A model for early diagnosis of Cardiac Autonomic Neuropathy (CAN)

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Abstract. Convolutional Neural Networks (CNN) are widely used as prediction models in medical diagnosis in the recent research. Remodelling the CNN architecture to make it more reliable for classification is the core of each finding. Cardiac Autonomic Neuropathy (CAN) is a severity amongst the diabetic population, who are subject to diabetes for long duration. The aim of this work is to provide a predictive mechanism that is designed for more reliable diagnostics by studying the ECG physiology and enhancing the diagnostics by artificial technique, like using a remodelled CNN architecture. Results of CNN show 95.42 % efficiency in classifying between groups of CAN+ and CAN- groups.

1. Introduction
As there is a steady increase in percentage of diabetic population around the globe, diabetic related comorbidities are under study in order to coin techniques for early diagnosis. Diabetes is spelled commonly above the age of 55 on an average with the age limit falling lesser every decade [2]. Diabetes leads to all types of Neuropathy that includes Diabetic Peripheral Neuropathy (DPN) and Autonomic Neuropathy (AN) [1]. However, the latter involves the risk of cardiac dysfunction which is termed as Cardiac Autonomic Neuropathy (CAN). CAN is strongly related to major cardiovascular events and arrhythmias that independently marks for increased mortality and morbidity [5, 7]. Hence, early diagnosis of CAN will be useful to provide medication for glycemic control by medical experts [6].

The electrical activity of heart is recorded using Electrocardiography (ECG) that reveals the functioning of heart and any abnormal changes [8]. Features extracted from ECG helps in understanding the condition prevailing in an individual. In order to have the useful information, all the unwanted noise from ECG has to be removed, as biomedical signals are subject to noise while being recorded. There had been quite a few researches on removal of artefacts from ECG [3, 4]. To have a more accurate predictive technique that removes the noise from ECG and carries out analysis from ECG, Convolutional Neural Networks (CNN) have been employed after pre processing the ECG data [9-11]. This study has investigated on ECG signal to identify specific segment changes that are profoundly related to identification of CAN.

2. Materials
In this study, ECG data was obtained from 13 Male and 6 Female participants. The data has two groups comprising of 10 normal (CAN-) and 9 CAN+ (both early CAN and definite CAN) subjects. ECG was measured with stable environmental temperature with 10 minutes of rest period in supine position. Signals were measured for 20 minutes with a sampling frequency of 400 Hz using lead II electrodes. The methodology is shown in Fig.1.
A sample of raw ECG signal from each group is shown here in Fig. 2.

Figure 2: Raw input signal of a) Normal b) eCAN and c) dCAN

The physiology of ECG wave is that it follows a self similar pattern normally, as ECG waves are electrical impulse; the activity of heart has been expressed as P, Q, R, S and T waves, referred as attributes. If there is any complication, the pattern of ECG wave gets altered. In order to make more efficient decision the physiology of ECG specific to CAN has been studied and four segments, say PR, QT, RR and ST have been selected for analysis.

3. Methodology

The time intervals of the selected segments was compared between the groups, as these are the segments reported in literature [12, 14] that are significantly varying. There are many techniques to study and classify among the group, this work concentrates on identifying the complexity of segments within the subject which can evolve in understanding the physiology of signal and makes is possible for early diagnosis which is the need.

3.1. Data Pre Processing

ECG data as shown in Fig.1 has mainly two types of noise based on recording; they are baseline wander (BW) and power line interference. In order to capture the usable information a series of filter has been applied on signal to remove artefacts. A 3 Hz HPF to remove BW and to remove power line interference a 50 Hz notch filter is used.
3.2. Convolutional Neural Network Architecture
The CNN architecture consists of 5 layers in total that is broadly divided into two sections for feature extraction and classification [14]. The layers are as follows: 2 convolution layers (C layer), 2 sub sample layers (S layer) in addition there is 1 input and 1 output layer.
The C layer takes care of feature extraction which acts like a filter in retrieving the segment information from ECG and S layer perform down sampling, where data is reduced in dimension and data is preserved, it also also performs pooling technique. The CNN architecture is designed for handling two dimensional data, however to be compatible for ECG the model has been restructure to handle one dimensional input, 16 convolution kernels with length of 6 sampling points are distributed in the first C layer (C1) and the second C layer (C2) also consists the same number of kernels.

4. Experiment

![Figure 3: Plot showing 20 seconds and 2.5 seconds of ECG signal after removal of artefacts.](image)

The raw data after pre processing has the noise removed and is given in Fig. 3 while Fig. 4 shows all the attributes marked in ECG wave, segments (PR, QT, RR and ST) are retrieved from these points. These segments have been analysed to give the FD value under each subjects, mean value of all points taken for an individual if shown in Fig. 4. The method employed to find FD value is Differential Box Count (DBC) method, as this method is fast and reliable.

5. Results And Discussion
The results of FD value obtained are graphically represented in Fig. 5 that shows a plot of mean and standard deviation (SD) between the individual subjects. CNN takes care of analysing the complexity changes within the individual as a result brings a predictive model for early diagnosis of CAN.
Instead of dividing (30-70 or 40-60) the data for training and testing in CNN, the data was tested using ‘leave out one method’ that takes one sample at a time for testing while all other data serves as training data. A training efficiency of 95.42% was achieved with an error rate of 0.0458 and learning rate of 0.01.

Table I. Confusion Matrix of CNN Classification

|     | N    | eCAN | dCAN |
|-----|------|------|------|
| N   | 874  | 0    | 62   |
| eCAN| 0    | 871  | 64   |
| dCAN| 0    | 0    | 881  |

6. Conclusion
The work has interpreted the data for four segments which are specific for CAN diagnostics. Moreover, apart from using only Heart Rate Variability (HRV) that is computed from RR interval; other segments have been considered to make an affirmative prediction. This study reveals that segment analysis alone cannot be considered for an predictive model, rather the complexity in segment over a period has to be considered.

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