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# Diabetes detection using deep learning algorithms

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**Abstract**

Diabetes is a metabolic disease affecting a multitude of people worldwide. Its incidence rates are increasing alarmingly every year. If untreated, diabetes-related complications in many vital organs of the body may turn fatal. Early detection of diabetes is very important for timely treatment which can stop the disease progressing to such complications. RR-interval signals known as heart rate variability (HRV) signals (derived from electrocardiogram (ECG) signals) can be effectively used for the non-invasive detection of diabetes. This research paper presents a methodology for classification of diabetic and normal HRV signals using deep learning architectures. We employ long short-term memory (LSTM), convolutional neural network (CNN) and its combinations for extracting complex temporal dynamic features of the input HRV data. These features are passed into support vector machine (SVM) for classification. We have obtained the performance improvement of 0.03% and 0.06% in CNN and CNN-LSTM architecture respectively compared to our earlier work without using SVM. The classification system proposed can help the clinicians to diagnose diabetes using ECG signals with a very high accuracy of 95.7%.


*Keywords:* Deep learning; Diabetes; Heart rate variability; ECG; CNN; LSTM

## 1. Introduction

Diabetes is a disease whereby blood sugar (glucose) is not metabolized in the body. This increases the glucose in the blood to alarmingly high levels. This is known by the name hyperglycemia. In this condition, body is unable to produce sufficient insulin. The other possibility is that body cannot respond to the produced insulin. Diabetes is incurable; it has to be controlled. A diabetic person can develop severe complications like nerve damage, heart attack, kidney failure and stroke. According to statistics in 2017, an estimated 8.8% of global population has diabetes. This is likely to increase to 9.9% by year 2045.

Hyperglycemia caused by diabetes, create abnormalities in the cardiovascular system independent of the possible presence of dyslipidemia, arterial hypertension etc. Diabetes causes cardiovascular autonomic neuropathy (CAN) which completely upsets the nervous system and results in diminished variability in heart rate. Thus, HRV is a marker to identify the presence of neuropathy due to diabetes [1].

Heart rate is the time interval between two consecutive QRS complexes lying adjacent in ECG. The variation in RR interval is represented by HRV. The main attraction is that HRV measurement is non-invasive and reproducible [2]. A variety of machine learning techniques has been proposed for the automated detection of diabetes in a non-invasive way. Deep learning techniques, which can self-learn from data, have been increasingly employed for detecting diabetes now-a-days. Conventional methodologies of feature selection and extraction are not required here.

In our present work, we analyse input HRV signals employing deep learning architectures of CNN, LSTM and its combinations. We achieve a high accuracy value of 95.7% employing CNN 5-LSTM architecture with SVM using 5-fold cross-validation. This work is the sequel to our published earlier work making use of deep learning techniques in diabetes detection with HRV as input data achieving an accuracy of 95.1%.

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**Table 1**
Summary of research works in diabetes detection with HRV data as input.

| Authors | Methods | Accuracy obtained (in %) |
|---|---|---|
| Ref [4] | Nonlinear | 86.0 |
| Ref [5] | Higher order spectrum | 90.5 |
| Ref [6] | Higher order spectrum | 79.93 |
| Ref [7] | Nonlinear | 90.0 |
| Ref [8] | Discrete wavelet transform | 92.02 |
| Ref [9] | Empirical mode decomposition | 95.63 |
| Ref [3] | Deep learning (CNN-LSTM) | 95.1 |
| Proposed method | Deep learning (CNN-LSTM with SVM) | 95.7 |

The remaining part of the paper has the following organization: Section 2 deals with previous important works for automated non-invasive diabetes detection. Section 3 deals with the crucial topic of deep learning and its architectural variants. Dataset is described in Section 4. Section 5 displays the proposed architecture. Section 6 gives information about experiments and results obtained. The paper concludes with Section 6.

## 2. Background topics and related works

A lot of research has happened on the non-invasive automated detection of diabetes using machine learning techniques. Machine learning was employed based on steps of feature extraction, feature selection and classification. There were a variety of works which differed in what type of features was extracted and what classifiers were tried upon. It was further observed that the performance of traditional machine learning algorithms is not up to the acceptable level in crucial artificial intelligence problems of speech recognition and object recognition mainly because of the fact that the dimension of the data handled is high. The shortcomings of machine learning boosted the deep learning research. Deep learning also has its applications in healthcare. Lot of works has recently been published mainly in anomaly detection in the area of healthcare. Related to diabetes detection, [3] used deep learning techniques to detect diabetes from the input HRV data with an accuracy value that closely matches with the maximum accuracy achieved for automated diabetes detection till that date. In the proposed paper, we achieve the highest accuracy value of 95.7% in diagnosing diabetes. Table 1 lists all the important works on the automated non-invasive detection of diabetes using HRV.

## 3. Deep learning

Deep learning is a form of machine learning. Unlike in machine learning, feature extraction and classification are not explicitly done in deep learning networks. The hidden layers of the deep learning network do all these implicitly within itself without involving the external researcher. A short description of deep learning networks is given below.

### 3.1. Recurrent neural network (RNN)

Recurrent neural network (RNN) is capable of extracting dynamic temporal behaviour from an input time sequence. Basic RNNs are a network of nodes emulating neurons, each with a directed (oneway) connection to every other node. Each node has a time varying real-valued activation. Each connection (synapse) has a real-valued weight which can be modified in every iteration. Nodes are either input nodes to receive data from outside of the network or output nodes that yields results, or hidden nodes that modify the data which passes through them via their route from input to output. The difference from the traditional feedforward neural networks is that RNN is capable of using its internal state, otherwise known as memory, to process sequences of inputs.

### 3.2. Long short-term memory (LSTM)

Long short-term memory (LSTM) units are a special type of building units for RNN. It can analyse, classify and predict temporal data sequences of time lags of any size. A typical LSTM network is made up of memory, input, output and forget gates. The memory in LSTM can remember values over arbitrary time intervals. Each of the three gates is a form of neuron (which computes an activation function of a weighted sum). More than that, these gates control the passage of values in LSTM layers; hence these special neurons are named as gates. By long short-term, the fact underlined is that LSTM's memory can really last for large time duration. LSTM tackles the issue of exploding and vanishing gradient problem which is an important issue while training traditional RNNs.

### 3.3. Convolutional neural network (CNN)

Convolutional neural network (CNN) is an improvised variant of multilayer perceptron. CNN is generally made up of an input, an output layer and many hidden layers. The hidden layers of a CNN typically are made up of convolutional, pooling, and fully connected layers.

### 3.4. Hybrid networks (CNN-LSTM)

In hybrid networks, the initial part is CNN consisting of convolution and maxpooling layers only. The maxpooling1D layer's output is fed to the input layer of the next deep learning architecture like RNN or LSTM used.

### 3.5. Support vector machine (SVM)

In support vector machine (SVM), each data sample is represented as a point in a space. It is ensured that a wide separation exists for samples of different categories. When a new data sample arrives, mapping to the space first happens. The category of the new sample is decided depending on what side of the dividing gap, the new data sample point lies. SVM's classification gap can be viewed as a hyperplane in case of binary classification. If more than two classes are present, then

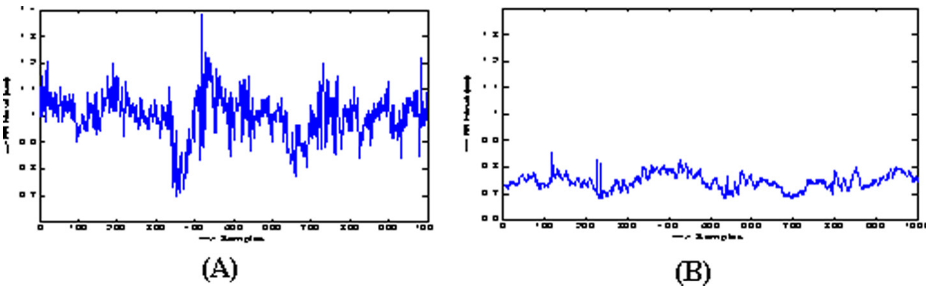


**Fig. 1.** (A) and (B) Sample heart rate signal for normal and diabetic subject.

the dividing gap can be viewed as a set of hyperplanes placed in a high dimensional space. The optimal hyperplane is chosen in such a manner that there is maximum possible distance from the nearest sample on each side to the separating hyperplane. In our case, classification is just to distinguish between the normal and diabetic HRV, hence the basic binary SVM classifier is used.

## 4. Description of dataset

The Electrocardiograms (ECG) of 20 people each from the diabetes and normal group were collected for 10 min with people lying down in a relaxed supine position. The heart rate time series data is derived from ECG signals using Pan and Tompkins algorithm. This real-time algorithm can effectively detect QRS complexes in an ECG signal based on its morphological features like slope, amplitude and width. It involves processes like digital bandpass filtering (to reduce false detections due to noise) and thresholding operations (to increase detection sensitivity). The ECG signal is sampled at 500 Hz. 71 datasets (same number for diabetic and normal group) each were extracted from the recorded data. Each dataset contains 1000 number of samples. The input data (Fig. 1) is passed to deep learning algorithms without any further pre-processing.

## 5. Proposed architecture

An overview of proposed architecture is shown in Fig. 2. This is composed of 3 main sections. In input layer, the heart rate variability of raw ECG signal are given as input to deep learning architecture. This contains 5 CNN layers and each layer follows maxpooling. First two CNN layers contain 64 and 128 filters with filter length 3 and maxpooling with pooling length 2. Next two CNN layers contain 256 and 512 filters with filter length 3 and maxpooling with pooling length 4. A last CNN layer contains 1024 filters with filter length 3 and maxpooling with pooling length 6. This feature map is passed into LSTM layer. LSTM contains 70 memory blocks which learns the time domain features. This follows dropout 0.1. This randomly removes the neurons along with its connections. Finally, the features are passed into SVM for classification. The SVM used RBF kernel. This is defined as follows with samples $s$ and $s1$

$$K(s, s1) = \exp\left(\frac{\|s - s1\|^2}{2\sigma^2}\right) \tag{1}$$

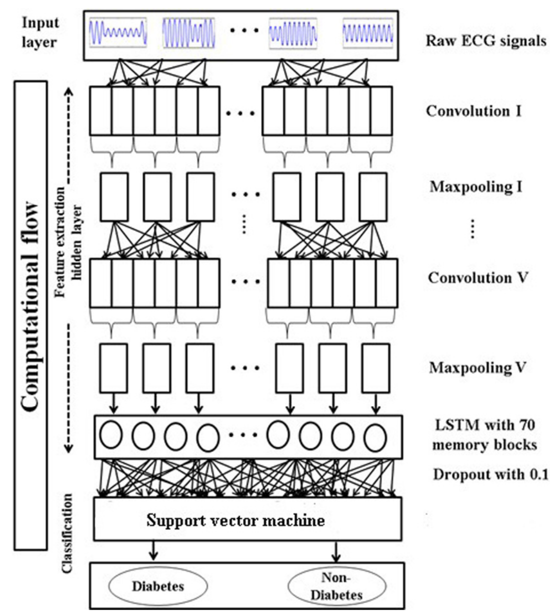


**Fig. 2.** Overview of proposed architecture.

## 6. Experiments and results

All experiments are run on GPU enabled TensorFlow [10] with Keras [11] framework. In this work, we use the same configuration that we had used in our early paper [3]. In this work, we extract features in deep learning network, comprised of CNN-LSTM architecture and pass into SVM for classification. LSTM has the capability to handle long-term dependencies in a data sequence. To decide the kernel function, we run two trail of experiment for SVM with linear and RBF kernel. SVM with RBF kernel performed better. These SVM model are implemented using Scikit-learn. The detailed 5-fold cross-validation accuracy is reported in Table 2. In almost all the network structures, SVM has performed better in 5-fold cross-validation with accuracy which is comparable to the fully connected linear with nonlinear activation function for classification. Thus, we claim that the combination of SVM in penultimate layer for classification with deep learning layers for feature extraction can achieve the best performance.

## 7. Conclusion and future work

Considerable part of human population is under the grip of diabetes which is incurable. If not managed well, diabetes can

**Table 2**
Detailed results.

| Architecture | Accuracy obtained |
|---|---|
| CNN 1 with SVM | 0.684 |
| CNN 2 with SVM | 0.755 |
| CNN 3 with SVM | 0.887 |
| CNN 4 with SVM | 0.913 |
| CNN 5 with SVM | 0.939 |
| CNN 1-LSTM with SVM | 0.743 |
| CNN 2-LSTM with SVM | 0.764 |
| CNN 3-LSTM with SVM | 0.853 |
| CNN 4- LSTM with SVM | 0.937 |
| CNN 5-LSTM with SVM | **0.957** |

lead to health hazards. Hence, early detection of diabetes is extremely crucial. Nerve damages caused by diabetes, affect the working of the heart. In the proposed work, HRV data is analysed to diagnose diabetes using deep learning techniques. The maximum accuracy value of 95.7% was obtained for CNN 5-LSTM with SVM network. This is the highest value published for the automated diabetes detection with HRV as input data. Our non-invasive, flexible and reproducible system can serve as a reliable tool to clinicians to detect diabetes. Further improvement in accuracy can be obtained using a very large sized input dataset. The potential of deep learning is so tremendous that it can take a big stride in future to the so far challengingly difficult area of anomaly prediction from the anomaly detection if sufficiently large sized input data is available for research. The anomaly prediction can be tried from the input data which may not have anomaly by extracting dynamic characteristics from the input data. The predicted information can serve as a warning signal for the patient as well as the doctor to take sufficient control and precautionary measures.

## Conflict of interest

The authors declare that there is no conflict of interest in this paper.

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