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FEEDFORWARD BACKPROPAGATION MODEL OF NEURON FOR BLOOD GLUCOSE ESTIMATION

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Abstract

One possible non-invasive technique for determining glucose levels is near-infrared (NIR) spectroscopy, but the accuracy of predictive models remains a challenge due to spectral noise and nonlinearity. This study explores a Feedforward Backpropagation Neural Network (FFBPNN) trained with Bayesian Regularization (BR) to enhance prediction accuracy and generalization. The BR training function optimizes the network by minimizing overfitting, adjusting weight distributions, and improving robustness against spectral variations. Preprocessing techniques such as Savitzky-Golay filtering, moving average filtering are integrated to extract meaningful time and frequency domain features. The proposed FFBPNN-BR model achieves superior accuracy compared to conventional training methods, with improved Clarke error grid analysis results. This approach demonstrates significant potential for real-time, non-invasive glucose monitoring, advancing wearable and clinical diagnostic applications. Future work focuses on edge deployment and multimodal sensor fusion for enhanced robustness.

Keywords - Noninvasive, Glucose, Neural Network, Photoplethysmography, Near Infrared.

I. Introduction

High levels of blood sugar are a hallmark of diabetes, a chronic illness that can lead to serious health issues if left untreated. The global prevalence of diabetes has been rising at an alarming rate over the past few decades. As of 2024, over 800 million adults worldwide are living with diabetes, a significant increase from previous estimates. Globally, the prevalence of diabetes has risen from 7% in 1990 to 14% in 2024, with Type 2 diabetes accounting for the majority of cases. Global healthcare systems face significant challenges as a result of the increased prevalence of diabetes, particularly in countries with low and middle incomes where access to treatment is limited. For instance, approximately 5–10% of diabetics in sub-Saharan Africa receive treatment, primarily due to the high expense of insulin and medications. [1][2] A common optical technique for noninvasively evaluating blood volume variations in microvascular tissues is photoplethysmography, or PPG. It is prevalently used in devices like pulse oximeters and smartwatches to monitor heart rate and oxygen saturation. Recently, there has been growing interest in using PPG for noninvasive blood glucose measurement (NIBGM). LEDs are used in PPG to emit light, while photodetectors are used to detect the reflected light (or transmitted) through the tissue. The amount of absorbed light depends on factors like blood volume, oxygenation, and glucose concentration. For blood glucose monitoring, the principle relies on Scattering & Absorption, Waveform Analysis, along with Machine Learning & Signal Processing. In scattering, Changes in glucose levels alter blood optical properties, affecting the way light is absorbed and scattered. Variations in PPG signal amplitude, shape, and frequency components correlate with glucose fluctuations in waveform analysis. AI-driven models help extract glucose-related features from PPG waveforms, compensating for noise and other physiological variations. PPG signal capturing is completely noninvasive, real-time, continuous in nature, and low-cost. Some challenges in PPG signal capturing are interference from other physiological factors like heart rate, hydration, skin characteristics, etc., and calibration issues. [3][4]

II. Related Work

Many researchers are working in this domain with hybrid sensor approaches combining PPG with NIR or with any spectroscopic method. Some researchers have proposed AI and deep learning models that enhance predictive accuracy by analyzing larger datasets. While promising, PPG-based blood glucose monitoring is still in the research phase and has not yet been FDA-approved for clinical use. However, with advances in AI and sensor technology, it may become a viable option for noninvasive glucose tracking in the future. Two short near-infrared wavelengths technique has been proposed by M. Naresh et al. [5] for the prediction of glucose. Using input data from NIR technology, Glucose concentration is computed via a feed-forward neural network regression procedure. The system performs a Surveillance Error Grid (SEG) analysis and calculates glucose evaluation metrics. the R-squared value and average absolute error are 0.99 mg/dl and 2.49, respectively. A comparison of the Partial Least Squares Regression (PLSR) model to the Back-propagation Artificial Neural Network (BP-ANN) towards blood urea and glucose level prediction was reported by Jivan Parab et al.[6] According to the study, the BP-ANN model significantly increased prediction accuracy when paired using principal component analysis (PCA). The model's accuracy was 95.96%, its R2 value was 0.96, and its root mean square error (RMSE) was 0.69 mg/dL for blood urea. For glucose, the model produced an accuracy of 98.65%, an R2 of 0.99, and an RMSE of 2.06 mg/dL. A noninvasive blood glucose determination method utilizing blend of dual-wavelength PPG along with bioelectrical impedance measurement technologies was proposed by Chih ta Yen et al.[7] The real component, imaginary component, phase, as well as the bioelectrical impedance measurement yielded data with an amplitude size of 11 frequencies. These are converted into characteristics using principal component analysis. In the end, a neural network using back-propagation (BPNN) that receives a collection of seven physiological indicators as input is used to forecast the blood glucose level. A coefficient of determination (R2) of 0.997, mean absolute error (MAE) of 5.0896, mean absolute relative difference (MARD) of 4.4321%, mean squared error (MSE) of 40.736, and root mean squared error (RMSE) of 6.3824 all show that the model performs well. Guang Han et al. [8] created a hybrid model that combines partial least squares regression (PLSR) with stacked auto-encoder (SAE)-based deep learning in an effort to improve the method's prediction accuracy and usefulness. In this paper, 19 healthy people had their palms' diffuse reflectance spectra examined at six different wavelengths. The prediction results of several samples show that the PLSR-SAE model's correlation coefficients are, on average, better than those of the regular PLSR model, rising from 0.3021 to 0.9216. Furthermore, the Support Vector Regression (SVR) approach has a prediction accuracy of 0.8243, while the PLSR-SAE model has a prediction accuracy of 0.9216 .

III. Methodology

1.Dataset Description: A blood glucose estimate system constructed with an artificial neural network methodology is described in this paper. A real-world dataset of 82 individuals was utilized to predict glucose levels, and the efficacy of several neural network techniques and training functions was examined. Blood glucose levels are predicted using regression models. There were 82 people in all, and the information was taken from reliable sources. The information was gathered by monitoring the PPG signal of individuals exhibiting a variety of medical problems. By using a pulse sensor, photoplethysmography (PPG) signals can be continuously recorded. Every patient's pulse signal is captured for a minimum of one minute. Fig. (1) shows the architecture diagram for proposed system.

2. Signal processing: A format was created from the data that the photoplethysmography signal gathered through the pulse sensor. Scaling, normalising, and handling any missing entries were all part of the pre-processing of the data. These measures made it possible to precisely analyze the information and use it for machine learning along with neural network applications in the future. The pulse sensor's output was not formatted correctly. Key observations include the existence of significant noise and the comparatively modest signal intensity. The signal must first be cleaned before being amplified to a certain degree in order to aid in further analysis.

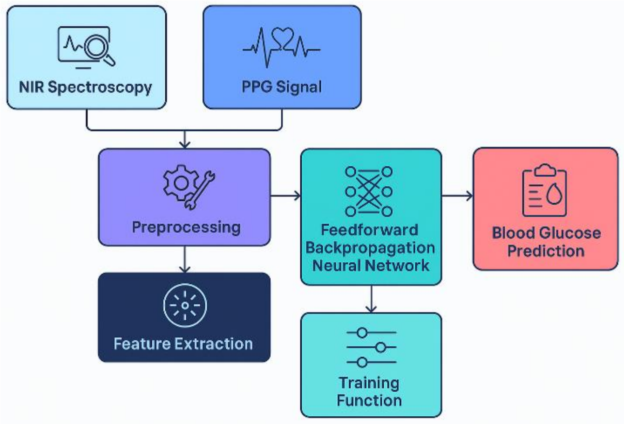

Fig. (1) Architecture diagram for proposed System

The moving average filter guarantees cleaner waveforms, whereas the Savitzky-Golay filter removes baseline drift for signal refining. The ten most recent samples are taken into consideration when calculating an average using a moving average filter. A moving average filter, which aggregates data over the preceding 100 milliseconds, is used to further process the signal because each sample has a sampling period of 10 milliseconds. Data smoothing over a 100 ms interval significantly improves the recorded waveform's processing efficiency. Fig. (2) shows data flow diagram for proposed system.

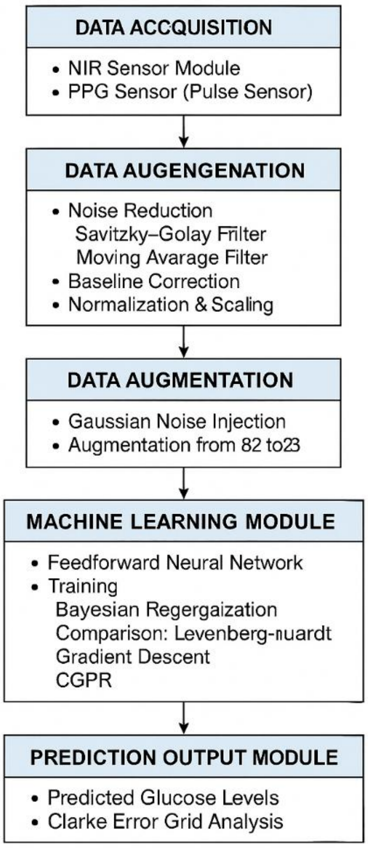

Fig. (2) Proposed Hybrid Noninvasive Glucose Monitoring System

3. Dataset Augmentation: The sample numbers are increased from 82 to 243 by adding different Gaussian noises to the training PPG signals. Those types of noises follow a normal distribution and were introduced with different standard deviations.[9]

4.Time and Frequency Domain Feature Extraction: Photoplethysmographic signals are widely used in physiological monitoring, such as blood pressure, oxygen saturation, and heart rate measurement. [10][11]

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Features collected from PPG signals can be categorized using both time-domain and frequency-domain characteristics. Directly derived from the PPG waveform, time domain features provide information about the statistical characteristics and signal morphology. Pulse width, amplitude, along with peak-to-peak interval are important time-domain characteristics. Heart rate variability is assessed using the peak-to-peak interval, which is the distance between two systolic peaks, and pulse width, which is a measure of the signal's duration at particular amplitude levels (e.g., half-max width). The difference between peak and baseline levels is pulse amplitude. Frequency domain features are derived using spectral analysis techniques like Fast Fourier Transform (FFT) or Wavelet Transform.[12] They help in analyzing periodic components of the PPG signal. Power Spectral density related to thermoregulation and sympathetic activity. Spectral Entropy measures the randomness in the frequency spectrum. Both time-domain and frequency-domain features are crucial for biometric authentication, cardiovascular assessment, and health monitoring applications. [13][14]

5. Neural Network Techniques:

Near-Infrared (NIR) spectroscopy is widely used for non-invasive glucose monitoring, but the spectral data is often complex, requiring robust machine learning models like neural networks for accurate glucose prediction. Determination of the ideal neural network design was done by contrasting various neural network models.[15][16]

5.1 Feedforward Backpropagation Network (FBNN)

In deep learning, this artificial neural network (ANN) is widely utilized. There are two main processes in it. In the feedforward stage, the input generates an output by moving layer by layer across the network. In the backpropagation process, the error (predicted minus actual output) is calculated and transmitted backward to modify the weights of the network. Multiple neuronal layers process input data. Every neuron carries out an activation function and a weighted sum. The output is provided by the final layer.[17][18]
Mathematically, the output of each neuron is given by Eq.(1).

$$z = W \cdot X + b \qquad (1)$$

$$a = f(z)$$

where:

W = Weight matrix

X = Vector at Input

b = Bias

a = output of the neuron

f(z) = Function of Activation like ReLU, Sigmoid

5.2 Generalized Regression Neural Network (GRNN)

It is an RBF network used in function approximatio5.n and regression; it is a non-parametric model that provides continuous estimates from training data and is particularly used when input and output are associated through complicated, nonlinear relationship.

5.3 Layer Recurrent Neural Network (LRNN)

It is classified as an RNN-based architecture that contains feedback connections in hidden layers to learn over time from past data; unlike normal feedforward networks, an LRNN has an internal memory that is useful in time-series forecasting, sequential data processing, and control systems.

5.4 Elman Backpropagation Network

It is a recurrent neural network (RNN) developed by Jeffrey Elman in 1990. It is designed to handle sequential and time-series data by incorporating context units, which allow it to retain memory of previous states. It is trained using backpropagation through time (BPTT), making it effective for tasks where past information influences present decisions.

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5.5 Radial Basis Function Neural Network (RBFN)

Radial basis functions are the ANN framework's activation functions within a radial basis function neural network. It works particularly well for classification, pattern recognition, and function approximation. Because of their unique structure and learning methodology, RBFNs are far more successful for non-linear issues than ordinary feedforward networks.

6.Training Functions:

6.1 Bayesian Regularization:

Bayesian Regularization (BR) to enhance generalization and prevent overfitting. By using a probabilistic framework to optimize the network weights, BR integrates Bayesian inference into the learning process. By treating the network weights as random variables having prior distributions, Bayesian Regularization adaptively adjusts the model's complexity in contrast to conventional regularization methods like L1 (Lasso) and L2 (Ridge) regularization.

The foundation of regularization is the minimization of a cost function that consists of a regularization term and the sum of squared errors. The following Eq.(2) is the expression for the objective function.

$$F=\alpha ED+\beta EW \tag{2}$$

Where

ED = sum of squared errors (data error term).

EW = sum of squared weights (weight decay term).

The regularization parameters α and β establish the trade-off between data fitting and model complexity.

6.2 Levenberg-Marquardt Optimization:

One of the best artificial neural network (ANN) training techniques is the Levenberg-Marquardt (LM) algorithm, particularly for moderately sized issues. It is an advanced second-order optimization technique that is highly effective for function approximation as well as pattern recognition applications because optimising performance is enhanced by combining Gauss-Newton and gradient descent techniques.

In nonlinear least-squares problems, the sum of squared errors is minimized using Levenberg-Marquardt optimization. The error function to be minimized for a neural network with weights WW is given by Eq.(3).

$$E(W)= N(yi-y\hat{}i)^2 \tag{3}$$

here:

- yi represents the actual output,
- y^i represents the predicted output,
- N represents the number of training samples.

6.3 Gradient Descent:

Gradient descent (GD) is arguably the utmost elementary optimization algorithm used for training ANNs. Grounded on the gradient of the loss function, it is an iterative method for modifying the weights of the network to lessen the discrepancy between expected and actual outputs. Because GD is simple, efficient, and applicable to a wide range of machine-learning models, it is widely used.

One essential optimization technique for neural network training is gradient descent. Despite being straightforward and effective, it requires careful hyperparameter tuning and may experience convergence problems. These are fixed by more recent improvements like Adam and RMSProp, which improve the efficacy of gradient-based optimization in deep learning. Gradient Conjugation with Polak-Ribiére.

6.4 Conjugate Gradient with Polak-Ribiére:

Conjugate Gradient optimization employing the Polak-Ribiére approach (CGPR) is an advanced neural network training optimization technique that is especially well-suited for situations where computing efficiency and memory are essential. By using conjugate directions instead of simple gradient steps, this second-order

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optimization approach performs better than standard gradient descent. This approach eliminates inefficiencies in large-scale neural network training without requiring Newton's method's high memory requirements.

Weights are adjusted in the steepest direction of descent using gradient descent, which frequently results in zigzagging and poor convergence. Conjugate Gradient (CG), on the other hand, finds the best path at each stage by using previous search paths in order to improve convergence. The CGPR algorithm updates weights using the following Eq(4).

W(t+1)=W(t)+αd(t)W^{(t+1)} (4)

where:

- W(t)W^{(t)} represents the weight vector at iteration t,
- d(t)d^{(t)} represents the conjugate search direction,
- α is the step size (learning rate), computed using a line search method.

IV. Results and Discussion

Eighty-two people were enlisted to take part in this research work, and each one underwent a one-minute duration photoplethysmographic (PPG) signal acquisition process. Data was collected using an earlobe sensor. After preprocessing, using different neural networks, glucose estimation was performed, and accuracy of each kind was evaluated using Clarke error grid analysis. Bayesian regularization performs well, keeping all data points in clinically accepted regions as shown in Table I.

Table I: Analysis of different Neural Networks

Sr. No.	Training Function	Clarke Error Grid Performance				
		A Region	**B Region**	**C Region**	**D Region**	**E Region**
1	Bayesian Regularization	92	8	0	0	0
2	Levenberg-Marquardt optimization	64	36	0	0	0
3	Gradient Decent	36	52	2	10	0
4	Conjugate Gradient with Polak	40	52	0	8	0

TABLE II: Feedforward Backpropagation Neural Network Performance with training functions

Sr.No.	Type of Neural Network	Clarke Error Grid Performance				
		A Region	**B Region**	**C Region**	**D Region**	**E Region**
1	FBNN	92	8	0	0	0
2	GRNN	36	52	6	6	0
3	LRNN	96	4	0	0	0
4	RBFNN	48	42	0	10	0

Analysis of different training functions with three layer (20,10,1) feedforward neural network was also done. As Table II demonstrates, feedforward backpropagation neural networks (FBNN) and layer recurrent neural networks outperform other models in terms of accuracy. Here are some data points from regions C and D of generalised regression neural networks and radial basis function neural networks. Regression analysis makes it easier to comprehend the kind and degree of correlations among dependent and independent variables. Regression analysis of Feedforward Backpropagation Neural Network is shown in Fig (3)

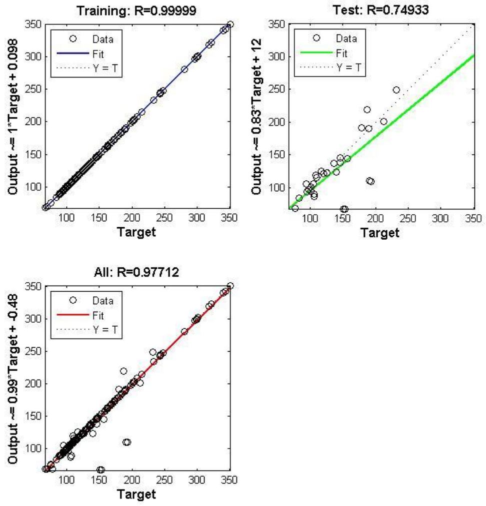

Fig.(3) Regression Analysis of Feedforward Backpropagation Neural Network with Bayesian Regularization training function

The independent variable or variables in the model account for approximately 97.712% of the variability in the dependent variable, according to an R-squared coefficient of determination of 0.97712. This suggests that the relationship and model fit are excellent. For real-time, non-invasive glucose monitoring, neural network models like FBNN and LRNN are the most promising, but they require large datasets and high computational power. If data is limited, Principal Component Analysis feature extraction can provide good accuracy with lower complexity. This research work can be extended in fusion of multiple bio signals using attention-based deep learning methods.

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