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Non-Invasive Glucose Diabetic Prediction using Deep Neural Network and PPG Signals

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Abstract: This study introduces a novel approach for predicting blood glucose levels using dual wavelength photoplethysmography (PPG), which offers a non-invasive alternative to the usual invasive methods for blood glucose measurement. This suggested system aims to alleviate the pain associated with traditional techniques while providing accurate blood glucose estimations for the purpose of diabetes prediction. The PPG signals that were obtained were subjected to pre-processing and subsequently underwent min-max scaling. Additionally, feature selection was performed. The use of the Deep Learning neural network (DNN) was utilised to forecast the blood glucose level for the purpose of diabetes prediction. In order to validate the system's operational reliability, this study gathered data from a total of 182 participants and generated a comprehensive database. Based on the empirical findings, the system exhibits a root mean squared error of 5.05 mg/dl surpassing the performance of the Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) regression models employed in this investigation. When compared with recent work, the proposed model in this study observed the RMSE of 5.05 mg/dl in comparison with 9.14 mg/dl in recent study.

Keywords: *Blood Glucose Diabetic Prediction, photoplethysmography Signal, Deep neural Network, Scaling*

1. Introduction

In current When the pancreas does not produce enough insulin or the body does not use enough insulin, a chronic medical condition known as diabetes results. Consequently, the person's capacity to regulate their blood sugar levels is compromised. Diabetes presents with clinical manifestations including polydipsia, polyphagia, and polyuria. Furthermore, individuals suffering from diabetes exhibit an increased vulnerability to several severe complications, such as retinopathy, renal disorders, neuropathy, and cardiovascular ailments.[1]. The aforementioned concerns possess the capability to detrimentally affect an individual's overall well-being and lead to prolonged disability. Therefore, in order to recognise and manage diabetes quickly, preventive medicine plays an essential role. Patients can seek out more precise diagnostic assessments at healthcare facilities in the initial phases of diabetes if they consistently monitor their blood glucose levels, which aids in fast identification and intervention.

The standard method for determining blood glucose levels often comprises drawing blood from the patient's finger using a lancet and an insulin strip [2]. The next step is to use an electronic gadget to analyse the data and turn it into a numerical number that represents blood glucose levels. Unfortunately, the treatment is not recommended for repeated usage due to the potential pain caused by the repetitive puncturing of the fingers, especially in cases when ongoing surveillance is needed. In addition to the possible risks of infection and tissue damage, finger pricking may also lead to a reduction in patient adherence[3]. Despite these drawbacks, invasive glucose monitoring now has a significant position as the major approach for detecting blood sugar levels, mostly because to the lack of non-invasive blood glucose monitors that demonstrate similar levels of dependability and cost.

In order to provide continual blood glucose monitoring without intrusive procedures, several researchers are now looking at different options. These approaches hold promise for attaining equal levels of accuracy to invasive treatments, all the while maintaining cost-effectiveness.[4][5]. Optical signal detection, ultrasonic wave evaluation, microwave measurement, and electrical signal measurement are the four main non-invasive methods for blood glucose level detection currently available. In order to determine characteristics associated to blood glucose and make predictions about blood glucose levels, this study combined electrical biological impedance data with optical photoplethysmography (PPG).

The PPG technology refers to a non-invasive approach for physiological monitoring, which use optical mechanisms to identify variations in blood volume. The device possesses the capacity to collect signals from many parts of the human body. The selection of measurement sites significantly influences the photoplethysmography (PPG) signals. It is essential to acknowledge that the suitability of body parts for the measuring of PPG signals varies. Previous study has

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demonstrated that the fingertips and earlobes are the most optimum places for measuring the photoplethysmography (PPG) signal[6]. Numerous studies have shown the value of non-invasive methods for assessing blood glucose levels, such as those that use photoplethysmography (PPG) signals. Using a system that integrates three sensors, Sen et al. introduced a novel method for tracking blood glucose levels. Three different types of light with distinct wavelengths—940, 660 and 660 nm—are used by these sensors. The rationale for utilising this approach stems from the fact that various wavelengths of light absorb blood glucose at varying rates. The refraction signal was collected by the researchers using two detectors operating at 940 and 660 nm, respectively. To further capture the reflected signal, a third 660 nm sensor was utilised. The next step was to run the numbers through analyses of variance[7]. Deepthi et al. utilised a 940 nm infrared light source in their research to establish a novel strategy for monitoring blood glucose levels. This technique demonstrated enhanced efficacy when compared to the conventional invasive measurement methods frequently utilised inside hospital settings. An average inaccuracy of 2.5% was displayed by the suggested technique, suggesting that the model could accurately predict blood glucose concentrations [8].

Given the advent of AI, several scholars have shifted their focus towards employing neural networks for the evaluation of properties pertaining to photoplethysmography (PPG) signals. The research undertaken by Hamdi et al. utilised artificially generated neural networks as a prediction mechanism for estimating blood glucose levels. In this work, the researchers utilised the hyperbolic tangent (tanh) function as the chosen activation function. The resulting mean square error was determined to be 6.43 mg/dL [9]. In order to compare predicted blood glucose readings, Prabhu et al. used a variety of classifiers in their study. These included feed-forward neural networks, DT, LR, RF, and SVM, among others. Using the diabetes dataset acquired from UCI, the researchers ran an analysis and found that deep belief networks were more accurate due to their much higher recall and precision rates[10]. The study conducted by Manurung et al. made use of 940 nm-designated transmission infrared light. Using high-pass and low-pass filters were among the first steps in processing the light before the investigation. The researchers used a number of patient variables as inputs for their investigation, including maximum and minimum values, genders, height, weight, colour of the skin index, and finger width. The model yielded an MAE of 5.855 mg/dL during the neural network training procedure [11]. Hina et al. introduced a unique device for monitoring blood glucose levels, specifically intended for individual wear. The technology employed infrared light with a specific wavelength to acquire photoplethysmography (PPG) data. In order to address the challenge posed by facial motion artefacts, the researchers included machine learning methods of regression into their system. The study involved a comparative investigation of three techniques: Savitzky-Golay (SG) filtering, average filtering, and wavelet transform. The researchers selected smooth filtering as their preferred approach for noise elimination due to its cost-effectiveness and efficacy in signal preprocessing[12].

Furthermore, empirical evidence has substantiated the efficacy of combining photoplethysmography (PPG) data with bioelectrical impedance, hence yielding accurate results. The authors Fouad et al. presented a novel non-invasive glucose monitoring system that effectively balances cost and accuracy. This system integrates multiwavelength infrared spectroscopy with bioelectrical impedance frequency sweep. The technique used by the researchers involved measuring bioelectrical impedance by scanning frequencies between 10 and 100 kHz, with a steady interval of 10 kHz. Additionally, infrared spectroscopy was used, with three separate wavelengths of 850,880 and 940 nm. According to the referenced study, the system's computed correlation coefficient of 0.91805 places it into region A of the Clarke error grid analysis (EGA)[13]. The research done by Nanayakkara et al. employed 940 nm infrared light and a frequency range of 3 to 100 kHz for the purpose of bioelectrical impedance measurement. The attributes that were gathered were thereafter subjected to comparison utilising both the methods of least squares regression and neural network approaches. The results of the study showed that the least squares regression method exhibited greater performance, while the combination of infrared light and bioelectrical resistance led to improved accuracy[14]. A multiwavelength near-infrared spectrum was acquired by Pathirage et al., who then used it to measure bioelectrical impedance parameters at 0.5 kHz intervals over the 50 to 100 kHz frequency range. In addition, the researchers used a widely accessible glucose metre to measure the subjects' blood glucose levels. After that, a RF regression model was trained using the aforementioned metrics, and it achieved an accuracy rate of 90.7%.[15].

In this study, a NN was utilised for the blood insulin prediction model, and statistical characteristics were retrieved from PPG data obtained from 182 patients using a pulse sensor. This paper is organised as follows for the rest of it. Methods for using PPG Signal in this study's implementation for diabetes prediction are detailed in Section 2. In Section 3, we examine the outcomes of the NN that was used and go into additional detail about it. The results of this investigation are finally presented in Section 4.

2. Methodologies

This research paper presents a description of a Deep Learning Neural Network model based on Artificial Intelligence (AI) for the purpose of predicting diabetes. We utilised a range of deep learning models and conducted a comparative analysis of their efficacy in predicting diabetes using a real-world dataset of 182 individuals. Through the use of several machine learning models, we may conduct a comparison study of multiple models in order to assess their performance. Various classification methods are employed for predicting diabetes, given its categorical nature. Conversely, regression models are utilised for predicting blood glucose levels.

2.1. Dataset Description:

The dataset was collected from real-world sources, comprising a total of 182 individuals. The data was acquired by the monitoring of the photoplethysmography (PPG) signal of diverse patients experiencing a range of health conditions. The capture of photoplethysmography (PPG) signals is facilitated by the use of a pulse sensor. The pulse signal of each patient is recorded for a minimum duration of one minute. In the present scenario, the anatomical region under investigation pertains to the distal portion of the index finger, situated on either the dexterous or sinistral hand. Once the data has been stabilised, the process of data collecting may commence, typically occurring within a time frame of around 10 seconds subsequent to the sensor being connected to the finger. The software executed on the Arduino Uno transmits the collected data over the Serial port, while the data is accessed on the personal computer using specialised software intended for monitoring Serial ports. The data is subsequently stored in a (CSV) file, which is subsequently imported into Excel for further analysis.

2.2. Pre-Processing of Data:

The data acquired from the pulse sensor using photoplethysmography signal was recorded in the (CSV) format. The dataset underwent pre-processing steps such as missing value handling, scaling, and normalisation. These procedures facilitated the accurate analysis of the dataset and prepared it for future utilisation in machine learning and neural networks. The ultimate goal of this preparation is to predict information related to diabetic patients. The acquired data comprises unprocessed information.

2.3. Moving Average Filtering

The data acquired from the pulse sensor was not in the appropriate format. The presence of excessive noise and the relatively weak strength of the signal are notable observations. To facilitate further signal analysis, it is necessary to initially perform signal cleaning and subsequently amplify it to a certain extent. In this scenario, a Savitzky-Golay filter is employed to eliminate baseline drift, while a moving average filter is employed to provide waveform smoothing. A moving average filter is employed to compute an average by considering the ten most recent samples. The acquisition rate for each sample is 10 milliseconds, leading to the moving average filter ultimately processing and averaging signals from the preceding 100 milliseconds. By applying a data smoothing technique with a time window of 100 milliseconds, there is a notable enhancement in the performance of the collected waveform. The subsequent discourse provides an elucidation on the utilisation of the mathematical formula for adjusting the mean of the Savitzky-Golay filter.

When a polynomial filter is utilised on a signal, it may be conceptualised as the process of fitting separate segments of a polynomial function onto the signal. The least squares (LS) approach is employed to ascertain the optimal alignment between the X matrix and the y vector, in the following manner:

$$y = Xb. \tag{1}$$

The conventional LS answer is provided by:

$$b = (XTX)\text{-}1XTy \tag{2}$$

For the purpose of smoothing, the following approximated values are utilised:

$$\hat{Y} = Xb = X(XTX)\text{-}1XTy = Hy \tag{3}$$

No matter what the value of y is, the hat matrix, or the product H = X(XTX)-1XTy, remains constant for every given polynomial. We may compute it once and keep it for when we need it. For different orders of polynomials and lengths of pieces n, Savitzky and Golay have accomplished this.

2.4. Normalization of Data

AI algorithms exhibit suboptimal performance when confronted with input quality that possess diverse scales or data kinds. This phenomenon can be attributed to several sources. Normalisation is widely recognised as a prominent method for data preparation. This approach facilitates the normalisation of the values in the numerical columns of the dataset, ensuring they are standardised to a uniform scale. While not mandatory for all datasets, the utilisation of normalisation techniques becomes relevant when the attributes of a dataset exhibit diverse ranges. Despite the absence of a mandatory need, its utilisation is seen. The inclusion of this factor enhances both the efficacy and reliability of a machine learning system. In situations where there is uncertainty regarding the precise distribution of features, the application of normalisation techniques to a machine learning model might prove to be a valuable asset. The two most often employed methods of normalisation are Min-Max scaling and standardisation scaling. The dataset undergoes a process known as Min-Max scaling, which involves moving and rescaling the values of its features. This approach ensures that the resulting values are confined within the range of 0 to 1. The mathematical expression for calculating the Min-Max scaled value is denoted as equation (4), which may be accessed at this location.

$$X_{scaled} = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (4)$$

Where x = single feature of the given dataset.

The standardisation technique has a unit standard deviation and centres values around the mean with zero as an attribute. As a result, the resulting distribution also has a unit standard deviation. Standardization helps to speed up the training process and improves the numerical stability of the model. This can be expressed mathematically by (5) as follows.

$$X' = \frac{X - \mu}{\sigma} \quad (5)$$

Where,

μ = mean of feature value

σ = standard deviation of feature value

2.5. Extraction of a Feature:

Feature extraction encompasses the examination of data in both the temporal and spectral domains. The examination of physical signals in relation to time is commonly known as time domain analysis, whereas the investigation of a signal in relation to its frequency is commonly referred to as frequency domain analysis. Statistical measures, including the mean (), quartiles (Interquartile range) (iqr), variance (), and skewness (skew), have been calculated for the aforementioned features.[16]. Statistical measures can be employed to quantitatively characterise or summarise the attributes of a set of facts or information. The mean statistic is employed to ascertain the overall pattern that may be observed within the data. The interquartile range is employed to assess the dispersion of data. The disparity lies in the quartiles situated at the 25th and 75th percentiles. One statistical measure that sheds light on the interconnections between numbers is the variance, which measures the degree that the individual values in a dataset differ from the mean. Finding the median of the squared discrepancies between the arithmetic mean of a collection of integers and each individual integer is what the computation is all about. A metric known as skewness measures the degree to which a normally distributed sample has been distorted or altered[17]. Several distinct frequency domain characteristics are retrieved, together with the statistical measures that are associated with each feature. In the next Section, we will explain a variety of deep learning techniques that may be utilised for experimentation[18].

2.6. Deep Learning Techniques:

The dataset utilised in this research study comprises 182 patient data points obtained from real-time Internet of Things (IoT) devices, as previously outlined. After performing preprocessing tasks such as addressing missing values and data cleansing, we proceeded to utilise the min-max scaling approach for the purpose of data normalisation. The primary aim of this study was to utilise a regression model including neural network techniques in order to make predictions regarding the occurrence of diabetes in patients.

By comparing various neural network models, we were able to determine the best design for a neural network, which significantly decreased the RMSE score. The neural network development frameworks TensorFlow and Keras were utilised to achieve this. We used 80% of the dataset for training and 20% for testing, splitting the dataset in half. The first neural network to be used was a 5-hidden-layer version of a Deep Sequential Neural Network built with TensorFlow. The research made use of Adam as its optimisation technique and ReLU as its activation function. The RMSE statistic was used to assess the loss. A grand total of 150 epochs were dedicated to training the neural network.

The second neural network included in the study was the Convolutional Neural Network (CNN). A total of five hidden layers were utilised in the model, with the activation function being the rectified linear unit (ReLU). The first and third hidden layers were implemented using the MaxPooling2D layer, while the second layer utilised the Conv2D layer with the 'Relu' activation function. The fourth layer was compressed, and subsequently, a dense layer was implemented as the fifth layer. The model underwent training for a total of 100 epochs, with an 80:20 split between the training and testing datasets.

The third neural network model chosen for our study is the Artificial Neural Network (ANN), which consists of five hidden layers. The activation function 'Relu' was employed, and for the dense layer, the normal kernel initializer was selected. The model underwent training using the Adam optimizer for a total of 150 epochs, with a train-test split ratio of 80:20. All three models were compared using the root mean square error (RMSE) as the performance metric.

3. Results and Discussion

Eight hundred and twenty-two people were enlisted to take part in the study, and each individual gave us seven minutes of their time. Continuous measurement of PPG signals and bioelectrical impedance were performed on a minutely basis. After performing the regression analysis with all three models discussed in methodologies section, we calculated the RMSE loss of all 3 neural networks. The results are described in following table 3.1.

Table 1: Result Comparison

Model Name	Test Loss (RMSE)
DNN	5.05
CNN	5.92
ANN	5.47

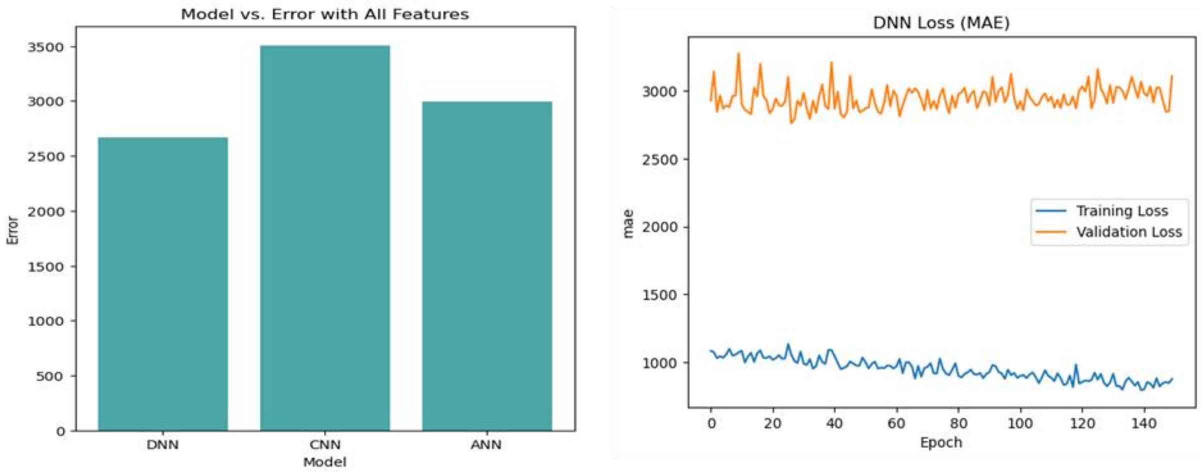

Fig 1: (a) Result Comparison (b) Training and Validation Loss DNN Model

When we compared the performance of all three models, it is observed that DNN gives us the best result with 5.05 as RMSE loss as compared to other 2 models. Figure 3.1(a) show the comparative analysis of the model. The train and validation loss were plotted for the best performing model over 150 epochs as shown in Figure 3.1(b).

3.1. Comparative Analysis:

We computed (RMSE) and (MSE) to perform the evaluation of our model and compared our result with the result of other recent work. Table 3.2 represents comparison of our work with previous work.

Table 2: Comparative Analysis

Reference	Category	RMSE (mg/dl)
Joshi et al. [19]	Non-invasive	13.57
Song et al. [20]	Non-invasive	19.00
Jain et al. [21]	Non-invasive	11.56
Agarwal et.al.[22]	Non-invasive	9.14
Proposed Work (DNN)	Non-invasive	5.05

From table 3.2, we found that our proposed work of DNN model performed better in comparison with most of recent work in terms of diabetes prediction in non-invasive category using PPG signal real time dataset.

4. Conclusion

This study made use of an input networking training database that included 182 individuals. When testing the suggested DNN Model, the root-mean-squared error (RMSE) for the predicted blood glucose readings was 5.05. In comparison to the results obtained using the other neural networks (CNN/ANN) utilised in this study, the results got from the approach suggested in this study using either PPG alone, bioelectrical impedance alone, or a combination of the two showed better accuracy in predicting the blood glucose sugar levels in diabetics. The selection of features and improving the results further by reducing MSE will be one of the future works.

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