Deep Learning based non-invasive diabetes predictor using Photoplethysmography signals

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***Abstract*—In 2016, World Health Organization (WHO) estimated that diabetes is the seventh leading cause of death causing 1.6 million casualties globally. In this paper, we propose a non-invasive solution through a Convolutional Neural Network (CNN)-based Deep Learning classifier. We use the scalograms generated out of transmissive Photoplethysmography (PPG) signals collected from MIMIC-III database to diagnose diabetes. Different sets of inputs were sent into a slightly modified VGGNet model, which were trained over data from 584 patients. We provide a probabilistic score of diabetes for every patient, which is further used for classifying patients into diabetic and non-diabetic. The best model obtained using a combination of PPG signals, hypertension classification, age and gender as inputs produced an accuracy of 76.34% and area under the curve (AUC) of 0.830 on 224 test patients. In our knowledge, this is among the first CNN-based approaches in the literature to detect diabetes using MIMIC-III waveforms dataset with a good performance.**

***Index Terms*—Photoplethysmography (PPG), Vital Signs Monitoring (VSM), Convolutional Neural Networks (CNN), MIMIC, Scalogram.**

I. Introduction

Diabetes is a chronic health condition that is characterized by increasing blood glucose levels causing severe health hazards [1]. It is reported by the World Health Organization (WHO) that over 422 million people across the globe suffer from diabetes. Currently, doctors utilize Oral Glucose Tolerance Test (OGTT), Fasting Plasma Glucose (FPG) test, Postprandial Plasma Glucose (PPG) test, Random blood sugar test and Haemoglobin A1C (HbA1c) test to diagnose diabetes in laboratories. But, they are invasive, expensive and time-consuming. Hence, a continuous, non-invasive screening tool that can diagnose diabetes accurately in quick time can be extremely helpful, especially in places that are deprived of medical care. This can also help in early detection of diabetes before being sent for the confirmatory diabetes testing using HbA1c.

Photoplethysmography (PPG) is a non-invasive medium which uses optical technique to measure the volumetric variations of blood circulations [2]. Light from the LED falls on the fingers/wrists and is backscattered or transmitted to the photodiode, which measures the amount of light detected in the form of a pulsewave. While the photodiode is placed in the opposite side of the LED in the transmissive PPG sensor, it is placed adjacent to the LED in the reflective mode. PPG signals are composed of pulsatile (AC) and non-pulsatile (DC) components [3]. While the AC component is synchronized with the heart & related to arterial pulsation, the DC component is related to light absorption in the tissue, vein & static blood. The AC component consists of systolic and diastolic phases separated by a dicrotic notch [2]. Literature suggests that PPG sensor is widely used in continuous physiological monitoring, vascular assessment and monitoring the autonomic functions like Heart Rate Variability (HRV) [4], neurology [5], etc. Some of the cardiovascular parameters that could possibly be detected using photoplethysmography include heart rate, blood oxygen saturation, blood pressure and arterial stiffness. These parameters not only aid PPG signals to assess hypertension [6], but also have direct influence on diabetic patients.

Lillia et. al. [7] says that diabetes is often associated with chronic vascular and microvascular complications. Kiran et. al. [8] emphasizes the risk of diabetes in older people. Bertoni et. al. [9] mentioned that diabetes plays a major role in causing cardiovascular disease and stroke. As PPG signals have been effectively used in the study of vascular diseases, we make use of them to study diabetes in patients. Chan et. al. [10] validates the same by reporting the correlation of HbA1c and arterial stiffness. Nirala et. al. [11] proposed a screening tool using Support Vector Machine to detect diabetes using the characteristics of toe photoplethysmogram by retrieving 37 features. Moreno et. al. [12] proposed a feature extraction based Machine Learning technique using Cepstral analysis and HRV that could serve as a screening tool for type 2 diabetes. Chirath et. al. [13] used Linear Discriminant Analysis on the short PPG waveforms dataset [14] to diagnose diabetes. The time domain and frequency domain features of HRV were extracted from the PPG signals to differentiate between the diabetic and healthy patients by Reddy et. al. [15]. The extracted PPG features, in time or frequency domain makes the existing approaches sensitive only to those features either from physiology point of view or from signal processing point of view.

Over the past few years, the advent of Deep Learning [16] has ushered in state-of-the-art innovations and cutting edge research. Artificial intelligence has significantly impacted the analysis of complex physiological signals [17]. Classification was performed over EEG data [18] using Convolutional Neural

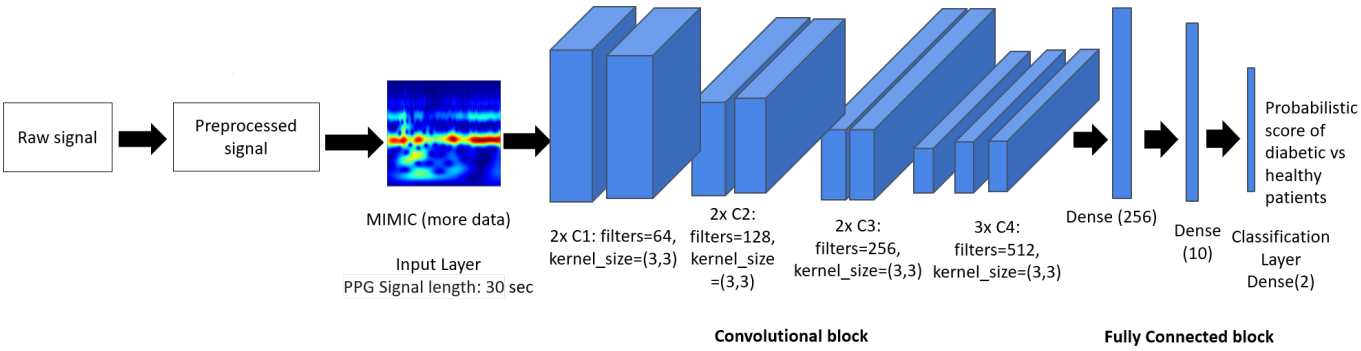

Fig. 1. The proposed CNN-based classifier for diabetes prediction, consisting of (i) preprocessing; (ii) scalogram generator; (iii) convolutional block; and (iv) fully connected block.

Networks (CNN) [19], where raw data was used as such without deductive feature selection. Porumb et. al. [20] worked on a Deep Learning based detection of Hypoglycemic events using ECG signals. Robert et. al. [21] presented a Deep Learning based approach which could serve as a potential biomarker to detect diabetic patients. But, most of the currently existing work on diabetes monitoring using PPG signals have been implemented on their own datasets. The public dataset by Liang et. al. [14] is too small a dataset to be used for Deep Learning, as short length signals may not possess high confidence of the obtained prediction, which may need validation from more subjects with longer PPG signals [13].

Hence, we use PhysioNet's MIMIC - III (Medical Information Mart for Intensive Care) Database [22] to predict diabetes using PPG waveforms in the MIMIC-III Waveform Database Matched Subset [23]. It possesses recordings of several physiological and vital sign signals along with the corresponding metadata. The physiological signals include ECG, arterial blood pressure, respiration and PPG signals while the vital sign signals include heart rate, oxygen saturation, systolic, mean and diastolic blood pressure. We identify the diabetes patients using the ICD-9 code which are labelled for every patient in the MIMIC-III clinical database. Our contribution is that we developed a CNN-based classification algorithm using PPG signals and metadata that can learn the characteristics of the diabetic patients from the PPG scalograms dynamically.

II. CNN-based Classification Algorithm

This sections explains the classification algorithm in details. It consists of (i) preprocessing; (ii) scalogram generation; and our (iii) CNN-based classifier.

A. Pre-processing

We utilize the PPG signals in the MIMIC-III waveform database to diagnose diabetes. These are transmissive signals collected from the fingertips of patients. The patient with ICD-9 code starting with 250 is labeled as a diabetic patient. The transmissive infrared PPG signals are collected at a sampling frequency of 125 Hz. The varieties of diabetes that are covered by type 1 and type 2 include diabetes mellitus, diabetes with ketoacidosis and diabetes with hyperosmolarity [24].

We use WFDB Python package to read and process the waveforms of MIMIC-III dataset. The ultra-low frequency signals are introduced due to respiration, which causes an effect known as baseline wandering [25]. A high-pass Butterworth filter of 0.5 Hz is implemented to remove the baseline wandering caused by motion, impedance of the sensor and respiration. The amplitude of the signals are already normalized by the dataset providers. We break the long signal into segments of 30 seconds each. In order to differentiate the important features in PPG from motion-induced noise, we need to reject the corrupted segments with motion artifacts, for which we design a simple signal quality check algorithm using template matching. We reconstruct the PPG signal using the peaks extracted, and perform least-square based linear regression of the reconstructed template signal with the original signal to check for correlation. The segments with correlation coefficient greater than 0.8 are considered to be uncorrupted signals that can be passed into our Deep Learning model. Signals which don't follow morphology (eg. Notch on the anacrotic phase of PPG cycle contrary to the usual catacrotic phase in the MIMIC-III dataset) are neglected from the dataset. With the advent of Deep Learning, it learns features specific to diabetic & non-diabetic patients by its own and learns to be indifferent to sudden disturbances observed in the signal.

B. Scalogram from PPG signals

We make use of a scalogram technique to pass the input as an image to the Deep Learning model in order to detect diabetes [26]. Scalogram is defined the absolute value of the Continuous Wavelet Transform (CWT) of a signal, plotted as a function of time and frequency [27]. Scalograms can identify the low-frequency and fast-changing frequency components of the signal. It is important to note that the PPG signals are one-dimensional vector signals. The one-dimensional temporal segments which pass the signal quality check are converted into a scalogram with 'jet' colormap that contains 30 seconds of PPG data. It is an RGB image obtained via Continuous Wavelet Transform to preserve the time-frequency localization parameters of non-stationary signals. Scalograms offer better time localization for short-duration, high-frequency events,

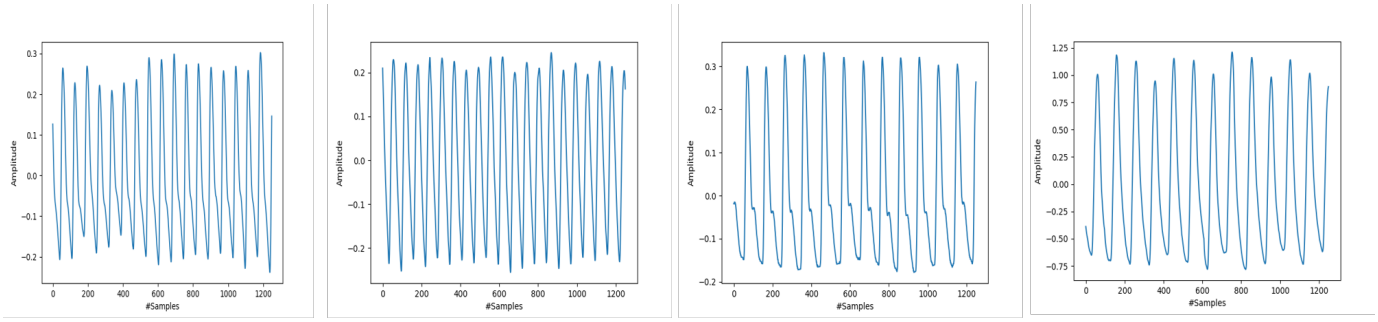

Fig. 2. PPG waveforms representing 10 seconds that indicate i) diabetic patients - a) and b) ; ii) non-diabetic patients - c) and d)

and better frequency localization for low-frequency, longer-duration events compared to Short Time Fourier Transform. It was learnt from Liang et. al. [26] that PPG signals have rich time-frequency domain information as they are a combination of heart activity, vascular relaxation processes, and microcirculation system status. The wavelet coefficients of a Continuous Wavelet Transform can be used to locate different frequency components. We extract the scalograms with 0.5-10 Hz bandwidth to study the time-frequency domain information of diabetic and non-diabetic patients. The RGB scalograms are very helpful for the CNN to extract the features efficiently and learn accordingly in the process of training over the dataset.

C. CNN architecture

Each scalogram has dimensions of 640 x 480 x 3. We normalize the pixel values of the image and resize it to 320 x 240 x 3 before feeding into the CNN so as to perform computation faster, by preserving the aspect ratio. The resized image was sent into a slightly modified VGGNet architecture [28]. The CNN performs the role of a feature extractor in this work, as followed by Liang et. al. [26].

As shown in Fig.1, the primary model possesses 9 convolutional layers, 3 pooling layers and 1 global average pooling layer. The same kernel size of 3x3 was used for all the convolutional layers. The first two convolutions are done successively in the following way where 64 3x3 filters are passed on to the input feed. Pooling is also done for this layer. We repeat the same using two convolutions of 128, 256 and three convolutions of 512 3x3 filters now, and then pool the convolved feed using global average pooling to obtain a one-dimensional arrangement of neurons. We pass this through a fully connected network containing 2 dense layers, and finally to a classifier which has 2 neurons, where each one represents a class - non-diabetic and diabetic. In addition to the PPG input, we add additional fully connected network modules with 3 dense layers for other inputs such as age, gender, hypertension classification and heart rate. We concatenate the additional models along with the primary PPG model before passing it through the Softmax classifier that can be used to classify non-diabetic and diabetic patients.

We use a batch size of 8, running for 20 epochs set at a learning rate of 0.001 using Adam optimizer and used Softmax classifier in the final layer of fully connected network to train different models with the above mentioned set of parameters as inputs. We made use of Tesla K80 GPU.

III. Evaluation and Results

A total of 808 patients are taken for the study randomly from the large MIMIC dataset, of which the data from 584 patients were used for training, and 224 patients for testing manually. Out of 808 patients, 341 patients are diagnosed with diabetes. 171 patients diagnosed as diabetic are male, and 170 patients diagnosed as diabetic are female. A total of 595 patients have hypertension, of which 290 patients also have diabetes. From this, we can infer that around 85.04% of diabetic patients have hypertension as co-morbidity. A slightly modified VGGNet model (Fig. 1) was used for training. The test results were output by averaging the probabilistic scores of diabetes obtained for various segments, thereby providing one score for each patient, ranging from 0 to 1. This score was thresholded with different cut-offs for each model obtained from ROC curve to classify a patient as non-diabetic and diabetic.

Out of several CNN architectures that were tried, VGGNet gave better results for the dataset that we used. This test was carried out with different set of inputs. Four different models were built using different set of inputs such as i) PPG, ii) PPG + hypertension classification, iii) PPG + hypertension classification + age + gender, iv) PPG + hypertension classification + age + gender + heart rate. We see that the combination of PPG signals in addition to the age, gender and hypertension classification parameter give us the best results. The confusion matrix (Fig. 3) provides us a better understanding of true and false predictions of diabetic and non-diabetic patients against the ground truth. In order to understand the diagnostic capability of the classification models at different thresholds to predict diabetes, we make use of Receiver Operating Characteristic (ROC) curve. Area under the ROC curve (AUC) gives an aggregate measure of performance across different classification thresholds. The ROC curve (Fig. 4) depicts

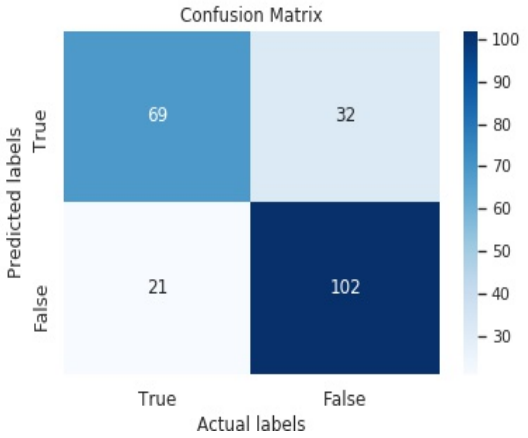

Fig. 3. Confusion matrix of the best performing model

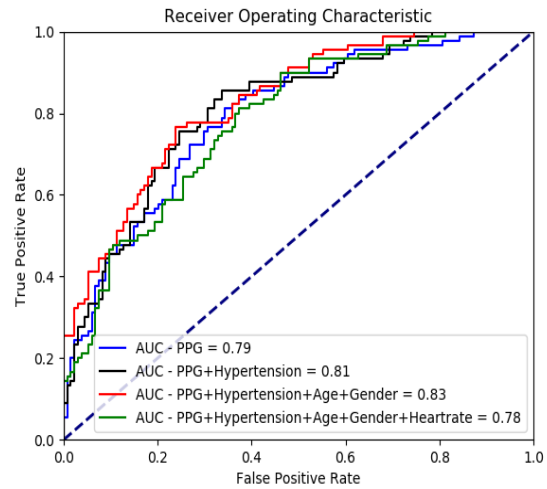

Fig. 4. ROC curves of different input combinations of PPG signals with age, gender, heart rate and hypertension classification. The dashed line represents non-discriminative test

that the input combination of PPG signals with age, gender, heart rate and hypertension classification achieved the best performance with an AUC value of 0.830. From the tabulation (Table II), we can observe that the sensitivity (Sens.) for our best model is 76.66 %, specificity (Spec.) is 76.11 % and accuracy (Acc.) is 76.34 %. The results are comparable to the gold standards shown in the tabulation I for diabetes monitoring and the few existing research works that are present in this area, performing better in a few study parameters. It can also be seen from the tabulation II the performance degrades on the addition of heart rate to the best performing model. This indicates that the model gets confused on the addition of heart rate. It can be keenly understood from the table II that the model with hypertension classification as an additional input along with the PPG signals performs relatively better than the model built using only PPG waveforms.

TABLE I
COMPARISON OF OUR RESULTS AGAINST EXISTING BENCHMARKS

Study	Ours	FPG	HbA1c	Avram [21]	Nirala [11]	Reddy [15]
Sens.	76.66	79.0	86.3	81.0	98.7	-
Spec.	76.11	82.8	75.8	54.0	96.6	-
Acc.	76.34	-	-	-	-	89.0
AUC	0.830	0.890	0.859	-	0.890	-

TABLE II
DIFFERENT INPUTS SENT AND THEIR RESPECTIVE VALUES

Parameters	Sens.	Spec.	Acc.	AUC	Cut-off
PPG	72.2	73.13	72.76	0.793	0.45
PPG + BP	71.1	76.8	74.55	0.808	0.41
PPG + BP + Age + Gender	76.66	76.11	76.34	0.827	0.50
PPG + BP + Age + Gender + HR	68.88	69.4	69.19	0.782	0.42

IV. DISCUSSION

It was mentioned in the work of Nirala et. al. [11] that an absence of dicrotic notch can be observed in the PPG signals of diabetic patients. But, on exhaustive analysis of the MIMIC-III dataset, we observe that the absence of dicrotic notch did not turn out to be a definitive feature for diabetes. On pursuing further research, it was found that the absence of dicrotic notch can be attributed to various other factors such as aging [29], cardiovascular diseases [30] etc. Hence, using the absence of dicrotic notch as a feature to detect diabetes might not be appropriate. In addition, the signals are very much susceptible to motion artifacts which can weaken the performance of the model. These are some of the main reasons as to why conventional hand-crafted Machine Learning techniques would not turn out to be very effective. Deep Learning can be very instrumental in such situations.

It has to be noted that few of the publications have highlighted the significance of very low frequency signals in understanding the cardiovascular diseases. But, a 0.5 Hz low-pass filter is very essential to correct the baseline wandering effect. Baseline wandering can be very detrimental in hampering the morphology of PPG signals. Hence, it is essential to check into ways of preserving very low frequency signals and perform baseline correction simultaneously.

We tried analyzing diabetes using the HRV feature, by retrieving the RMSSD values of 30 sec segments of patients. The results were not satisfactory. We learnt from [31] that time-domain analysis of HRV can be more suitable for longer signal lengths. We obtain better results on adding age, gender, hypertension classification as input along with the PPG input. In our knowledge, this is the first work of diabetes prediction over the MIMIC-III Waveform Database, which was publicly released in April 2020. It is also the first work that uses a scalogram technique combined with CNN to diagnose diabetes.

V. Conclusion

Through this work, we show that our proposed CNN-based classifier can perform as accurate as invasive techniques available for diabetes monitoring and progression. Deep Learning based medical diagnostics can significantly impact healthcare by providing instantaneous diagnoses thereby keeping check of the health of patients efficiently without much manpower. This technique can be used by doctors as a screening test for diabetes before proceeding with the medical checkup. This can further be improved by increasing the training dataset size by adding more data from the MIMIC-III dataset, which could boost the performance of our model to reach FPG test level. We also explained that Deep Learning techniques can function better than conventional hand-crafted Machine Learning techniques due to the presence of motion artifacts and difficulty in determining marked changes in the morphology of PPG signals. We could further improve the model by testing it over our in-house PPG dataset with appropriate clinical ground truths. The Deep Learning model could be trained to neglect the artifacts from the data by itself in future iterations.

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