed system.

Furthermore, the prototype was tested by comparing measurements of the device with a reference glucometer with 10 test samples having an average MAE of 12.7mg/dl with 90% of the predictions falling within a 20 percent range. The findings indicate that a low-cost non-invasive technique of glucose monitoring is possible as the system has the ability to predict glucose trends with PPG signals and machine learning. Table 1 and figure 4 shows the glucometer versus non-invasive prototype reading.

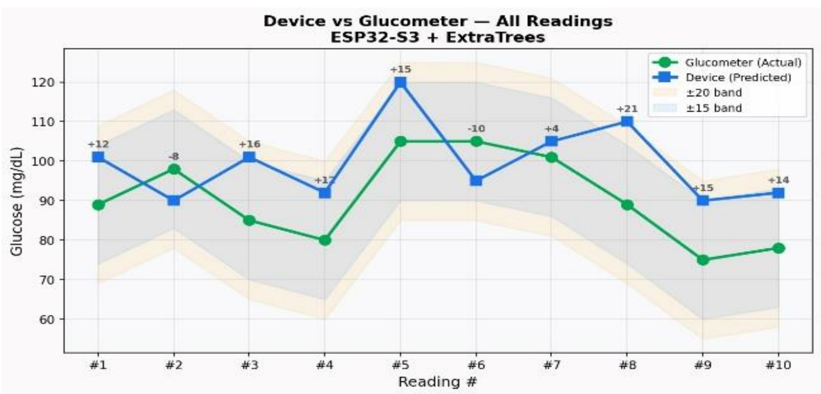

Figure 4 graph showing prototype vs invasive glucometer readings

Table 1 Device validation results showing the comparison between the measurements obtained from the prototype and the reference method

S.No	Glucometer reading (mg/dL)	Device reading (mg/dL)	% Error
1	89	101	13.50%
2	98	90	8.20%
3	85	101	18.80%
4	80	92	15.00%
5	105	120	14.30%
6	105	95	9.50%
7	101	105	4.00%
8	89	110	23.60%
9	75	90	20.00%
10	78	92	17.90%

IV. Conclusion and Future work

This paper has proposed a design and developed a non-invasive glucose monitoring device that relies on photoplethysmography signals and machine learning. The system was implemented with the help of a sensor (MAX30102) and ESP32 microcontroller to obtain and analyze physiological signals and an ExtraTrees regression model to predict glucose levels. It was demonstrated that the system could reach a sensible level of prediction accuracy with a Mean Absolute Error of approximately 19-21 mg/dL, which demonstrated the potential of the PPG-based feature analysis as a non-invasive glucose estimation system.

In the future, the accuracy and reliability of the system will be improved through gathering more and more varied datasets and experimenting with more advanced machine learning models or deep learning models. Other enhancements can involve the provision of better signal quality, minimization of motion artifacts, and the provision of the system as a small wearable device that is connected either to the mobile or the cloud to monitor glucose continuously and remotely.

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