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Leveraging ECG Signals for Automated Diabetic Patient Detection using CNN

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ABSTRACT

Increasing blood glucose (BG) levels can lead to diabetes, affecting millions of adults worldwide. Insulin facilitates glucose absorption into cells for energy, and severe hypoglycemia in insulin-treated diabetics may cause abnormal ECG changes. Therefore, continuous monitoring of BG levels is critical. Traditional monitoring involves invasive finger pricks, whereas non-invasive methods, such as this study's approach, avoid the need for blood samples. This research proposes an IoT-based, non-invasive BG monitoring system that uses near-infrared (NIR) light and ECG signals. The ECG data are preprocessed using a Butterworth filter and analysed with a convolutional neural network (CNN). Several machine learning algorithms were compared to thirty subjects' ECG readings to test their performance and achieved almost 95% accuracy in detecting diabetic (DM) or healthy (non-DM) status.

1. Introduction

Diabetes is a global health issue, significantly impacting cardiovascular health, with ECG signals showing promising potential for early detection. Six million persons in Malaysia who are 18 years of age or older have diabetes, according to the country's National Health and Morbidity Survey (NHMS) [1]. Diabetes comes in three different forms: Blood glucose levels rise because of the body's inability to manufacture insulin, which leads to type 1 diabetes. It usually manifests quickly, usually in young adults, and requires daily insulin shots to survive. The body's inability to use insulin properly is the hallmark of type 2 diabetes, which is typically diagnosed in older adults and requires monthly monitoring to maintain normal blood glucose levels. Pregnant women who have gestational diabetes are more likely to eventually develop type 2 diabetes. Although it normally goes away after birthing, the newborn may be at risk for health problems [2]. Abnormalities such as altered T-wave morphology, bradycardia, and QT prolongation are commonly observed in diabetic patients,

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particularly during hypoglycemia [3]. Recent advancements in deep learning and machine learning have opened new avenues for automated diabetic patient detection using non-invasive ECG data.

Recent studies suggest that diabetes can impact cardiovascular health, with patients experiencing electrocardiogram (ECG) abnormalities such as bradycardia, altered T-wave morphology, and QT prolongation, particularly during hypoglycemic events [3]. Given this, ECG signals are increasingly being explored as non-invasive biomarkers for blood glucose (BG) monitoring. Deep learning models, specifically convolutional neural networks (CNN), have shown promise in automatically detecting diabetic conditions from ECG data. By leveraging CNN's ability to identify subtle patterns in ECG signals, researchers aim to improve non-invasive glucose monitoring and diabetic patient detection [4].

Convolutional neu0ral networks (CNN) are particularly effective in identifying diabetic patterns from ECG signals due to their ability to process complex, high-dimensional data. A study by Cordeiro et al. [2] successfully demonstrated the use of deep learning to detect hyperglycemia using heartbeat patterns from ECG signals [2]. Another significant contribution is by Zhang et al. [5], who trained CNNs on large datasets of ECG signals for detecting cardiovascular diseases, highlighting their adaptability for diabetic diagnosis as well.

In recent years, several studies have explored the application of deep learning and machine learning in detecting diabetes using ECG signals. Cordeiro et al. [6] proposed a novel deep learning architecture for identifying hyperglycemia through ECG heartbeats. This approach is promising due to its non-invasive nature and high accuracy in detecting hyperglycaemia episodes. However, a limitation is that it focuses primarily on hyperglycemia without addressing other diabetic stages, such as pre-diabetes, and it relies on a relatively small dataset that may limit its generalizability. Kulkarni et al. [7] developed a machine-learning algorithm to detect diabetes and pre-diabetes using ECG signals. This study stands out for its ability to detect early signs of diabetes, which is crucial for preventative care. However, a limitation is that it does not consider integration with continuous monitoring systems, which would enhance its practical application in real-world settings. Another study by Kim et al. [8] focused on using deep learning to predict long-term diabetes risk based on ECG data. While the study highlights the potential for proactive diabetes management, its limitation lies in its exclusive reliance on ECG data without incorporating other clinical factors that could improve predictive accuracy. Finally, Lin et al. [9] combined ECG and HbA1c levels for more accurate diabetes detection, especially in patients with fewer comorbidities. Although the combination improved detection rates, the need for HbA1c measurements limits the method's non-invasive potential [10],[11]. These studies highlight the strengths of using ECG for diabetes detection, though further advancements are needed in dataset size, integration with continuous monitoring, and combining other diagnostic metrics to enhance accuracy and applicability.

The following are our main contributions:

- IoT-Driven Non-Invasive Blood Glucose Measurement – The paper presents a novel IoT-based model for the non-invasive monitoring of blood glucose using near-infrared (NIR) difference modulation and electrocardiogram (ECG) identification, of patients, sparing them from finger puncturing procedures.
- Deep learning for diabetes detection – The deep learning approach in ECG signal processing based on the convolutional neural network (CNN) produced high accuracy (~95%) in distinguishing diabetic (DM) from non-DM human subjects proving that deep learning can be successfully used for non-invasive detection of diabetes.

A comparative study of machine learning algorithms – This research assesses different machine learning algorithms on ECG data and helps to understand their effectiveness to classify diabetes therefore aiming to enhance the field of AI-based diabetes diagnostics monitoring.

2. Methodology

This section focuses on the methodology employed in the project to monitor changes in ECG signals correlated with blood glucose levels. The experiment aims to observe how different ECG segments respond to varying blood glucose states (high or low). Simultaneously, blood glucose concentration will be measured using Near-Infrared (NIR) technology, while ECG signals are recorded. The NIR sensor helps to proves that changes in the blood glucose level correlate with changes in ECG signal.

2.1 Hardware Development

The hardware setup for this project includes a Near-Infrared (NIR) LED (TSAL6400), which acts as the transmitter, and a photodiode (BPW34) as the receiver to capture reflected signals as in Fig. 1. This NIR sensor is responsible for non-invasively measuring blood glucose levels based on absorption characteristics. Alongside this, an ECG sensor is used to collect the subject's heart signals. The data from both the NIR and ECG sensors are processed using the NodeMCU ESP8266 microcontroller, which handles signal acquisition and processing. Self-collected datasets are employed to train a convolutional neural network (CNN) model that will analyze the collected ECG signals to predict blood glucose variations.

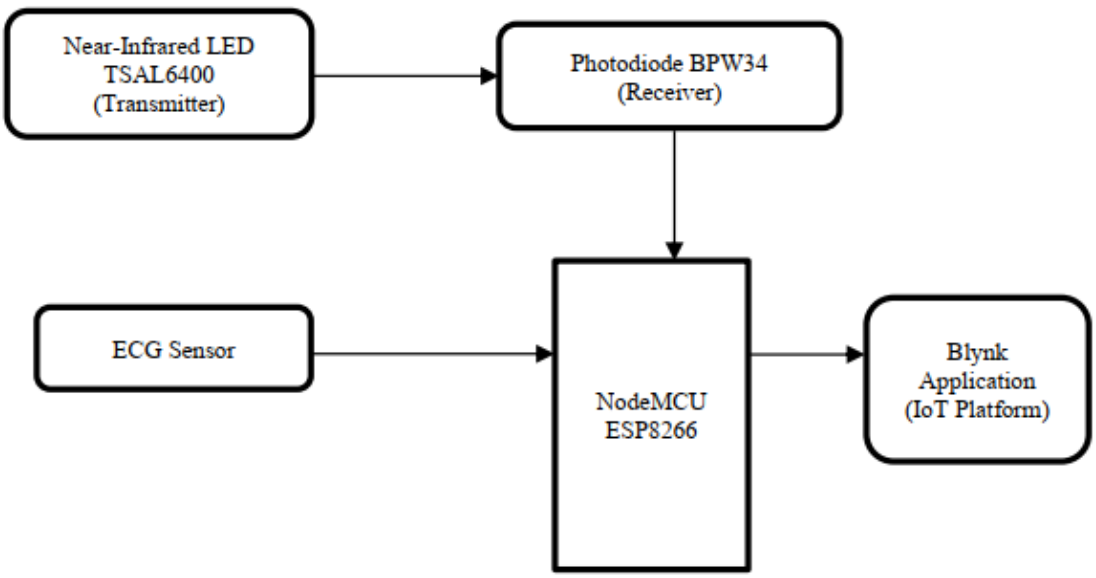

Fig. 1. Block diagram of the hardware setup

This circuit compose of two circuit which is the receiver circuit use photodiode (BPW34) and the transmitter used the NIR LED (940nm/TSAL6400). When a fingertip is placed between the NIR LED and the photodiode, the NIR LED will transmit the light pass through the finger tissues and be reflected to the photodiode. The TSAL6400 LED can emits 940nm signal wavelength while the photodiode BPW34 typically works between 400 and 1100 nanometers (nm). The output from the fingertips will be passed to the analog input of microcontroller which is NodeMCU ESP8266. The microcontroller is powered by 9V battery via the NodeMCU base.

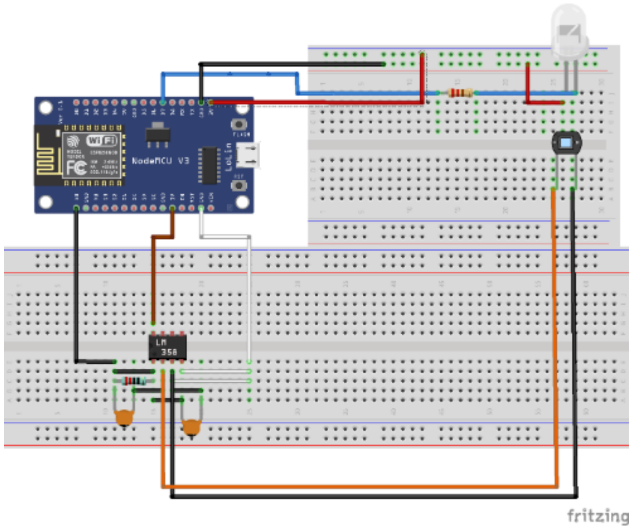

Fig. 2. Transimpedance and amplifier LED circuit

Figure 2 shows the transimpedance and amplifier LED circuit. The NIR circuit diagram of the designed system consists of transimpedance stage and amplification stage. The transimpedance amplifier functions to convert the small current of the sensor into a voltage signal. In the amplified circuit, there is an operational amplifier and feedback resistor (Rf) where is often combined [12]. In this project LM358 is used as an operational amplifier and will act as current converter and signal conditioning. In order to maintain the stability of the circuit, a feedback resistor (Rf) and capacitor (Cf) are needed. The Rf can balance the desired gain with system stability and noise consideration.

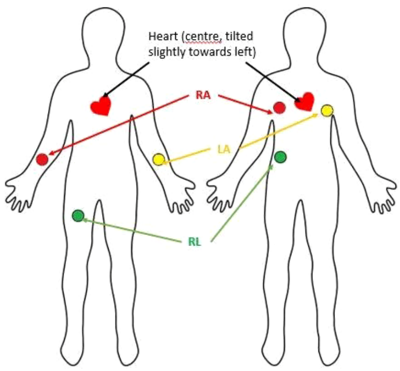

Fig. 3. Two methods of electrode ECG placement

This ECG sensor is using AD8232 ECG sensor to measure the electrical activity of the heart. Development of hardware of this project are using NodeMCU ESP8266, ECG sensor with three electrode and jumper wire. Heart rate signals are transmitted via three electrodes. There are two methods for electrode placement which are shown in Fig. 3. Electrode placement needs to be placed on the right place because it will affect the signal reading. This ECG sensor has three lead systems which is Right arm (RA), Left arm (LA) and Right leg (RL). It is advised to attach the sensor pads to the leads before applying them to the body. Positioning the pads closer to the heart improves measurement accuracy. The cables have color-coded therefore it’s easy to identify the correct placement. By combining NIR-based glucose measurement and ECG signal analysis, the methodology provides an integrated non-invasive approach to monitor blood glucose levels while identifying potential ECG changes associated with diabetic conditions [13].

2.2 Dataset Processing and Software Requirements

The ECG signal undergoes several important steps to provide the features needed for determining blood glucose concentration (BGC). These steps include filtering, segmentation, and prediction. Due to the presence of noise in raw ECG data, signal filtering is a crucial first step. It removes unwanted artifacts and improves the quality of the signal, making it easier to isolate relevant segments for further analysis. Once the signal is filtered, segmentation is performed to break down the ECG into different components, such as the P-wave, QRS complex, and T-wave [14]. These segments are then analyzed to detect which parts of the ECG are most affected by changes in blood glucose levels. This step is essential, as variations in glucose levels can induce subtle changes in heart electrical activity, which are reflected in the ECG [15].

After segmentation, feature extraction is carried out using a convolutional neural network (CNN) model. The CNN model is trained to extract key features from the ECG data that correspond to either healthy or diabetic states. The model, developed on the Jupyter Notebook platform, leverages the hierarchical structure of CNNs to automatically learn and identify patterns related to glucose variations. This approach allows for an efficient and accurate prediction of diabetic conditions based on ECG data, offering a non-invasive method for monitoring glucose levels.

The recorded ECG data undergo preprocessing to extract relevant features, which are then used as testing dataset to classify samples as either healthy (non-DM) or diabetic (DM). The recorded ECG signals include data from 20 healthy subjects and approximately 10 diabetic subjects. Each subject performed at least 5 times of test. In total 100 ECG data for healthy subject and 50 ECG data for diabetic subjects. The prepossed ECG data computed metrics involve SDNN, RMSSD, pNN50, meanHR, mean_RR, MEDIAN_RR, LF, HF, and HF_LF, serve as the primary features. MEDIAN_RR, LF, HF, and HF_LF were selected to replace the parameters nn_50, SDHR, TINN, and HRVIndex.

The simulations were conducted using Intel® Core™ i7-1185G7 @3.00GHz processor 1.80 GHz of RAM and 64-bit Windows OS. The coding was develop using a range of tools and frameworks, including Phyton, Tensor Flow and Keras tools.

2.3 Convolution Neural Network (CNN) Model

Many machine learning algorithms have played an important role in the prediction of diabetes [16-20]. Among these, deep learning algorithms particularly CNN have shown strong potential. CNNs are multilayered architectures composed of convolutional, pooling and output layers combines with activation functions that enable the network to learn complex patterns. Activation functions help model nonlinear relationships between input features and outputs, enhancing the model's ability to distinguish between healthy and diabetic cases. After filtering and segmenting the ECG dataset, the CNN model shown in Fig. 4 is employed for training. The model includes dense layers using the ReLU activation function, where each neuron receives input from every neuron in the preceding layer. The final output layer is designed to classify the ECG readings as either non-diabetic (non-DM) or diabetic (DM).

To further improve the model's performance and generalization, several architectural enhancements were implemented. The network depth was increased with the addition of four Conv1D layers, allowing the extraction of more hierarchical and temporally rich features from the ECG signals. Dropout layers were inserted after each pooling layer to introduce regularization, reducing overfitting and encouraging the learning of robust representations. The traditional Flatten layer was replaced with a GlobalAveragePooling1D layer, which not only minimizes the number of trainable parameters but also improves generalization by aggregating information across time steps. Additionally, the Dense layer size was increased to expand the model's capacity for capturing complex decision boundaries between healthy and diabetic signal patterns. Overall, these improvements produce a more expressive, stable and generalizable CNN model for accurate diabetic patient detection based on ECG signals.

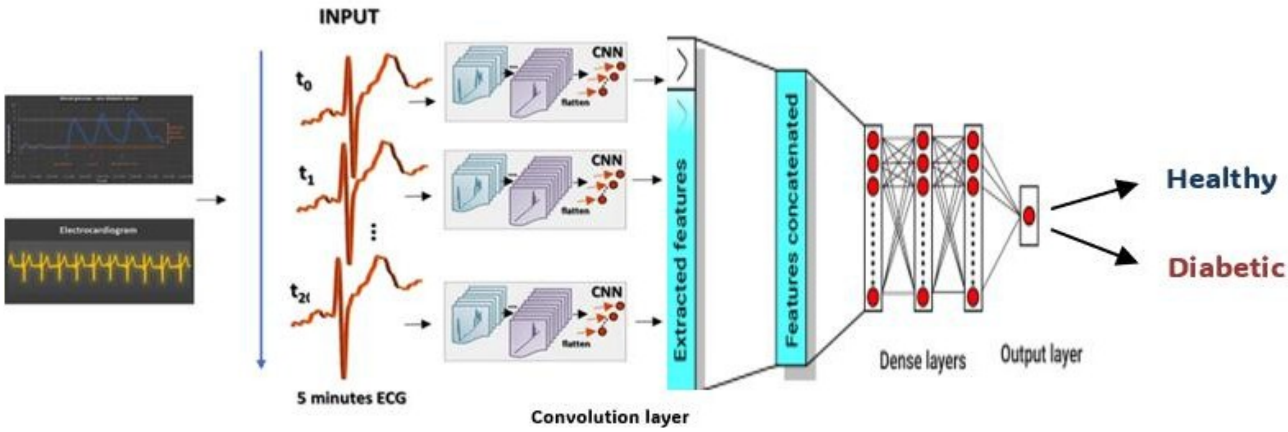

Fig. 4. CNN Architecture Model

The ADADELTA adaptive learning rate method was integrated into the proposed CNN to eliminate the need for manually setting the learning rate. This technique adjusts the learning rate uniquely for each parameter during each iteration. The core of this approach involves accumulating the squared gradients over a fixed-size window of recent gradients. The running average of the squared gradient is computed as follows:

$$E\left|g^2\right|_t = \rho . E\left|g^2\right|_{t-1} + (1-\rho).g_t^2 \qquad ( )$$

Where, g_t is the gradient of the current time t and ρ is a decay constant. Table 1 tabulate the detailed architecture of the proposed model.

2.4 Signal Filtering and Segmentation

Since the ECG signal from the sensor is raw data, noise is present, and it must be filtered to identify the ECG segments that had an impact on the blood glucose level. Python in Jupyter Notebook has been used to filter the ECG. The ECG signals were filtered using the Butterworth low pass technique to eliminate extraneous noise that can ruin the signal and facilitate the identification of certain segments. The ECG's one or more segments have been used in a variety of ways to measure blood glucose. The potential of the QT interval segment to monitor blood glucose levels has been well studied [14]. Several fundamental components compose the ECG signal, which is recorded as a wave sequence known as the R-Peak, QRS complex, and QT wave. The R- Peak wave is a small upward deviation that indicates atrial depolarization. The QRS complex then leads to ventricular depolarization (approximately 160 ms after the onset of the P wave). Finally, there is the QT wave, which represents ventricular repolarization.

Table 1
Detailed architecture of the proposed model

Layer (Type)	Output Shape	Number of Parameters (Param #)	Description
Input Layer	(None,128 , 8)	0	Input layer for ECG features
Conv1D	(None, 128, 64)	2624	1D convolution layer with 64 filters, kernel size 5
BatchNormalization	(None, 128, 64)	256	Normalizes the data for stable and faster learning
MaxPooling1D	(None, 64, 64)	0	Reduces data size through pooling size 2
Dropout	(None, 64, 64)	0	Dropout layer with rate=0.3 to prevent overfitting
Conv1D	(None, 64, 128)	41,088	1D convolution layer with 128 filters, kernel size 5
BatchNormalization	(None, 64, 128)	512	Normalizes the data for faster learning
MaxPooling1D	(None, 32, 64)	0	Reduces data size through pooling
Conv1D	(None, 32, 128)	24,704	1D convolution layer with 128 filters
BatchNormalization	(None, 32, 128)	512	Normalization
MaxPooling1D	(None, 32, 128)	0	Reduces data size through pooling size 2
Dropout	(None, 32, 128)	0	Dropout layer with rate=0.3 to prevent overfitting
Conv1D	(None, 32, 256)	98,560	1D convolution layer with 256 filters
BatchNormalization	(None, 32, 256)	1,024	Normalizes the data for stable learning
MaxPooling1D	(None, 16, 256)	0	Reduces data size at pooling size 2
Dropout	(None, 16,	0	Dropout layer rate=0.4
Conv1D	(None, 16, 256)	196,864	1D convolution layer with 256 filters, kernel size 3
MaxPooling1D	(None, 8, 256)	0	Reduces data size through pooling size 2
Dropout	(None, 8, 256)	0	Dropout layer rate=0.4
GlobalAveragePooling1D	(None, 256)	0	Global average pooling reduces temporal dimension
Dense	(None, 128)	32,896	Fully connected layer with 128 neurons
Dense	(None, 2)	258	Output layer for Healthy vs Diabetic Class

2.5 ECG Features Extraction

Pre-processing is a crucial step to ensure that the raw electrocardiogram (ECG) signal is free from noise and artifacts that can interfere with accurate feature extraction. The preprocessing of the ECG signal involves two key steps. First, the ECG signal is sampled at a rate of 250 Hz, which is adequate for capturing the essential frequencies related to heart activity, such as the P-wave, QRS complex, and T-wave, with minimal distortion. This sampling rate is commonly used in clinical and research settings to ensure high-quality signal representation [19]. Second, the signal undergoes bandpass filtering to remove unwanted low-frequency components (e.g., baseline wander) and high-frequency noise (e.g., muscle artifacts). The filter uses cutoff frequencies of 3Hz and 45Hz, employing a Butterworth filter of order 2, which provides a smooth response with minimal phase distortion, ensuring an accurate and clean ECG signal.

The R-peak, the most prominent peak in the QRS complex of an ECG signal, corresponds to ventricular depolarization and is crucial for further analysis, such as determining QRS duration and heart rate variability [20]. To detect R-peaks in the filtered ECG signal, the peaks function is employed with specific parameters: a height threshold of 0.5 mV to ensure that only significant peaks are detected, and a minimum distance of 0.3 seconds (equivalent to 75 samples at a 250 Hz sampling rate) between consecutive peaks to avoid detecting spurious noise. The result is a set of R-peaks, representing maximum depolarization, which are further refined by focusing on a defined sample range to isolate the region of interest.

The QRS complex, representing the rapid depolarization of the ventricles, is a crucial feature in ECG analysis as its duration provides insights into various cardiac conditions. For each detected R-peak, the QRS complex is identified by assuming it starts 80 milliseconds before the R-peak and ends 150 milliseconds after the R-peak. The QRS complex is then extracted from the filtered ECG signal, and its amplitudes are recorded for further analysis, such as calculating heart rate variability or detecting ventricular abnormalities. Finally, the filtered ECG signal is plotted, highlighting both the QRS complexes and R-peaks, to ensure successful feature extraction.

3. Results and Analysis

In this section, we present the results of ECG signal and glucose concentration measurements, highlighting key differences between healthy and diabetic subjects. A detailed comparison of ECG segments, including the QT interval, QRS complex, and R-peak, reveals significant variations between the two groups. Additionally, we describe the process of training and validating a convolutional neural network (CNN) model using ECG signals to predict diabetic conditions. The results showcase the effectiveness of CNN in distinguishing between healthy and diabetic subjects based on ECG data.

3.1 ECG Signal and Glucose Concentration Measurement

ECG signal readings were taken simultaneously with glucose concentration measurements using the NIR sensor. An average of 8,500 ECG signal cycles was obtained from each subject. The signal was filtered using a Butterworth filter to facilitate easier segmentation. Fig. 5 illustrates the electrode placement for the ECG sensor used to capture the signals. The recorded data was saved in a CSV file for further processing, where signal filtering was applied to identify differences in the QT interval, QRS complex, and R-peak between healthy and diabetic subjects.

Fig. 5. Electrode placement for signal reading on subjects

Figure 6 displays the raw and filtered ECG signals for a healthy subject, while Fig. 7 presents the same for diabetic subjects. The readings from the NIR sensor helped verify changes in ECG segments corresponding to fluctuations in blood glucose levels.The signal filtering was performed using Python code in Jupyter Notebook.

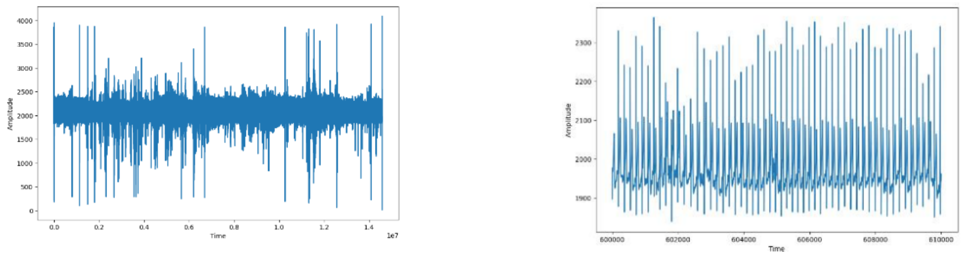

Fig. 6. ECG signal for Healthy subject: Raw ECG signal (left) and Filtered ECG signal (right).

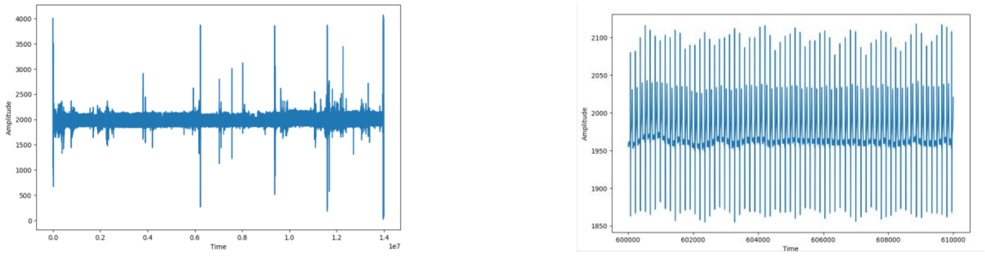

Fig. 7. ECG signal for Diabetic subject: Raw ECG signal (left) and Filtered ECG signal (right).

The results show that healthy subjects had a higher R-peak amplitude compared to diabetic subjects. In terms of the QT interval, healthy individuals maintained a constant QT interval, while diabetic subjects exhibited a prolonged QT interval. Notably, ECG waveforms at low glucose levels showed a larger QRS complex amplitude compared to those at moderate or high glucose levels. The key ECG features varied across different glucose levels: at low glucose, the primary focus was on the onset of the P wave, PR segment, and QT interval. Conversely, at high glucose levels, the key features were observed in the posterior part of the QRS complex and the T wave. Fig. 8 presents the results of ECG of R-peaks segment comparison between healthy and diabetes patient.

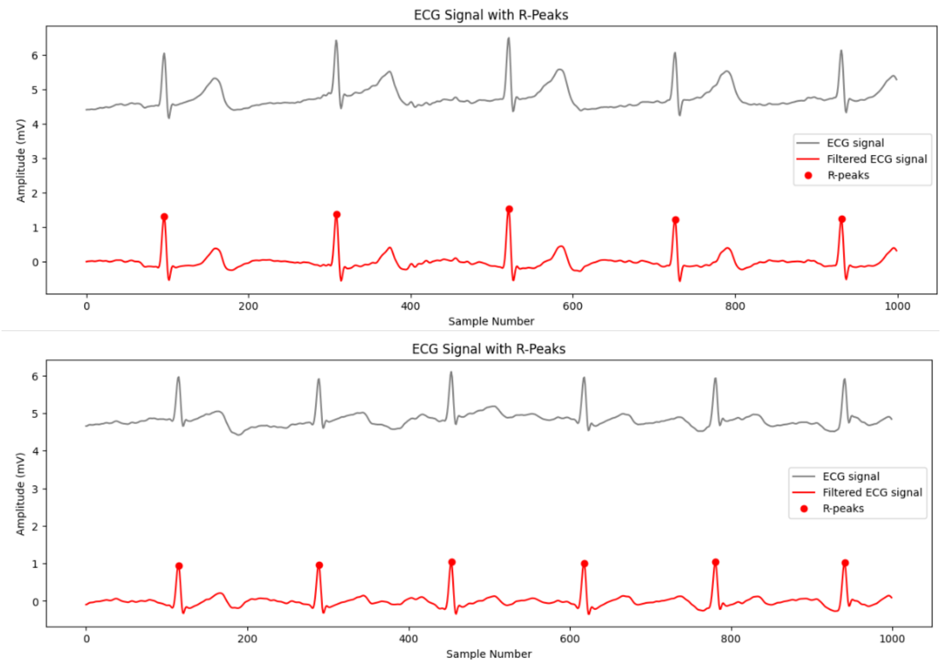

Fig. 8. Comparison of ECG Segments (R-peaks) Between Healthy (Top) and Diabetic (Below) Subject

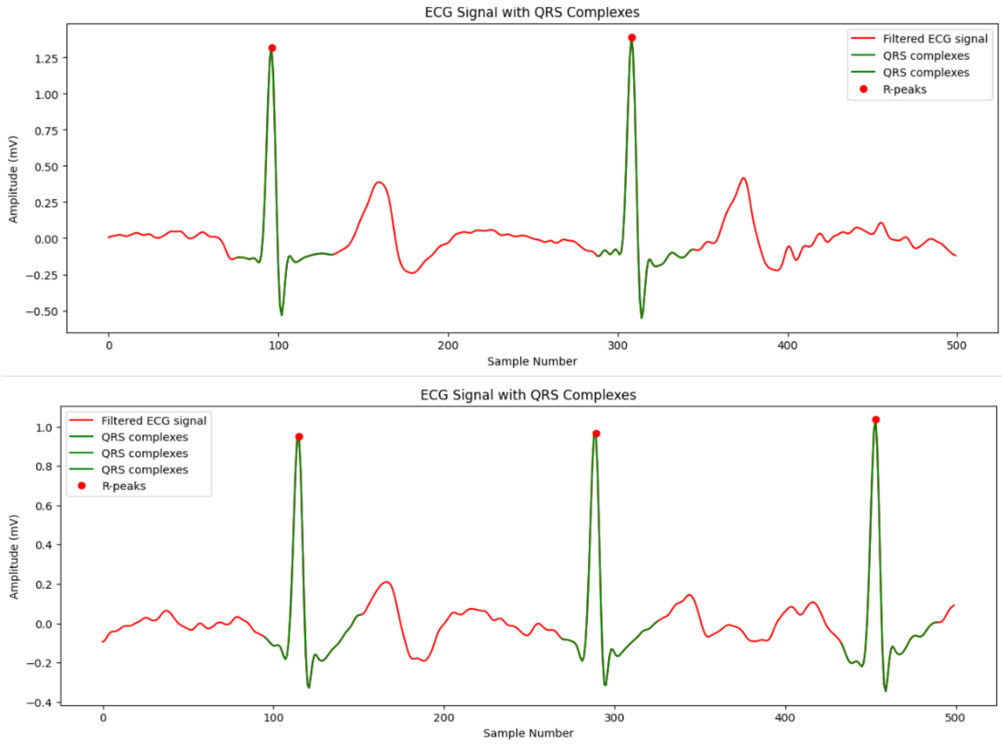

Fig. 9. Comparison of ECG Segments (R-peaks) Between Healthy (Top) and Diabetic (Below) Subject.

The R-peak in an ECG segment represents ventricular depolarization, a crucial component of the heart's electrical cycle. In healthy individuals, the R-peak shows a consistent amplitude and duration, indicating stable ventricular depolarization. This consistency reflects a well-functioning cardiac cycle, where the electrical signal is transmitted efficiently across the ventricles, leading to proper heart contractions. The uniformity of the R-peak amplitude and duration in healthy individuals is a key marker of normal heart rhythm and function.

In diabetic individuals, however, the R-peak amplitude is notably reduced. This reduction suggests impaired ventricular depolarization, potentially caused by diabetes-related complications like autonomic neuropathy, which affects the heart's electrical signals. The diminished R-peak may indicate weaker heart muscle contractions and less efficient blood pumping, further reflecting the cardiovascular strain often associated with long-term diabetes. The comparison highlights how the R-peak can serve as a diagnostic indicator for detecting heart irregularities in diabetic patients.

The QRS complex is a crucial component of the ECG waveform that represents the depolarization of the ventricles, initiating their contraction. Fig. 9 shows the comparison of QRS complex between healthy and diabetic subject. In a healthy individual, the QRS complex typically lasts between 70 to 100 milliseconds. This duration indicates efficient electrical conduction through the ventricles, resulting in strong, coordinated contractions necessary for pumping blood effectively.

In contrast, a diabetic individual often shows a slight widening of the QRS complex. This widening reflects delayed ventricular depolarization, possibly due to diabetes-related cardiovascular complications, such as diabetic cardiomyopathy or autonomic neuropathy. These conditions can impair the heart's electrical pathways, slowing down conduction and weakening the efficiency of ventricular contractions.

The difference in the QRS complex between healthy and diabetic subjects underscores the impact of diabetes on cardiac function. While healthy subjects maintain a narrow, consistent QRS complex, diabetic individuals experience a broader waveform, suggesting underlying complications affecting heart performance. The widened QRS in diabetic subjects may lead to inefficient blood ejection and long-term cardiovascular risks.

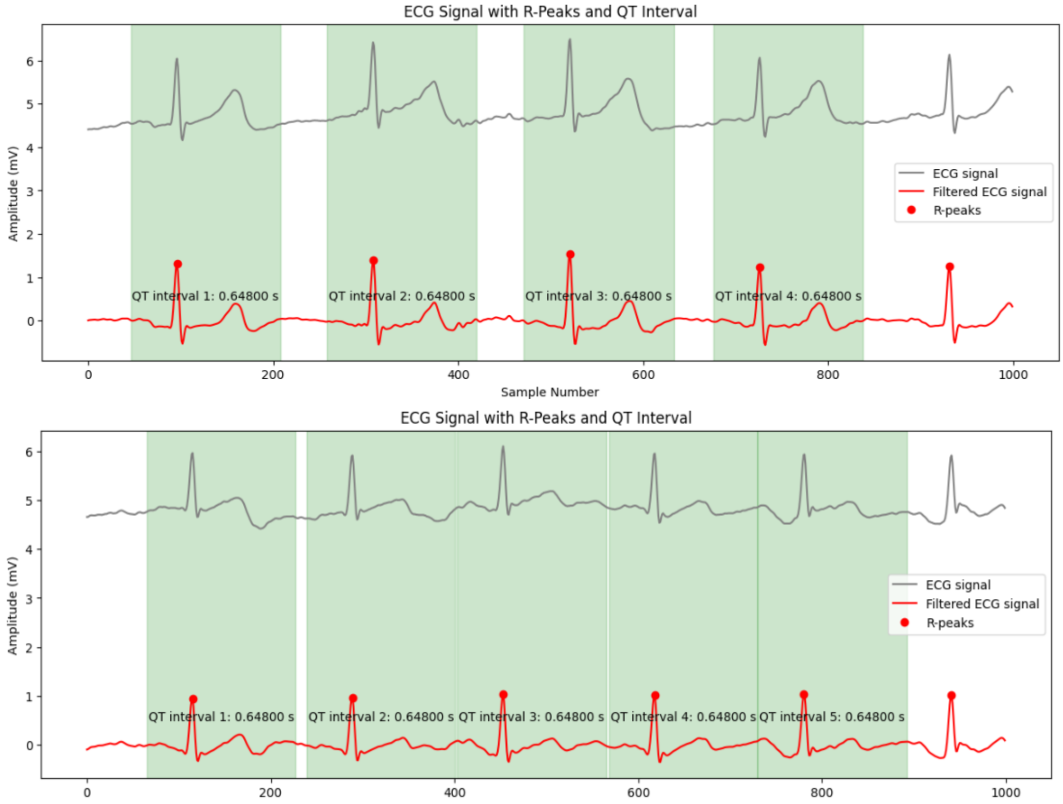

Fig. 10. Comparison of R-Peaks and QT interval Between Healthy (Top) and Diabetic (Below) Subject

The QT interval of the ECG signal in Fig. 10 represents the time taken for the ventricles to both depolarize and repolarize. In healthy individuals, the QT interval typically ranges from 350 to 450 milliseconds. This range reflects normal ventricular function, where the heart's electrical system operates efficiently, ensuring timely contraction and relaxation of the ventricles. A consistent QT interval within this range indicates a lower risk of cardiac issues such as arrhythmia.

In diabetic individuals, however, the QT interval is often prolonged, exceeding the 450-millisecond upper limit. This prolongation indicates delayed ventricular repolarization, increasing the risk of developing arrhythmias. The prolonged QT interval is a sign of electrical instability in the heart, commonly linked to diabetes-related complications such as autonomic neuropathy or cardiac fibrosis. These conditions slow down the heart's recovery phase, heightening the possibility of dangerous arrhythmic events, including sudden cardiac death. The comparison highlights how diabetes affects the heart's electrical stability, making continuous monitoring of the QT interval crucial for early detection and management of cardiac risks in diabetic patients.

3.2 Training and Evaluation of Convolutional Neural Network (CNN) Model

The model was trained with self-collected data from 30 subjects. Preprocessed ECG signals consist of 15,300 datapoint for diabetic (DM) and 17,950 datapoints for healthy (non-DM). The test, validation and training dataset were divided into 5:4:11 ratio, or about 30:70 for testing and training plus validation set. First, the CSV file containing the extracted features was imported into the model, and any null values were removed from the dataset. Next, the data were normalized, and the labels were binary encoded as healthy (1) and diabetic (0). The neural network was trained for 20 epochs. The architecture of the neural network used in this model included minor modifications. The Adam optimizer and the ReLU activation function were employed, along with the binary cross-entropy loss function.

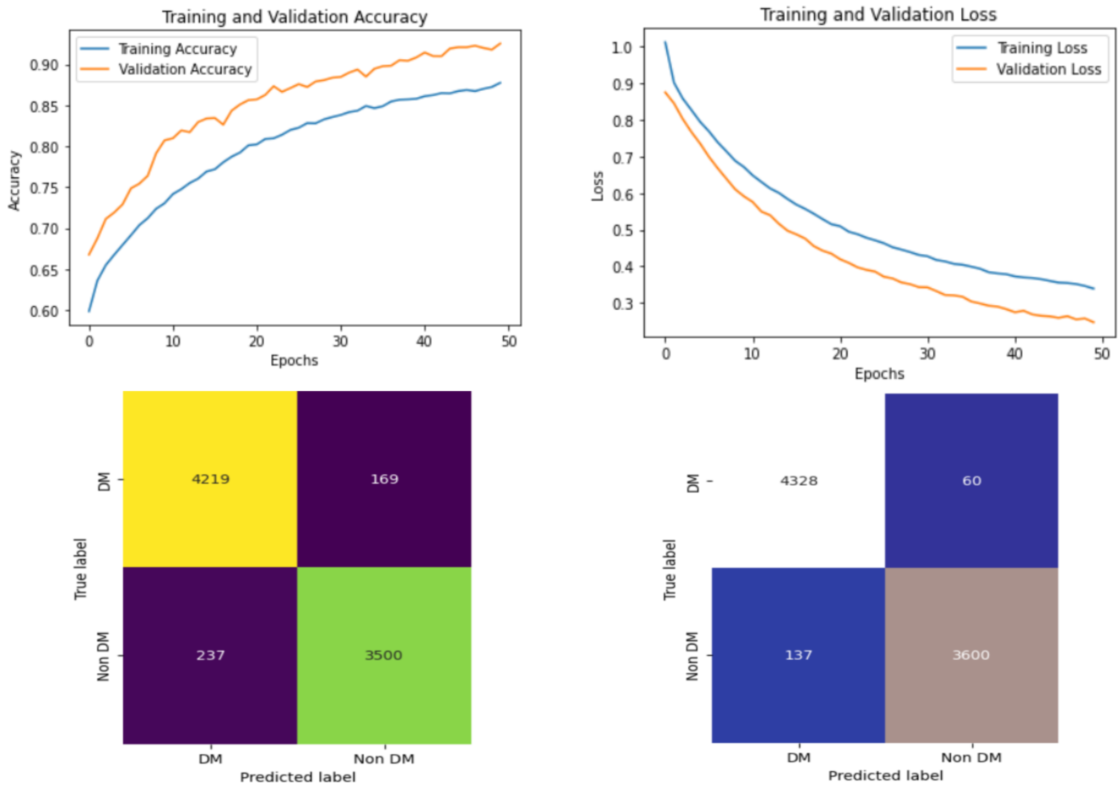

Fig. 11. Plot of Accuracy and Loss (Top), Confusion matrix of prediction result (Bottom).

Fig. 11 (top) shows a plot of the training and validation data loss and accuracy, while Fig. 11 (bottom) presents the prediction report for healthy and diabetic cases. The figure illustrates the model's accuracy and loss during training and validation, alongside its performance on the test and validation datasets using confusion matrices. The model achieves a high accuracy with relatively low error, although there is some indication of overfitting, as seen in the slight gap between the training and validation results. Both confusion matrices show that the model can classify most cases correctly, with relatively few misclassifications. Based on these results, the accuracy for the tested data was 95.4% as shown in Table 1. Several factors could contribute to this lower accuracy, including insufficient data quality. The dataset used may not be large or diverse enough, causing the model to underfit. Therefore, larger and more diverse datasets should be prepared. Additionally, the model architecture might be too simple to capture the underlying patterns in the data and could be improved by using more complex architecture.

Table 2 highlights the significant advancements in diabetic detection methodologies, showcasing how the integration of deep learning architectures. The comparison of different methods for ECG and HRV signal classification highlights the effectiveness of deep learning and ensemble techniques in achieving high accuracy. Traditional machine learning approaches, such as the Decision Tree (86.90%), performed lower than modern deep learning architectures like CNN, CNN-LSTM, and DenseNet. Among the HRV-based methods, Yildirim et al. achieved the highest accuracy (93.62%) using STFT with DenseNet, showcasing the potential of time-frequency domain features in classification tasks. For ECG-based models, deep learning approaches consistently performed better than conventional methods. Lin et al. employed a generic deep learning model, reaching 94.00%

accuracy, while Kulkarni et al. utilized XGBoost with an accuracy of 94.80%, demonstrating the power of gradient boosting techniques in handling structured ECG features. Our proposed CNN model outperformed all other approaches, achieving 95.40% accuracy, indicating its strong ability to learn robust features from ECG signals. This result suggests that a well-designed convolutional network, even without additional feature engineering or hybrid models, can yield superior performance for ECG-based classification.

Table 2
Related Work on Comparison of Diabetic Detection

Authors	Features	Method	Accuracy
Swapna et al. [17]	HRV Signals	CNN-LSTM	90.90
Yildirim et al. [18]	HRV Signals	STFT with DenseNet	93.62
Acharya et. al. [19]	HRV Signals	AdaBoost	90.00
Gupta and Bajaj [20]	ECG Signals	Decision Tree	86.90
Lin et. al. [9]	ECG Signals	Deep Learning	94.00
Kulkarni et. Al. [7]	ECG Signals	XGBoost	94.80
Our Work	ECG Signals	Proposed CNN	95.40

Common metrics evaluation such as sensitivity and specificity are not taken into account because of the imbalance dataset between DM and non-DM. Because the model could achieve high specificity (by predicting most cases as non-diabetic) or high sensitivity (by predicting most cases as diabetic) without being accurate across both classes. Sensitivity (true positive rate) and specificity (true negative rate) measure the model's performance on each class independently, rather than giving a combined measure of how well the model distinguishes between diabetic and non-diabetic samples. In diabetic prediction, we're usually more concerned with how well the model can discriminate between these two classes overall.

The findings suggest that deep learning, specifically CNN architectures, provides significant advantages in ECG signal classification. The proposed CNN model demonstrated the highest accuracy (95.40%), surpassing other machine learning and deep learning approaches. This improvement is likely due to CNN's ability to automatically extract relevant spatial and temporal patterns from raw ECG signals. The results also emphasize the importance of selecting appropriate features. While HRV-based methods performed well, ECG-based deep learning approaches showed slightly better results, reinforcing the importance of leveraging raw ECG signals for classification.

4. Conclusion

In conclusion, QT interval, QRS complex, and R-peak of the ECG segment can be identified, allowing for the classification of patients as diabetic or normal based on blood glucose concentration. The ECG segment is identified using a CNN model with a 1D CNN layer applied. Blood glucose reading taken from NIR sensor helps to prove that changes in the blood glucose level correlate with changes in ECG signal. When blood glucose is higher, the QT interval is longer compared to normal patients. The proposed system enables diagnostic results to be obtained without the need for invasive procedures, thereby eliminating physical discomfort for patients. The prediction result of ECG signals can be segmented with an accuracy of 95.4% using the proposed CNN algorithm. Overall, our CNN based method offers a promising approach for accurate ECG classification, contributing to advancements in automated cardiovascular disease detection.

The accuracy could be improved with diverse data profiling and higher data quality. Future work may explore hybrid models that integrate HRV and ECG features or utilize more advanced architectures such as Transformer-based models for further improvements. The enhancements could incorporate advanced techniques such as residual connections between Conv1D layers to facilitate deeper learning, attention mechanisms to focus on the most informative signal segments plus squeeze and excitations blocks to enable dynamic channel-wise feature recalibration.

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