IJIE

Penerbit UTHM

INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

Vol. 18 No. 1 (2026) 129-141
https://publisher.uthm.edu.my/ojs/index.php/ijie

Blood Pressure Monitoring from Photoplethysmography Based for Diabetes Detection

Syaidatus Syahira Ahmad Tarmizi[1,2]*, Nor Surayahani Suriani[1]*, Ezrat Samadi[3]

[1] *Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), Batu Pahat, Johor 86400, MALAYSIA*
[2] *Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM), Segamat, Johor 85000, MALAYSIA*
[3] *Department of Orthopedic Surgery Physiotherapy and Rehabilitative Care, KPJ Batu Pahat Specialist Hospital, Batu Pahat 86400, Johor, MALAYSIA*

*Corresponding Author: syahiratarmizi@uitm.edu.my, nsuraya@uthm.edu.my
DOI: https://doi.org/10.30880/ijie.2026.18.01.010

Article Info

Received: 14 December 2025
Accepted: 28 March 2025
Available online: 17 April 2026

Keywords

Blood pressure, blood glucose, photoplethysmography, 2-D InceptionResNetV2

Abstract

Electrophysiological signals such as photoplethysmography (PPG) are useful for collecting human vital signs in clinical practice, especially when used wearable sensors like finger pulse oximeters for continuous diabetes monitoring. The PPG has been evaluated across subjects with varying anthropometrical characteristics to address challenges related to morphological properties. This study employed PPG-based methods for assessing diabetes by analyzing the relationship between the existence of blood glucose levels and blood pressure fluctuations. In this context, PPG-BP datasets were utilized to extract important features associated with pathological diabetes. As a result, PPG spectrogram images were utilized as inputs for a pre-trained deep learning model to effectively learn intrinsic signal patterns between healthy and diabetic individuals. The results suggested that the 2-D InceptionResNetV2 model was the most effective network for the classification problem, with an average accuracy of 95.95% using PPG data.

1. Introduction

Measuring blood pressure with a sphygmomanometer or blood pressure cuff is vital for health monitoring for the reason that abnormal readings can indicate a higher risk of cardiovascular problems. However, both blood pressure and blood glucose parameters are essential biomarkers for diabetes detection that need to be continuously tracked to identify patterns and adjust treatment accordingly. Managing diabetes becomes more difficult due to diagnostic criteria related to blood glucose thresholds and hemoglobin A1c (HbA1c) concentration values. This could lead to underdiagnosis, as some patients may meet the glucose-based criteria even though their HbA1c values are below 46 mmol/L (6.5%), which is currently within the normal range of 39-46 mmol/L as advised by the American Diabetes Association (ADA) [1], [2]. These diagnostic uncertainties and the complexity of treatments may make it more difficult to achieve medication adherence and overall effective management.

Noninvasive approaches to measure blood glucose include the measurement of acoustic waves, electromagnetic sensing, electrical, and optical glucose signals [3]. Optical glucose signals, such as photoplethysmography (PPG) sensors, are the most popular methods due to their non-invasive nature for wearable integration. Recent advancements in digital sensor technology have demonstrated that the PPG sensor has become a useful biological sensing tool for diabetes-related cardiac output analysis at a low cost. This enables the clinician to perform a quick screening with minimal sensor usage, making them particularly useful in resource-limited or remote healthcare settings. It can help patients receive immediate feedback and improve the early detection of diabetes and hypertension by eliminating the discomfort and inconvenience of finger-prick blood tests.

PPG has become a promising technique for exploring the occurrence, development, and transformation of diseases by measuring blood pressure. This can be achieved by extracting a specific frequency of interest from different sites on the body using a photoelectric sensor [4], [5]. Not all body parts are equally suitable for measuring blood pressure, as signal quality and identifiable waveform shape vary depending on physiological conditions. The anatomical sites, such as the wrist, fingers, toes, and non-contact facial imaging (by observing light intensity distribution on the cheeks), are among the best sites for clinical guidance and treatment due to the rich arterial supply. Alternatively, previous studies have suggested using the toe area for diabetes estimation, particularly in cases where increased blood flow is not detected in the fingers [6]. This disparity could be attributed to the effects of diabetes on the autonomic nerves that control blood vessel constriction. The nerves in the lower limbs are longer and more susceptible to damage from high concentrations of blood glucose. Among these anatomical sites, PPG signals measured by finger-type probe are noted for their stability and are less corrupted by motion artifacts during static conditions, resulting in higher sensitivity to volumetric blood fluctuations [7-9].

A finger-type optical probe sensor emits light into the skin and detecting changes in light absorption or reflection caused by fluctuations in blood volume, primarily because of hemoglobin in the blood. Hemoglobin absorb light differently depending on its oxygenation state and these absorption changes correspond to the cardiac cycle during the heart is contraction (Systolic Blood Pressure (SBP)) and relaxation (Diastolic Blood Pressure (DBP)) [10]. However, environmental light sources can degrade measurement accuracy by adding noise or false signals that can interfere with the sensor's readings. Blood glucose has a different absorption rate at different wavelengths of light that will be used to estimate the blood glucose. Increasing glucose concentration would have significant impact to the structure of the protein that can trigger a change in dipole formed by positive and negative charges that can be captured by the sensor. A commercial PPG-based glucose monitor showed limited accuracy, with only 18.5% of readings meeting International Organization for Standardization (ISO) and 67.25% within clinically acceptable zones, suggesting that some current devices require additional improvement in hardware and algorithms [11].

Good identification of PPG signals remains challenging due to the subject-specific characteristics that may affect the light absorption, scattering and blood flow properties [12-14]. Through experiments and evaluations, researchers have verified that darker skin tones have a higher melanin concentration, which may reduce light absorption and subsequently lower the signal quality. However, a few studies appear to demonstrate inconsistent associations with skin tones, which is likely the result of physiological and device variance due to the small number of subjects specifically for darker skin tones. An increase in body mass index (BMI) may lead to increased skin thickness and subcutaneous fat, which increases the depth of blood vessels and produces greater scattering before it reaches the detector. Unproductive aging groups (≥40 years) can hasten the disappearance of key waveform features due to increased vascular resistance and arterial stiffness in older individuals. Data on cardiovascular disease (CVD) history between healthy and T2DM individuals also have significant effects on PPG signals as health status indicators.

From the literature search, fewer studies have deployed deep learning models for PPG-based diabetes detection as opposed to conventional machine learning algorithms. Deep learning may require extensive and high-quality datasets to address signal variability and the substantial computational resources needed for model training. Here, deep learning models have been successfully applied to detect diabetes using two-dimensional (2-D) time-series PPG signals. It can be used to optimize model and enhance accuracy by reducing training time. The main objective of this study was to evaluate deep learning models for diabetes detection using PPG data.

The main contributions of this paper are as follows:

- Learning intrinsic patterns from time-frequency domain images. The images include the original, filtered versions and their derivatives, such as velocity, accelerated, jerk, and snap.
- Optimizing hyperparameters to boost model performance. The research investigates how fine-tuning hyperparameters using PPG data can enhance the deep learning models.
- The proposed model are trained on large mixed datasets to improve the efficiency of detection.

This paper is structured as follows. Section 2 describes the background of the study. Section 3 presents the experimental designs in this study by including the datasets used, signal preprocessing, feature extraction process, and deep learning models. Section 4 analyzes the results and discussion of the experiment. Finally, section 5 presents the conclusion of this study.

2. Background of Study

Photoplethysmography is an inexpensive and convenient method that is widely used in various wearable sensor devices or smartphones to assess blood pressure and blood glucose levels. Abnormal blood pressure increases the risk of future health complications, particularly among the elderly, such as silent cerebral infarction, which can progress to clinical stroke and cognitive impairment over time. Observations have indicated that BP typically decreases by 10-20% at night during sleep compared to daytime levels, known as nocturnal dipping, which may lead to increased cardiovascular load on the heart and blood vessels [15]. This highlights the importance of considering the timing of data collection, either during the daytime and the nighttime when designing experimental settings for diabetes estimation. Furthermore, the occurrence of incorrect diagnoses can be influenced by factors such as the type of probe contact devices, finger temperature, skin thickness or hydration, skin pigmentation, arteriosclerosis, and vascular movement [16].

Table 1 *Summary of diabetes detection using photoplethysmography based method*

References	Database	Sensors	Region of interest	Performance measure
Monte-Moreno [18]	410 subjects (331 healthy, 79 diabetic)	iPod digital oximeter	Finger	The coefficient BP (R^2_{SBP} = 0.91, R^2_{DBP} = 0.89) and blood glucose (R^2_{BGL} = 0.90)
Nilara et al. [6]	141 subjects (58 healthy, 83 diabetic)	PPG sensor (SS4LA)	Toe	SVM models attains the best performance of 92% accuracy.
Xu et al. [19]	40 subjects (21 healthy, 19 diabetic)	PPG sensor	Finger	SBP (3.22±0.66) mmHg and DBP (2.11±1.11) mmHg.
Islam et al. [20]	52 subjects (390 males, 13 females)	Smartphone camera (IOS and android)	Finger	SEP = 17.02 mg/dl
Gupta et al. [21]	219 subjects (657 samples)	PPG senor probe SEP9AF-2	Finger	A dSVRI metric is managed to identify the correlation of DM and BP measurements.
Zanelli et al. [22]	DB_ shapes (300 subjects), DB_ HT (181 subjects), DB_ DT2 (100 subjects),	DB_ shapes (wrist PPG E4, pOpmétre, iPhone SE camera), DB_ HT (PPG senor probe SEP9AF-2), DB_ DT2 (pOpmétre),	Finger, Wrist	CNN models without transfer learning achieve the highest (AUC = 75.5) using DB_ DT2 database.
Gunathilaka et al. [23]	120 subjects (60 male, 60 female)	Lutech Datalys 760, BP cuff, SpO_2 probe	Finger	CNN model attains the best performance of 92% accuracy.
Shuzan et al. [24]	139 subjects (81 male, 58 female)	QU-GM device	Wrist	BET gains (R=0.90) for blood glucose estimation and the KNN model outperform 98.12% for classification
Ali et al. [25]	PPG-BP (55 subjects), MIMIC II (40 subjects), BGL dataset (52 subjects)	PPG-BP (PPG senor probe SEP9AF-2), MIMIC II (PPG sensor), BGL dataset (smartphone camera)	Finger	SBP (2.53±273), DBP (1.47±1.84) and BGL (1.36 mg/dl)

The benchmark table from research studies was analyzed to identify the appropriate number of subjects required for reliable data collection and to determine the most preferred anatomical sites for detecting PPG biosignal, as illustrated in Table I. Each anatomical site offers different advantages in terms of signal quality and susceptibility to motion artifacts for diabetes applications. The use of diverse datasets from multiple sensor devices to analyze the signature of the blood volume may introduce extraneous noise, signal distortion and variances in signal morphology. In this context, wearable sensor devices or smartphones offer accessibility and convenience, making them suitable for personal use and improving the accuracy of real-time diabetes monitoring. However, inconsistent contact pressure range and variable ambient light interference for smartphones may degrade signal quality, resulting in lower sampling rates for diabetes detection when compared to wearable PPG devices, which are stable for continuous monitoring to detect diabetes-related changes. The placement and positioning of the PPG measurement site may affect signal quality and consistency. Reference [17] showed that varying wrist positioning for wearable PPG devices produces distinct motion artifacts, demonstrating that the contact pressure between the sensor and human skin can significantly influence PPG morphology.

Monte-Moreno [18] estimated blood glucose, SBP and DBP from PPG features. The coefficients of determination for BP (R^2_{SBP} = 0.91, R^2_{DBP} = 0.89) and blood glucose (R^2_{BGL} = 0.90). The accuracy of BP matched with Grade B of the British Hypertension Society (BHS) standard, which is good for clinical accuracy and blood glucose was characterized using the Clarke error grid, which falls within 87.7% Zone A, 10.3% Zone B, 1.9% Zone D. Prediction under Zone A can only be able to detect hypoglycemia and hyperglycemia correctly. Nilara et al. [6] evaluated PPG signals collected from the toe subjects of the right leg in a supine position to assess the effects of the nerve damage due to diabetes. Because PPG is an extremely sensitive signal, ethanol was used to clean the dirt on the toe to avoid extraneous noise. The study managed to get optimal results by employing a voting-based hybridizing approach to demonstrate the potential of toe-based PPG measurements. Xu et al. [19] performed experiments by acquiring PPG signals from subjects positioned supine in a hospital bed for 10 minutes while in a resting position. The ECG and reference BP signals were continuously captured alongside the PPG signals in an attempt to analyze their synchronization errors. The finding demonstrated that the proposed feature-based produced satisfactory performance in terms of both absolute mean errors and standard deviation for SBP and DBP which have meet the BHS standard and the Association for the Advancement of Medical Instrumentation (AAMI) error acceptance criteria.

Reference [20] examined blood perfusion variation associated with diabetes in three color channels (red, green and blue) with varied wavelengths from recorded frames using four models of the smartphone camera for a duration of 60 s is allowed for acceptable PPG data. The red channel is less absorbed near the surface that make it have a longer wavelength of 620 nm, allowing to penetrate deeper into the blood vessels, resulting in more prominent and less noisy PPG signals. The experiments demonstrate that selecting of this channel can minimize the standard error of prediction (SEP) to 17.02 mg/dl when analyzed using partial least square regression (PLS). Gupta et al. [21] presented dynamic systemic vascular resistance index (dSVRI) metrics to explore the correlation of diabetes and the elongating duration between the SBP and DBP. It was reported that this metric can enhance physiological interpretability by correctly classifying diabetic subjects whose blood vessels tend to constrict.

Zanalli et al. [22] evaluated the performance of their proposed models by using three different selection of databases with an additional of feature-based selection algorithms. The designated convolutional neural network (CNN) model is proposed and evaluated with or without transfer learning to assess its effectiveness. The study highlighted that the DB_ DT2 database yielded the most significant results when trained with low-complexity models. Another research [23] suggested diabetes detection by using a multi-parameter vital assessment that encompasses of BP, mean arterial pressure, oxygen saturation and pulse rate. The collection of PPG signals with exclusion of individuals with chronic infections or undiagnosed medical conditions is essential for ensuring a reliable assessment of health status for a minimum duration of one minute. By eliminating any extraneous PPG signals, the transforming of the data into standardized images and directly input into the CNN model without applying any feature-based selection algorithms to assess the model's accuracy.

Reference [24] utilized a wearable IoT-based glucose monitoring device, QU-GM which features a lightweight pulse sensor worn on the wrist. The device transmits PPG data to a mobile application every 10 seconds. Here, the Bag Ensembles Tree (BET) achieving a high recall of 0.90 for blood glucose estimation, outperforming both the Decision Tree and Gaussian Process Regression (GPR) models. Additionally, the K-nearest neighbor (KNN) model demonstrated superior performance in classifying diabetic severity, achieving an accuracy of 98.12%, surpassing the Support Vector Machine (SVM). The work by [25] simultaneously monitoring of BGL and BP using selective PPG features. The proposed work managed to achieve the lowest mean absolute error (MAE) and STD for BGL (1.36 mg/dl), SBP (2.53±273) and DBP (1.47±1.84). The analysis demonstrates that 99.86% of the prediction fall into ISO Zone A, indicating an accurate and clinically acceptable result.

3. Experimental Design

The proposed detection of diabetes is shown in Fig. 1, which involves the collection of the original raw PPG signal in the time domain and the exploration of changes in amplitude that may have a positive correlation with the concentration of blood glucose levels. The random raw PPG biosignals were chosen to portray the waveform sample between healthy and T2DM subjects. The T2DM sample tends to have the bell-shaped PPG waveform without any subsequent peaks as compared to the healthy sample with a slightly elongated shape in the diastolic phase. Then, preprocessing methods is applied to eliminate distorted signals, and the feature selection algorithm is deployed to reduce the amount of the processing and to transform the signals into spectrogram images. By selecting optimal hyperparameter settings for the development of a 2-D InceptionResNetV2 network, the input data containing the raw, filtered and its derivatives was trained to classify the input sample based on its corresponding class label. The use of derivative information in this case, may provide the significant improvements for better exploring the fiducial points related to the PPG blood pressure signal. A more detailed explanation can be found in the following subsections.

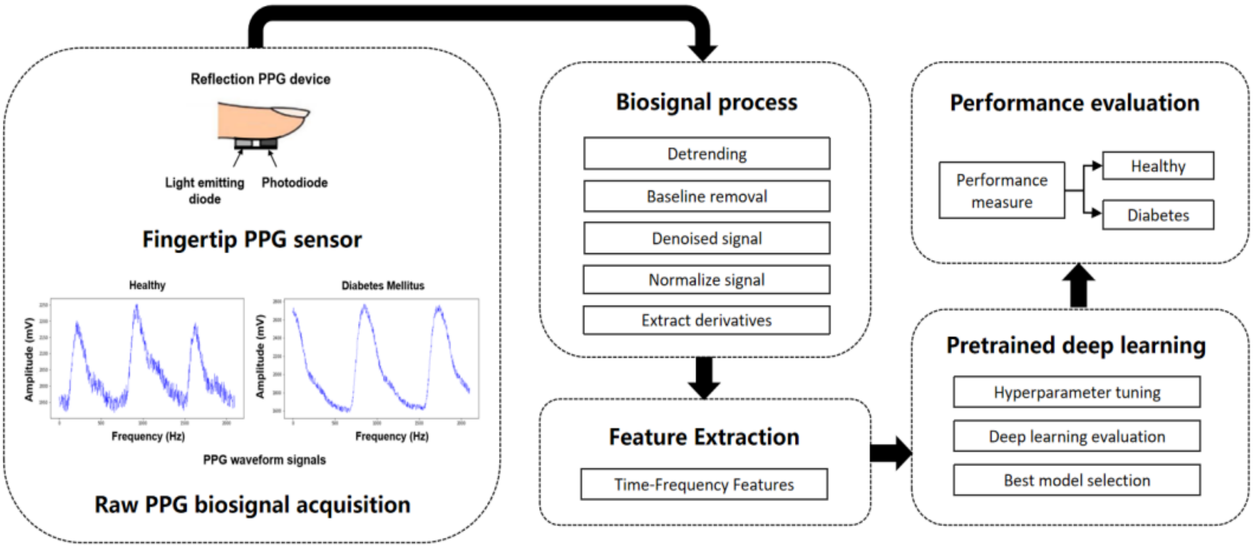

Fig. 1 *The workflow of the experiments using PPG-BP datasets*

3.1 Data Description

The experiments were conducted using the PPG-BP datasets collected from the Guilin People's Hospital [26]. This open-source dataset is extensively used to analyze PPG waveform for blood pressure monitoring and is available on Figshare [27]. PPG waveforms were recorded at a sampling frequency of 1kHz using a PPG senor probe SEP9AF-2, with data sampled at 2100. For each subject, an average of three unique PPG samples (2.1 seconds) from the fingertips of the left index finger in a controlled setting. Reference BP readings were obtained using the Omron HEM-7201 device. In total, 216 raw PPG biosignal samples were collected from 72 subjects (36 males, 36 females), consisting of 36 healthy individuals with normal BP readings and 36 T2DM patients suffering from prehypertension or hypertension.

Table 2 *Physiological characteristics of the study population (N=72)*

Parameters	Healthy		T2DM		Pearson correlation (r)	P Value (two-tailed)	95 % CI of the measure
	Min	Max	Min	Max			
Age (years)	40	75	42	84	-0.1170	0.0439	-0.34, 0.12
Weight (kg)	43	87	42	90	0.0706	0.0368	-0.16, 0.30
Height (cm)	150	175	145	183	0.5066	0.4703	0.31, 0.66
BMI (kg/m^2)	15.94	36.44	16.41	35.34	0.0941	0.0405	-0.14, 0.32
SBP (mmHg)	80	118	98	174	0.0667	7.26E-09	-0.17, 0.29
DBP (mmHg)	42	76	57	104	0.0412	0.0003	-0.19, 0.27
Heart rate (b/m)	52	106	55	98	0.0932	0.7880	-0.14, 0.32

The supplementary clinical information is presented in Table 2 to verify the clinical changes associated with bodily dysfunction. Pearson correlation analysis is used to examine the association between these parameters between the healthy and T2DM. The observation showed that the diabetic subjects were older ($r = -0.1170$, $p < 0.05$, 95% CI: -0.34 to 0.12) in which healthy persons ranged in age from 40 to 75 years (59.83 ± 10.77) and the T2DM patients ranged in age from 42 to 84 years (54.61 ± 9.23). Additionally, some diabetic subjects had lower BMI ($r = 0.0941$, $p < 0.05$, 95% CI: -0.14 to 0.32) and heart rate ($r = 0.0932$, $p > 0.05$, 95% CI: -0.14 to 0.32). In contrast, the SBP ($r = 0.0667$, $p < 0.05$, 95% CI: -0.17 to 0.29) and DBP ($r = 0.0412$, $p < 0.05$, 95% CI: -0.19 to 0.27) values showed consistently higher values because of the correlation between aging and the progression of diabetes.

The subject who developed diabetes has experienced a more pronounced gain in both weight and height. During the experiments, they were found to be heavier ($r = 0.0706$, $p < 0.04$, 95% CI: -0.16 to 0.30) and taller ($r = 0.5066$, $p < 0.47$, 95% CI: 0.31 to 0.66). Increased weight gain could be a risk factor for the early onset of CVD diseases. However, the dataset does not include information on the duration of diabetes or blood glucose concentration levels, which restricts additional clinical evaluation. Medication intake is also not reported in databases, which could have an impact on the actual physiological reading.

3.2 Photoplethysmography Signal Preprocessing

The PPG signals obtained from the finger areas were detrended using a linear regression algorithm to reconstruct blood pressure rhythm. The baseline removal was performed using the IModPoly algorithm with a fourth-degree polynomial. Then, a low-pass infinite impulse response (IIR) filter functions, specifically a fourth-order Chebyshev Type II filters are deployed with a cutoff frequency of 15 Hz [5]. The filtered signal is further utilized to extract its derivative waveform, such as the first derivative of the velocity photoplethysmogram (VPG), the second derivative of the accelerated photoplethysmography (APG) which reflects the blood's velocity, the third derivative of the jerk photoplethysmogram (JPG) to show the changes in velocity and the fourth derivative of the snap photoplethysmogram (SPG) to clarify the jerk transformation [28]. As a result, a total of sixth characteristics of the PPG signal, including the raw, filtered and its derivatives are transformed into spectrogram images to visually determine the subtle changes of the spectral content by altering frequencies and amplitudes for each signal. This makes it easier to distinguish between information about healthy and T2DM conditions.

3.3 Time-Frequency Features

In this paper, the short-time Fourier transform (STFT) function was used to extract the features from the processed PPG signal before it was converted into the spectrogram images. The fast Fourier transform (FFT) function was adjusting with the size to 1024 and the hop length was set to 256. The hamming window function is then applied with a size of 50 with the purposed to produce smooth segment transitions. The STFT image size with standard 224x224 pixels can help to minimize the computational load. Fig. 2 illustrates the spectrogram images that used to portray the visual content of the signals in the frequency spectra from the original raw PPG signal to the fourth derivatives over time.

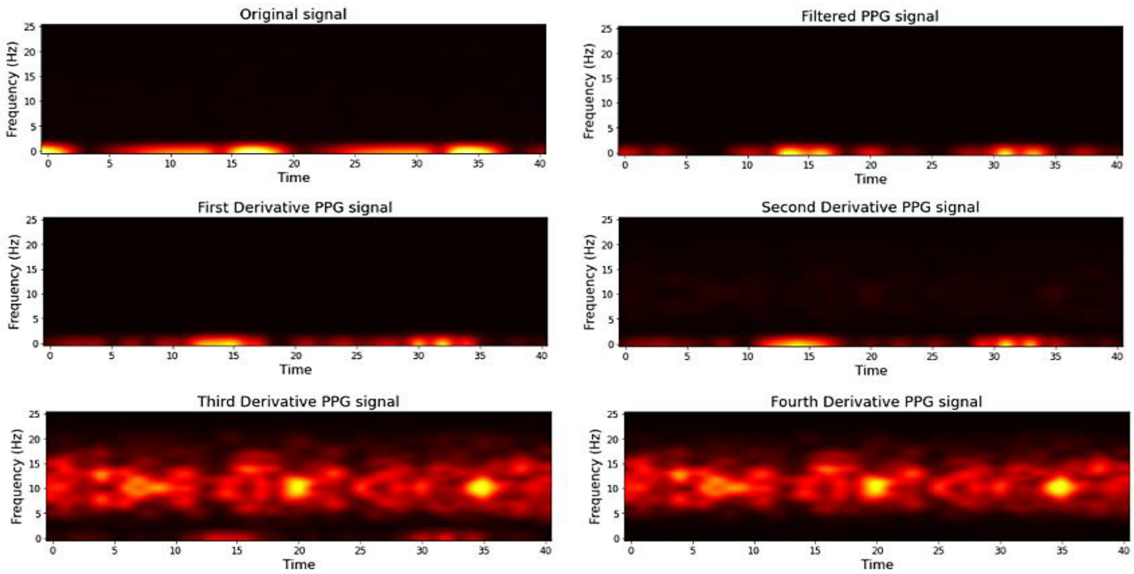

Fig. 2 *Spectrogram images for representing the original, filtered and its derivatives signals*

In a spectrogram, the higher intensity corresponds to dominant frequencies, while darker areas indicate the lower signal energy. The original versions have notably lower frequencies due to the presence of noise and motion artifacts, in contrast to the filtered versions which more clearly demonstrate the efficacy of noise reduction. The transitions from the first to the second derivative exhibit smooth patterns over time with energy slightly thickening and extending to higher frequencies. The higher-order derivatives significantly illustrate rapid local changes, resulting the spectrum spreads much more into higher frequencies. It can provide valuable information for feature extraction and advanced signal analysis.

3.4 Classification Networks Model

In this paper, the 2-D InceptionResNetV2 network is proposed to assess the performance and efficiency of the classification model. This network is introduced to leverage the benefits of the GoogleNet Inception network for computational efficiency and the ResNet to mitigate gradient vanishing problems in deeper networks [5]. Hyperparameter optimization is applied to improve the performance of the proposed networks, as shown in Table 3. The training set is utilized to train and fine-tuned the model parameters to prevent overfitting problems in the case when the deep learning models tend to perform well on training data but underperform on testing or validation data. In order to analyze the changes in loss and accuracy in each iteration process, the experiments were ran for 50 epochs and the average accuracy value was calculated. The input of the networks may have 80% of the data used for training and the remaining of 20% for testing, as suggested in [29]. Each sample sets with the label of the two classes might contain 216 sample splits randomly divided into 173 images for the training and 43 images for testing. However, to help build robust models for better learning intrinsic patterns of the image signal, the inclusion of the mixing PPG signals which contained 1296 samples were randomly divided into 1037 training images and 259 testing images.

Table 3 Hyperparameter tuning and its optimal values for pretrained networks

Hyperparameter	Optimal value
Input image	224 x 224 x 3
Weighted	ImageNet
Learning rate	0.0001
Loss function	Binary cross-entropy
Batch input size	32
Optimization algorithm	Root mean squared propagation (RMSprop)
Function for hidden layer	Rectified linear unit (ReLU)
Function for output layer	Sigmoid function
Dropout	0.2, 0.3

4. Results and Analysis

Photoplethysmography biosignals are highly complex and represent multi-dimensional data due to the signal's multivariate characteristics, such as waveform shape, width, and timing intervals. Understanding and leveraging the PPG data is essential for developing interpretable and robust algorithms, particularly with the advancement of machine learning and deep learning methods. Furthermore, the incorporation of physiological parameters and multivariate signal analysis plays a critical role in advanced biosignal analysis and modeling. Feature extraction has been proposed as a golden method in extracting meaningful characteristic information about the input signal and its behavior. This process reduces the number of computational resources required for analyzing the input data while preserving the most important information of the signals.

Table 4 *Diabetes detection using 2-D InceptionResNetV2*

Signals	Accuracy	Precision	Recall
Original Raw	85.04	79.07	82.76
Filtered	94.24	90.82	89.23
Velocity PPG	95.32	94.69	94.39
Acceleration PPG	96.54	95.37	95.93
Jerk PPG	95.71	94.06	94.24
Snap PPG	97.16	96.94	97.05
PPG (mixing signals)	95.95	95.78	95.96

Table 4 showcases the evaluation of the proposed 2-D InceptionResNetV2 by the signal characteristic selection. The finding implies that the networks may provide the highest values, reaching more than 85% accuracy on the original raw, transformed versions, and mixing signals. The higher values indicate the need for further adjustments that may necessitate investigating the applicability of the networks when trained on large datasets. Simulation results obtained show that it can achieve 95.95% accuracy. The results of various algorithms that have been suggested for extracting and selecting relevant feature-based algorithms from filtered PPG signals is presented in Table 5. These algorithms aim to minimize redundancy and enhance the accuracy to support the clinical acceptance of machine learning and deep learning models.

Table 5 *Comparison of photoplethysmography based method for diabetes detection*

References	Data samples	Features	Network models	Results
Nilara et al. [6]	141 subjects	Time domain and PCA based	SVM	Accuracy = 97.87%; sensitivity = 98.78%; specificity = 96.61%
Qawqzeh et al. [30]	587 subjects (506 healthy, 81 diabetic)	PPG based, feature derive from derivatives, demographic	Logistic regression	Accuracy = 92.30%
Srinivasan and Foroozan [31]	584 subjects	PPG based, demographic and clinical	VVGNet	Accuracy = 76.34%; sensitivity = 76.66%; specificity = 76.11%; AUC = 0.827
Deng et al. [32]	219 subjects	Short-time Fourier transform (STFT), statistical and demographic	DNN	Accuracy = 90.25%
Zanelli et al. [22]	840 samples	Physiological parameter, PPG based	CNN	Specificity = 76%; sensitivity = 75%; AUC = 75.50%
Susana et al. [33]	224 subjects (114 healthy, 114 diabetic)	Short-time Fourier transform (STFT)	SVM	Accuracy = 91.30%; FI score = 91.99%

References	Data samples	Features	Network models	Results
Shuzan et al. [24]	512 samples	Time domain, statistical, Mel-frequency cepstral coefficients (MFCC), demographic and clinical	K-nearest neighbor	Accuracy = 98.12%; AUC = 0.998
Soliman et al. [34]	269 samples (23 subjects)	Only the PPG signal	CNN-GRU	MAE = 2.96 mg/dl; MAPE = 2.40%; R^2 score = 0.97; RMSE = 3.94 mg/dl
Zeynali et al. [35]	VitalDB (6388 subjects), MUST (67 samples)	Only the PPG signal	ResNet34	RMSE = 27.48 mg/dl; MAE = 18.54 mg/dl; MSE = 755.23 mg/dl; MARD = 15.53 %; R^2 score = 0.40
Proposed work	1296 samples	Short-time Fourier transform (STFT)	2-D InceptionResNet V2	Accuracy = 95.95%; precision = 95.78%; recall = 95.96%

Machine learning models are extensively employed for diabetes-related PPG analysis in contexts of limited data, resource constraints and less computational power. The models resulted in substantial improvements in accuracy for PPG-based applications. A study by [6] utilized 10 out of 37 features in their studies to evaluate whether the selected features could effectively provide information about variation in the catacrotic and anacrotic phases of the PPG signal associated with the presence of diabetes. The hybridizing approach was employed to calculate the voting score across multiple eight selection algorithms for identifying the top 10 most informative features. The study achieved a high performance metric, reaching an accuracy of 97.87%, a sensitivity of 98.78% and a specificity of 96.61% when trained with an SVM classifier that utilized using a radial basis function (RBF) and polynomial kernel.

Qawqzeh et al. [30] claimed that 3 out 9 features remained significant as this parameters contribute to the prediction of blood glucose test scores. The overall performance reached 92.3% when utilizing the logistic regression model. However, the number of correctly classified diabetics was limited, necessitating appropriate validation to enhance the assessment of diabetes risk. Reference [33] discusses the implementation of time-frequency analysis to classify blood glucose levels and to assess the noise present in PPG signals. The findings of the study showed that SVM classifiers without using kernels outperformed both Naive Bayes and KNN, achieving an accuracy of 91.3% and F1 score 91.99%. This make SVM is suited for analyzing PPG signals due to its ability to manage nonlinearities and its robustness for processing a limited number of sample data. Shuzan et al. [24] proposed the minimum redundancy maximum relevance (MRMR) algorithm to determine the most relevance multi-features and total 44 out of 139 features were chosen. The overall performance indicates that the K-nearest neighbor effectively classified the severity levels of diabetes as normal, warning and dangerous.

Technological advancements have significantly accelerated the use of deep learning models in large-scale diabetes research, allowing for more complex architectures that potentially enhance accuracy. In the experiment described in [31], four different set combinations of feature parameters were chosen for training with the proposed VGGNet. However, the results were not satisfactory as it can successfully achieved the accuracy of 76.34%, sensitivity of 76.66%, specificity of 76.11% and AUC of 0.827. Through this work, diabetes progression in addition of the age, gender and hypertension, produced the best results. Deng et al. [32] integrated the wavelet transform (WT) with statistical measures and demographic information about the subjects to efficiently extract the intrinsic patterns of the signal. The results indicate that the deep neural network (DNN) may obtain a higher rate of 90.25% in nonlinear correlation analysis.

Zanalli et al. [22] discovered that only the DB_ DT2 databases produced compromise results when training using the CNN models without transfer learning. In their studies, the feature-based selection is revised with the purposed to minimize the error risks by incorporating physiological parameter such as age and gender. Then, seven PPG based features were extracted directly from the raw PPG signals without converted into derivatives. Despite using fewer parameters, the CNN model managed to deliver the compromised results in detecting diabetes with the presence of hypertension. In a study by Soliman et al. [34], the experiments used only the PPG signal to analyze diabetes using the hybrid CNN-GRU network. The CNN model is proposed for feature extraction, while a Gated Recurrent Unit (GRU) is employed to identify sequential patterns in PPG data, aiming to enhance the hybrid model efficiency in diabetes detection. Most estimated values are within a range of ±20% of the referenced measures.

Reference [35] conducted an experiment by utilizing varied deep learning methods including ResNet34, VGG16 and CNN-LSTM-Attention using 1-second and 10-second PPG segments. The analysis demonstrate that ResNet34 using 1-second PPG segments allows for more thorough analysis that potentially increasing the accuracy of diabetes by using both the VitalDB and Must datasets. In this work, the results reveal that the proposed 2-D InceptionResNetV2 models manage to provide a high classification accuracy of 95.95% on the mixed PPG signals. The metrics have also achieved 95.78% for precision and a recall of 95.96%. Remarkably, this performance was achieved despite the use of a relatively simple feature representation limited to the short-time Fourier transform domain, highlighting the effectiveness of the architecture in learning discriminative features directly from minimally processed PPG signals. The training data was repeated multiple times until the networks produced the expected and convincing results.

Most studies have used subject-based that consists both healthy and diabetic participants as their data sources. Most of them often have a limited number of sample size, which may result in including a relatively small number of diabetic participants, especially for subgroup analyses that may requiring further investigation in verifying results. Diabetes may have varying prevalence rates may across populations, making it challenging to recruit them without extensive resources to identify significant effects or associations. Furthermore, it may requiring specialized testing and longer study duration to assure the validity of results. Determining the appropriate number of features to eliminate the overfitting or underfitting of the signal is important. Based on the studies, utilizing a limited but highly informative feature-based algorithms can result in the highest accuracy, sometimes outperforming models using many significant features may do better, as proposed by Shuzan et al. [24]. This synergy can improve the model's ability to understand complex relationships that leading to better data representation.

It can be seen that machine learning provides more robust training as compared to the deep learning primarily because to its lower complexity and simpler structure, which makes it more stable when training with insufficient of data. Note that machine learning does not fully capture the complexity of the data because it heavily depends on the quality of handcrafted features. If these features are not well designed for resilient to noise and artifacts, the model might not perform well, leading to information loss and lessened accuracy. Deep learning is indeed more capable for automatic extracting features from raw or minimally processed signals, although it may require substantial computational resources due to the complexity and depth of these models that require longer training time. Even though the traditional KNN model performed well, the proposed deep learning models, such as 2-D InceptionResNetV2 managed to get the best results through careful designing optimized hyperparameter. It can be concluded that to create a more reliable model, hybrid models should be proposed to leverage the strengths of both machine learning and deep learning models. Revising feature-based algorithms to incorporate varied sample data collections helped improve the model's generalization in real-world clinical applications.

5. Conclusion

Early identification of diabetes is important for preventing the progression of cardiovascular diseases. In this paper, PPG signals were used along with other anthropometrical parameters to continually analyze the correlation between the concentration of the blood glucose and abnormal blood pressure patterns. Changes in blood glucose levels can contribute to higher blood pressure due to decreased vessel diameter and greater resistance to blood flow. According to studies, these cases can enhance the clarity of the PPG signal, allowing for earlier detection and better management of these abnormalities, which could help prevent complications in clinical research findings. However, further analysis is required to eliminate a drawback of PPG signals, such as the suitability of the proposed algorithm to ensure the quality of the signals pairs. Thus, this paper introduced the proposed diabetes detection models, which may have simpler structures, fewer learning parameters and faster feature extractions. In the future, this study will explore diverse feature-based algorithms to enhance the classification accuracy, which might be applicable to a variety of diabetes-related studies.

Acknowledgement

This research was supported by the Ministry of Higher Education (MOHE) through Fundamental Research Grant Scheme (FRGS/1/2021/TK0/UTHM/02/12).

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Syaidatus Syahira Ahmad Tarmizi, Nor Surayahani Suriani;* ***data collection:*** *Syaidatus Syahira Ahmad Tarmizi, Nor Surayahani Suriani, Ezrat Samadi M.D;* ***analysis and interpretation of results:*** *Syaidatus Syahira Ahmad Tarmizi, Nor Surayahani Suriani, Ezrat Samadi M.D;* ***manuscript preparation:*** *Syaidatus Syahira Ahmad Tarmizi, Nor Surayahani Suriani. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Jiale Zhang, Zhuoya Zhang, Kaiqi Zhang, Xiaolei Ge, Ranran Sun & Xu Zhai (2023) Early detection of type 2 diabetes risk: limitations of current diagnostic criteria, Frontiers in Endocrinology, 14, 1-7, https://doi.org/10.3389/fendo.2023.1260623

[2] Narmatha Chellamani, Saleh Ali Albelwi, Manimurugan Shanmuganathan, Palanisamy Amirthalingam, Emad Muteb Alharbi, Hibah Qasem Salman Alatawi, Kousalya Prabahar, Jawhara Bader Aljabri & Anand Paul (2025) A deep sparse capsule network for non-invasive blood glucose level estimation using a PPG sensor, Sensors, 25(6), https://doi.org/10.3390/s25061868

[3] Chih-Ta Yen, Un-Hung Chen, Guo-Chang Wang & Zong-Xian Chen (2022) Non-Invasive blood glucose estimation system based on a neural network with dual-wavelength photoplethysmography and bioelectrical impedance measuring, Sensors, 22, 1–13, https://doi.org/10.3390/s22124452

[4] Meng Rong and Kaiyang Li (2021) A blood pressure prediction method based on imaging photoplethysmography in combination with machine learning, Biomedical Signal Processing and Control, 64, 1–11, https://doi.org/10.1016/j.bspc.2020.102328

[5] Syaidatus Syahira Ahmad Tarmizi, Nor Surayahani Suriani, Mohd Norzali Bin Hj Mohd, Susama Bagchi, Sanjoy Kumar Debnath & Syed Mehr Ali Shah (2025) Photoplethysmography bio-signal extraction for classifying diabetes mellitus diseases using pretrained deep learning networks, SN Computer Science, 6(2), pp 1–14, https://doi.org/10.1007/s42979-024-03589-4

[6] Neelamshobha Nirala, R. Periyasamy, Bikesh Kumar Singh & Awanish Kumar (2019) Detection of type-2 diabetes using characteristics of toe photoplethysmogram by applying support vector machine, Biocybernetics and Biomedical Engineering, 39(1), 38-51, https://doi.org/10.1016/j.bbe.2018.09.007

[7] Shing-Hong Liu, Han-Chi Liu, Wenxi Chen, Tan-Hsu Tan (2020) Evaluating quality of photoplethymographic signal on wearable forehead pulse oximeter with supervised classification approaches, IEEE Access, 8, 185121 - 185135, https://doi.org/10.1109/ACCESS.2020.3029842

[8] Vera Hartmann, Haipeng Liu, Fei Chen F, Qian Qiu, Stephen Hughes & Dingchang Zheng (2019) Quantitative comparison of photoplethysmographic waveform characteristics: Effect of measurement site, Frontiers in Physiology, 10, 1-8, https://doi.org/10.3389/fphys.2019.00198

[9] Yulong Jia, Yu Zheng, Zhong Wang & Yuee Li (2025) Non-invasive blood glucose based on dual-wavelength transmission ppg signal, IEEE Sensors Journal, 25(7), 11876-11884, https://doi.org/10.1109/JSEN.2025.3539604

[10] Syaidatus Syahira Ahmad Tarmizi, Nor Surayahani Suriani & Fadilla 'Atyka Nor Rashid (2022) A review of facial thermography assessment for vital signs estimation, IEEE Access, 10, 115583–115602, https://doi.org/10.1109/ACCESS.2022.3217904

[11] Himel Mondal, Sairavi Kiran Biri, Neha Pipil & Shaikat Mondal (2024) Accuracy of a non-invasive home glucose monitor for measurement of blood glucose, Indian Journal of Endocrinology and Metabolism, 28(1), 60-64, https://doi.org/10.4103/ijem.ijem_36_23

[12] Francesco Scardulla, Gloria Cosoli, Susanna Spinsante, Angelica Poli, Grazia Iadarola, Riccardo Pernice, Alessandro Busacca, Salvatore Pasta, Lorenzo Scalise & Leonardo D'Acquisto (2023) Photoplethysmograhic sensors, potential and limitations: Is it time for regulation? A comprehensive review, Measurement, 218, 1-20, https://doi.org/10.1016/j.measurement.2023.113150

[13] Ginting Johannes B., Suci Tri, Ginting Chrismis N. & Girsang Ermi (2023) Early detection system of risk factors for diabetes mellitus type 2 utilization of machine learning-random forest. In: Journal of Family and Community Medicine, 30(3), 171-179, https://doi.org/10.4103/jfcm.jfcm_33_23

[14] Peter H. Charlton, Vaidotas Marozas, Elisa Mejía-Mejía, Panicos A. Kyriacou & Jonathan Mant (2025) Determinants of photoplethysmography signal quality at the wrist, PLOS Digital Health, 4(6), https://doi.org/10.1371/journal.pdig.0000585

[15] Moajjem Hossain Chowdhury, Md Nazmul Islam Shuzan, Muhammad E. H. Chowdhury, Zaid B. Mahbub, M. Monir Uddin, Amith Khandakar &Mamun Bin Ibne Reaz (2020) Estimating blood pressure from the photoplethysmogram signal and demographic features using machine learning techniques, Sensors, 20(11), 1–24, https://doi.org/10.3390/s20113127

[16] Mohammad Feli, Kianoosh Kazemi, Iman Azimi, Pasi Liljeberg & Amir M. Rahmani (2025) Multitask learning approach for PPG applications: Case studies on signal quality assessment and physiological parameters estimation, Computers in Biology and Medicine, 188, 1-14, https://doi.org/10.1016/j.compbiomed.2025.109798

[17] Matthew Yiwen Ho, Hung Manh Pham, Aaqib Saeed & Dong Ma (2025) WF-PPG: A wrist-finger dual-channel dataset for studying the impact of contact pressure on PPG morphology, Scientific Data, 12(1), 1-11, https://doi.org/10.1038/s41597-025-04453-7

[18] Enric Monte-Moreno (2013) Non-invasive estimate of blood glucose and blood pressure from a photoplethysmograph by means of machine learning techniques, Artificial Intelligence in Medicine, 53, 127-138, https://doi.org/10.1016/j.artmed.2011.05.001

[19] Yang Xu, Zhipei Huang, Jiankang Wu & Zhongdi Liu (2021) Continuous blood pressure monitoring method based on multiple photoplethysmography features, Computer Methods in Medicine and Health Care, 84-92, https://doi.org/10.3233/ATDE210246

[20] Tanvir Tazul Islam, Md Sajid Ahmed, Md Hassanuzzaman, Syed Athar Bin Amir & Tanzilur Rahman (2021) Blood glucose level regression for smartphone PPG signals using machine learning, Applied Sciences, 11(2), 1-20, https://doi.org/10.3390/app11020618

[21] Shresth Gupta, Anurag Singh, Abhishek Sharma & Rajesh Tripathy (2022) dSVRI: A PPG-based novel feature for early diagnosis of type-II diabetes mellitus, IEEE Sensors Letters, 6(9), 1-4, https://doi.org/10.1109/LSENS.2022.3203609

[22] Serena Zanelli, Mounim A El Yacoubi, Magid Hallab & Mehdi Ammi (2023) Type 2 diabetes detection with light CNN from single raw PPG wave, IEEE Access, 11, 57652-57665, https://doi.org/10.1109/ACCESS.2023.3274484

[23] Hiruni J. Gunathilaka, Rumesh Rajapaksha, Thosini Kumarika, Dinusha Perera, Uditha Herath, Charith Jayathilaka, Janitha A. Liyanage & Sudath R. D. Kalingamudali (2024) Pilot study for non-invasive diabetes detection through classification of photoplethysmography signals using convolutional neural networks, Journal of Multidisciplinary & Translational Research, 9(1), 85-95, https://doi.org/10.4038/jmtr.v9i1.17

[24] Md Nazmul Islam Shuzan, Moajjem Hossain Chowdhury, Muhammad E. H. Chowdhury, Khalid Abualsaud, Elias Yaacoub, Md Ahasan Atick Faisal, Mazun Alshahwani, Noora Al Bordeni, Fatima Al-Kaabi, Sara Al-Mohannadi, Sakib Mahmud & Nizar Zorba (2024) QU-GM: An IoT based glucose monitoring system from photoplethysmography, blood pressure, and demographic data using machine learning, IEEE Access, 12, 77774-77790, https://doi.org/10.1109/ACCESS.2024.3404971

[25] Noor Faris Ali, Ibrahim M. Elfadel & Mohamed Atef (2025) Multi-datasets transfer multitask learning for simultaneous blood glucose and blood pressure monitoring using common PPG features, Computers in Biology and Medicine, 195, 1-14, https://doi.org/10.1016/j.compbiomed.2025.110434

[26] Yongbo Liang, Zhencheng Chen, Guiyong Liu & Mohamed Elgendi (2018) A new, short-recorded photoplethysmogram dataset for blood pressure monitoring in China, Scientific Data, 5, 1–7, https://doi.org/10.1038/sdata.2018.20

[27] Yongbo Liang, Guiyong Liu, Zhencheng Chen & Mohamed Elgendi (2018) PPG-BP database, Figshare, https://doi.org/10.6084/m9.figshare.5459299.v5

[28] Mohd Zubir Suboh, Rosmina Jaafar, Nazrul Anuar Nayan, Noor Hasmiza Harun & Mohd Shawal Faizal Mohamad (2022) Analysis on four derivative waveforms of photoplethysmogram (PPG) for fiducial point detection, Frontiers in Public Health, 10, 1–12, https://doi.org/10.3389/fpubh.2022.920946

[29] Junfeng Yang, Yuwen Huang, Ruili Zhang, Fuxian Huang, Qinggang Meng & Shixin Feng (2021) Study on PPG biometric recognition based on multifeature extraction and Naive Bayes classifier, Scientific Programming, 2021, 1–12, https://doi.org/10.1155/2021/5597624

[30] Yousef K. Qawqzeh, Abdullah S. Bajahzar, Mahdi Jemmali, Mohammad Mahmood Otoom & Adel Thaljaoui (2020) Classification of diabetes using photoplethysmogram (PPG) waveform analysis: Logistic regression modeling, BioMed Research International, 2020, 1-6, https://doi.org/10.1155/2020/3764653

[31] Venkatesh Bharadwaj Srinivasan and Foroohar Foroozan (2021) Deep Learning based non-invasive diabetes predictor using photoplethysmography signals, In 2021 29th European Signal Processing Conference (EUSIPCO), 1256-1260, https://doi.org/10.23919/EUSIPCO54536.2021.9616351

[32] Hanghang Deng, Luqiao Zhang, Yu Xie & Shasha Mo (2021) Research on estimation of blood glucose based on PPG and deep neural networks, In IOP Conference Series: Earth and Environmental Science, 693(1), 1-6, https://doi.org/10.1088/1755-1315/693/1/012046

[33] Ernia Susana, Kalamullah Ramli, Prima Dewi Purnamasari & Nursama Heru Apriantoro (2023) Non-Invasive classification of blood glucose level based on photoplethysmography using time–frequency analysis, Information, 14, 1-20, https://doi.org/10.3390/info14030145

[34] Abdelrhman Y. Soliman, Ahmed M. Nor, Octavian Fratu, Simona Halunga, Osama A. Omer & Ahmed S. Mubark (2024) Non-Invasive glucose level monitoring from PPG using a hybrid CNN-GRU deep learning network, In 2024 Advanced Topics on Measurement and Simulation (ATOMS), 299-302, https://doi.org/10.1109/ATOMS60779.2024.10921552

[35] Mehdi Zeynali, Khalil Alipour, Bahram Tarvirdizadeh & Mohammad Ghamari (2025) Non-invasive blood glucose monitoring using PPG signals with various deep learning models and implementation using TinyML, Scientific Reports, 15(1), 1-23, https://doi.org/10.1038/s41598-024-84265-8