A Non Invasive Glucose Level prediction using PPG signal from smartphone

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***Abstract*—In our pioneering work, we exclusively focus on glucose level prediction, acknowledging the imperative need for precise and non-intrusive methods in blood glucose monitoring for individuals with elevated blood sugar. Our innovative smart system harnesses Photoplethysmography (PPG) signals to predict the continuous and real numerical values of blood glucose concentrations. Employing a unique methodology, we extract distinctive features from both temporal and frequency domains of PPG signals acquired through non-invasive means, specifically films. The heart of our approach lies in regression techniques within machine learning, allowing us to forecast actual blood glucose levels rather than categorizing them. Rigorous evaluation on an extensive dataset of 60 subjects attests to the efficacy of our system, achieving a notable mae of in predicting blood glucose concentrations. This underscores the promising potential of our approach for daily and clinical applications in non-invasive blood glucose testing, emphasizing its role in accurate and continuous glucose level monitoring without resorting to intrusive methods.**

***Index Terms*—PPG, deep learning, Non Invasive, feature extraction, GLucose level Monitoring.**

I. Introduction

The management of blood glucose levels is paramount for individuals with diabetes, requiring frequent monitoring to prevent health complications. In pursuit of user-friendly and non-intrusive solutions, this research introduces a novel approach to glucose level prediction using Photoplethysmography (PPG) signals acquired from smartphones. Leveraging the ubiquity of smartphones, our method aims to provide an accessible and efficient means of predicting blood glucose concentrations without the discomfort associated with traditional invasive methods. By tapping into the PPG signals, which capture variations in blood volume through the smartphone's built-in camera and light source, our system employs advanced machine learning techniques for regression analysis. This innovative approach seeks to not only enhance the convenience of glucose monitoring but also to contribute to the development of personalized and portable healthcare solutions.

In the subsequent sections, we delve into the methodology, algorithms, and experimental findings of our non-invasive blood glucose monitoring system. We believe that this research contributes significantly to the field of mobile health, potentially revolutionizing how individuals manage their blood glucose levels. Moreover, the integration of smartphone technology makes our solution accessible to a broad range of individuals, regardless of their geographic location or access to healthcare facilities.

Motivation: The motivation behind conducting research on ”A Non-Invasive Glucose Level Prediction Using PPG Signal from Smartphone” stems from the pressing need for improved and user-friendly methods of blood glucose monitoring, particularly for individuals with diabetes.Recognizing the ubiquity of smartphones and their embedded capabilities, our project aims to leverage Photoplethysmography (PPG) signals captured by smartphone cameras to provide a non-intrusive and convenient solution for predicting blood glucose levels.However, traditional invasive methods, such as fingerstick tests,often involve pricking the skin to draw blood for glucose measurement can be uncomfortable, painful, and inconvenient for patients. These barriers to regular monitoring can result in suboptimal disease management, leading to health complications. The motivation for this research is rooted in the need to develop a more patient-friendly and accessible approach to diabetes monitoring.

One significant aspect motivating this study is the stark difference between invasive and non-invasive approaches to glucose prediction.Non-invasive methods, such as using PPG signals from smartphone cameras, offer a pain-free and convenient alternative. By utilizing widely available technology, we seek to overcome the barriers associated with traditional monitoring techniques, fostering greater adherence to regular glucose level assessments. With this motivation,the research involves a comprehensive approach that includes the following key steps:

- **Data Collection**: we have collected both glucose data and smartphone video recordings, specifically focusing on the index finger, from a targeted group of individuals..
- **Model Development**: Create a robust machine learning model capable of accurately predicting glucose level.
- **Technology Advancement**: Our approach signifies a technological leap by demonstrating the feasibility of non-invasive glucose level prediction through smartphone video recordings, offering a user-friendly alternative to traditional monitoring methods.

II. Related Works

Due to numerous advancements in optics and data science, noninvasively monitoring blood glucose levels is now possible. We concentrate on research that relates to monitoring blood sugar levels and determining whether or not diabetes is present based on PPG signals, and we summarise the key studies as follows.

In [1], data were collected using a wearable device, and the accuracy was respectable (0.795), but there was a lot of noise in the data that affected the model. The MAX 30105 Pulse Oximeter Module was used by S. Hossain [2] to collect the raw data signals, and the arduino was used for processing and predicting the glucose value. They utilised a 1d CNN for their model and obtained an RMSE of 0.15, but the patient had to carry the device around. In [3]The the finger was put in the LED board and the video recording was collected, the ppg signal was extracted by taking the red channel of the video frames using appropriate filters, after which the time domain based features were extracted and applied to the machine learing and deep learning models and got highest R^2 value of 0.832 using ANN model. In [4] The author calculated the continuous PPG signal using the total pixel intensity variations of each video frame. A threshold is set for each frame The PPG value is determined by the total number of pixels in the frame whose intensity exceeds a certain threshold. The PPG signal is obtained by summing the intensities of the individual pixels in each frame. then he applied Gaussian filtering to extract the required features and applied a machine learning model and classified into normal, borderline and warning. The author in [5] used clinically collected data and used majorly used Energy based features like Kaiser-Teager Energy , Spectral Entropy with DNN and results showed that their test success rate reached 90.25

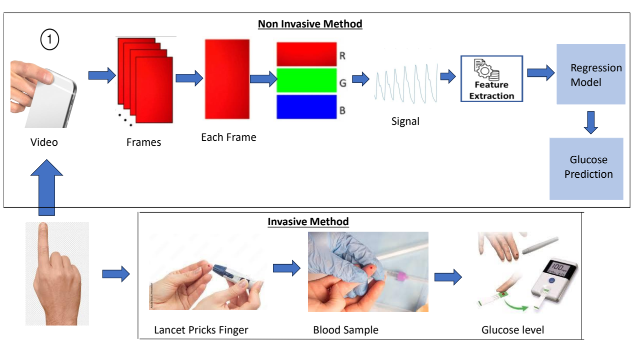

Fig. 1. Overview of the proposed Model

III. Proposed Methodology

A. Dataset

In our Project, we have collected both blood glucose levels and smartphone video recordings capturing the index finger of users. Leveraging these video recordings, we have implemented a process to extract PPG signals, capturing the subtle variations in blood volume over time. Subsequently, we have focused on extracting pertinent features from these PPG signals. This dataset has been instrumental in the development and training of our machine learning model for diabetes prediction and monitoring. The dataset includes both training and testing splits, enabling us to effectively train and evaluate the model's performance.basic overview of projec tin given in Fig. **??** By leveraging this comprehensive dataset, we aim to harness the power of PPG signals and modern technology to provide users with a non-invasive and accessible tool for accurate diabetes prediction and monitoring.

B. Retrieval of PPG Signal

The retrieval of PPG signals is based on the principle that the absorption of light by blood is associated with changes in finger blood volume, which are reflected in video recordings.A threshold is set for each frame, and the PPG value for each frame is determined as the sum of pixels with intensity greater than the specified threshold as given in Eq. 1. By analyzing the pixel intensity of the same area in adjacent frames of the video, a continuous PPG signal is calculated as given in Eq. 2.

$$\text{Threshold} = 1.01 \times (\text{intensity}_{\text{max}} - \text{intensity}_{\text{min}}) \quad (1)$$

$$\text{PPG signal}[i] = \sum_{\text{total pixels}} 1_{\text{intensity}>\text{Threshold}} \quad (2)$$

The PPG signal is then generated by plotting these calculated sums for each frame. The selection of an appropriate threshold involves careful consideration to ensure an accurate waveform while avoiding excessive smoothing or the introduction of unwanted peaks. In this system, the red channel is found to provide the clearest PPG signals, reflecting the periodic variations in blood volume during cardiac cycles, while the green and blue channels typically require additional complex processing to extract useful information.

C. PPG Signal Pre-Processing

In the preprocessing of a Photoplethysmography (PPG) signal, the initial step involves acquiring the raw PPG signal, often recorded using devices like a pulse oximeter or a smartphone camera, which captures variations in blood volume. Subsequently, a critical filtering stage is implemented, employing a bandpass Butterworth filter with specified passband frequencies, such as 0.15 Hz to 8 Hz, to suppress noise and highlight cardiovascular activity. This filtering process aids in eliminating artifacts and mitigating interference from ambient light. Following the filtering step, the normalized signal is obtained by scaling it to a common amplitude range, typically between 0 and 1. This normalization ensures consistency across diverse recordings, facilitating meaningful comparative analyses in subsequent stages of signal processing and analysis.

D. Feature Extraction

Features in machine learning are discrete, quantifiable attributes or traits of the data that are fed into a model. Attributes, variables, and independent variables are other names for features. Using features aims to extract pertinent information from the data that supports the machine learning model's ability to recognize patterns, anticipate outcomes, or carry out a particular function. Feature extraction in the context of PPG (Photoplethysmogram) signal processing involves identifying and quantifying relevant characteristics or patterns from the PPG waveform. PPG signals are obtained by measuring variations in light absorption or reflection caused by blood flow through the skin, and they carry valuable information about cardiovascular activity. we extracted Time domain features, frequency domain features and used Auto-Encoder to extract more features from the processed signal

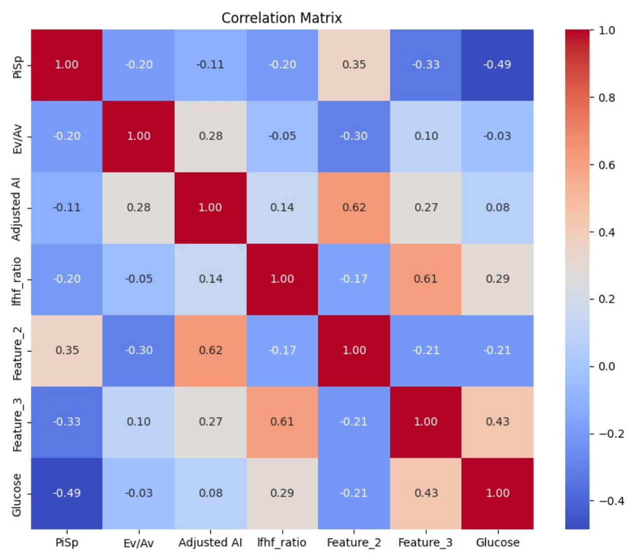

Fig. 2. Feature Correlation Heatmap

A.Systolic Peak(SP)

The systolic peak refers to a specific feature of the PPG waveform that corresponds to the contraction of the heart, known as systole. The PPG signal is typically obtained by shining light into the skin, often on a fingertip, and measuring the amount of light absorbed by the blood vessels. The resulting signal represents the pulsatile blood flow caused by the heartbeat.

B.Diastolic Peak(DP)

Definition: Points in the PPG signal corresponding to the minimum pressure in the arteries during the cardiac cycle.Diastolic peaks are crucial for determining diastolic blood pressure and assessing the heart's relaxation phase.

C.Augmentation Index (AI)

The Augmentation Index (AI) is defined as the ratio of pulse interval to systolic peak amplitude.

$$AI = \frac{\text{DP}}{\text{SP}}$$

D.Pulse Interval to Systolic Peak Ratio (PiSp)

The Pulse Interval to Systolic Peak Ratio (PiSp) is defined as the ratio of pulse interval to amplitude of the systolic peak.

$$PiSp = \frac{\text{Pulse Interval}}{\text{SP}}$$

E.EV/AV

The EV/AV ratio is defined as the ratio of the average of the second derivative to the average of the first derivative.

$$\text{EV/AV} = \frac{\text{Average of Second Derivative}}{\text{Average of First Derivative}}$$

F.Power spectral density Power Spectral Density (PSD) is a measure of the distribution of power across different frequencies in a signal. For a digital signal, the PSD is often estimated using methods like the Fast Fourier Transform (FFT). The PSD provides insights into the frequency content of a signal.

$$S_{xx}(f) = \frac{1}{N} |X(f)|^2 \tag{3}$$

$$X(f) = \sum_{n=-\infty}^{\infty} x[n] \cdot e^{-j2\pi fn} \tag{4}$$

GLF/HF Ratio

The LF/HF Ratio, also known as the Low Frequency to High Frequency Ratio, is a feature commonly used in the analysis of physiological signals, particularly in the context of heart rate variability (HRV) studies

The LF/HF Ratio is calculated using the following formula:

$$\text{LF/HF Ratio} = \frac{\text{Low Frequency Power}}{\text{High Frequency Power}} \tag{5}$$

We leveraged a feature correlation heatmap as shown in Fig. 2 to identify and select non-correlated features, a step that significantly improved the accuracy of our non-invasive blood glucose level prediction model. By emphasizing unique and complementary information, this process enhanced the model's performance and resulted in more reliable blood glucose predictions.

E. Prediction Model

A. Linear Regression

Linear regression is a machine learning technique used to model the relationship between a dependent variable and one or more independent variables. It assumes a linear connection, seeking the best-fitting line to minimize the difference between observed and predicted values. The equation for a simple linear regression is $Y = \beta_0 + \beta_1 X$, where Y is the dependent variable, X is the independent variable, β_0 is the intercept, β_1 is the slope.

B. Lasso regression

Lasso regression, or L1 regularization, is a linear regression technique that adds a penalty term based on the absolute values of the regression coefficients. It is used for feature selection and regularization by shrinking some coefficients to exactly zero, effectively excluding those features from the model. Lasso helps prevent overfitting and simplifies the model by encouraging sparsity in the feature space, making it particularly useful when dealing with datasets with a large number of features.

C. Random Forest Regression

Random Forest Regression is an ensemble learning technique that constructs a multitude of decision trees during training and outputs the average prediction of the individual trees for regression tasks. It provides high flexibility, reduces overfitting, and excels in capturing complex relationships within the data.

D. K-Nearest Neighbors (KNN) Regression

K-Nearest Neighbors (KNN) Regression is a non-parametric algorithm for regression tasks that predicts the output of a data point by averaging the values of its k nearest neighbors. It is based on the principle that similar data points in the feature space tend to have similar target values. KNN Regression is simple to understand, adaptable to various data distributions, and requires minimal assumptions about the underlying data structure. Adjusting the parameter 'k' influences the balance between model complexity and smoothness.

E. Artificial Neural Network

Artificial Neural Network involves training neural networks with multiple layers to learn complex patterns and relationships within data, automatically extracting features from the input. It excels in handling large-scale datasets and capturing intricate dependencies, offering a versatile approach for regression tasks. The architecture, activation functions, and hyperparameters can be tailored to specific data characteristics, enabling deep learning models to achieve high predictive accuracy in diverse applications.

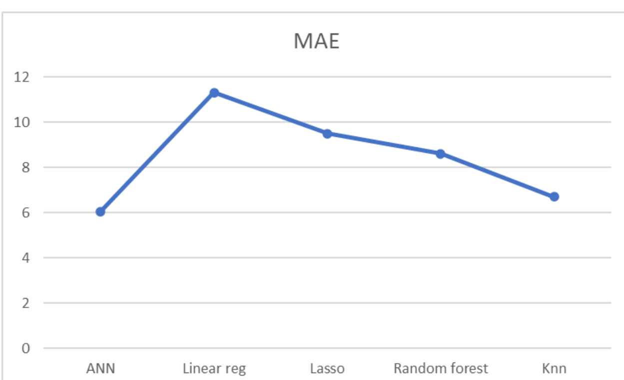

Fig. 3. MAE of Model

To ensure accurate predictions, we plotted feature importance as shown in Fig. 3, allowing us to understand the significance of each input variable in our model. This insightful analysis guided us in fine-tuning our system for non-invasive blood glucose monitoring, ultimately enhancing the precision and reliability of our output plots.

IV. Results and Discussion

We delve into the performance of our predictive model for non-invasive blood glucose monitoring and explore the significance of various features and algorithms employed. The results offer insights into the effectiveness of our system, shedding light on its potential for practical applications in healthcare and diabetes management.

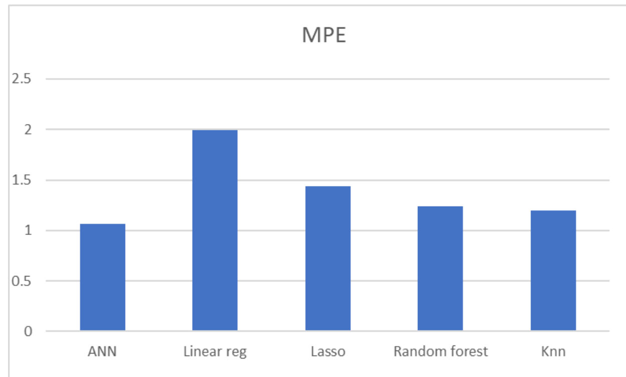

Fig. 4. MPE of Model

A. Model Choice

In our quest to select the most suitable predictive model for non-invasive blood glucose level prediction, we explored five distinct approaches. The results reveal that the deep learning model, ANN, exhibited superior performance with a mean absolute error (MAE) of 6.06 as shown in Fig. 3and a mean percentage error (MPE) of 1.054, showcasing its effectiveness in capturing intricate relationships within the data. Among the traditional regression models, Random Forest outperformed others, yielding an MAE of 8.6 and an MPE of 1.24 as shown in Fig. 4. Linear Regression and Lasso Regression demonstrated competitive yet slightly higher errors, with MAE values of 11.3 and 9.5, respectively, and MPE values of 1.9 and 1.44, respectively. The KNN Regression model achieved the lowest MAE of 6.7 and an MPE of 1.197, emphasizing its efficacy in leveraging the proximity of data points for accurate glucose level predictions. These findings underscore the importance of selecting appropriate regression models for PPG-based glucose prediction, with ANN and KNN showcasing notable promise in this context. Further investigations and fine-tuning of model parameters could potentially enhance predictive accuracy for real-world applications.

TABLE II
Performance Metrics for Different Models

Model	Performance Metrics		
	MAE	MPE	
ANN	6.06	1.054	
Linear Regression	11.31	1.993	
Lasso Regression	9.5	1.442	
KNN regression	6.75	1.197	
Random forest regression	8.65	1.247	

V. Conclusion and Future Scope

Our project has successfully introduced a non-invasive blood glucose monitoring system based on smartphone PPG signals and machine learning algorithms, achieving a commendable MAE of 6.067 and MPE of 1.054. However, there is substantial future scope for improvement and expansion. We can also envision developing a dedicated mobile application for accurate PPG data collection, enhancing the quality and quantity of input data. Additionally, exploring a wider array of features in both time and frequency domains holds the potential to further boost prediction accuracy. Furthermore, we aim to optimize the model by exploring quick, lightweight machine learning or deep learning models that demand fewer computational resources, making real-time monitoring and widespread adoption more feasible and efficient. These future endeavors will advance the capabilities of our system and contribute to more precise and accessible non-invasive blood glucose monitoring solutions.

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