DEEP NEURAL NETWORK FOR PHONOCARDIOGRAM SIGNAL CLASSIFICATION

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Abstract: The methods for diagnosing the patients of cardiovascular diseases have advanced from period to period. Based on the PhysioNet challenge 2016, this work concentrates on the Phonocardiogram (PCG) data classification. The PCG data of heartbeat can be analyzed to get the condition of heart. For this, the data has to be pre-processed and need to be fed to a classifier. In the present work, deep neural network (DNN) architecture classifies the PCG data into normal and abnormal classes. To improve the accuracy of the classifier, we have proposed the DNN architecture with seven layers. The proposed DNN architecture for PCG data classification provides high accuracy, when compared to all the classical machine learning algorithms.

Keywords: - Component,formatting,style,styling,insert.

I. INTRODUCTION

Heart auscultation is an action to diagnose heart sound typically with the help of stethoscope. But, perfect analysis can't be obtained by listening to sound. Now-a-days, cardiovascular disease (CVD) is increasing among the people in a wide range, which is becoming a major challenge in the world of medical science [2]. Electrocardiography (ECG) is introduced, which is used in obtaining the electrical behaviour of heart by recording the pattern as polarised and depolarised signal at every systole and diastole of heart beat [8].But, ECG is used to assess only the electrical activity of heart. It fails to sense other important quantities like noise, murmurs and various physiological behaviour of the heart [1].

To overcome this problem, phonocardiography (PCG) is used to record the advance muscular activities of the heart. During cardiac cycle, some contractions held in between the arteries and the valve, which produces a sound like murmurs, snaps, clicks and noises are recorded. These contractions will be held at four different states of recording sounds, which is S1, Systole, S2 and Diastole [1]. In each phase, the sound produced is different, which decides the functionality of heart. . These sounds have been recorded for the analysis of cardiac cycle. Using data from PCG, PhysioNet came up with large database of heart sounds from various medic environments as a classification challenge in the recent past year 2016 [1]. These sounds were recorded in major blood pumping areas like aortic, pulmonic, tricuspid and mitral. The dataset includes a total number of 2,33,512 samples of heart sounds from 1,16,865 heartbeats for normal and abnormal classes with different problems [1].

Using this data, many works have been implemented in the area of signal processing mainly focussing on sound. We consider classifying this data using the latest advanced methods like classical machine learning and deep neural network (DNN) [3]. Machine learning algorithms are realm of big data and applied at various fields. In advancement to this, DNN made breakthrough various fields, which come up with huge computation task leading to high accuracy [4]. DNN is a hierarchy of multiple neural networks which helps to train complex data and learns the generalized pattern of the data [5].

II.Related Works

In this paper, we came up with classical machine learning and deep learning approaches on heart sound classification using the PCG data, which is required to understand the detail functional behaviour of the heart [2]. Previously, many research works were done using different signal processing techniques. Considering sound as an important factor, the features from time, frequency and wavelet domain were derived [2]. To analyse the heart sound features, there are no existing studies on deep learning until PhysioNet challenge has released a dataset in 2016. Using this data, few research papers have been proposed related to deep learning and machine learning [1]. Automatic classification is done by all deep learning algorithms among which, we are using artificial neural network (ANN), which learns the features based on the training data. There are different classifiers in machine learning like Support Vector Machine (SVM), k-nearest neighbor (KNN), Logistic Regression (LR), AdaBoost, which are applied to identify pathological sound features of heart beat.

Logistic regression (LR) differentiates the time interval, systolic murmurs and classifies into a step wise spectrum of signals [8]. The Deep belief network is used for feature engineering and SVM for classification in image processing.[14]. Like wise in signal AdaBoost ensemble based classifier decomposes the main four frequency bands of cardiac cycle and is fed to a convolution neural network (CNN) [13]. CNN computes time series signals and overlapped segments length, which is used for training and testing the model [7].Considering time series into account, recurrent neural network (RNN) and long short term memory (LSTM)

comes with more accuracy than CNN and SVM classifier [6]. Using RNN, long range contextual information of the time series is modeled with multiple stacking recurrent hidden layers, by stacking feed forward method over layers is used by conventional networks [5].

Deep long short-term memory derives the potentiality of signals by using Hidden Markov model, which is helpful in pre-processing like filtering, peak value and peak point detection of signals [6]. If RNN is processed, the performance becomes low due to the long term temporal dependencies. To solve this problem and to obtain a higher performance, LSTM architecture is suggested[12]. LSTM is a special kind of RNN, which helps in explicit long term dependency problem. Using a single neural network layer, there are four different ways to perform the processing of LSTM, which results in lower complexity and short-run time of data.To overcome all these drawbacks, deep neural network (DNN) is used in this paper. Unlike the RNN, the proposed architecture learns and extracts the features by learning the input data and process the information without any vanishing gradients.

III.Proposed Experiment

In this experiment, the data is classified using classical machine learning (CML) and deep neural network (DNN) algorithms. In CML, seven classifiers are used for classification namely: Logistic Regression (LR), Naïve Bayes (NB), K-Nearest Neighbors, Decision Tree (DT), Ada Boost, Random Forest(RF),Support Vector Machine-Radial Basic Function (SVM-rbf), Support Vector Machine Linear (SVM -L) as shown in fig1.

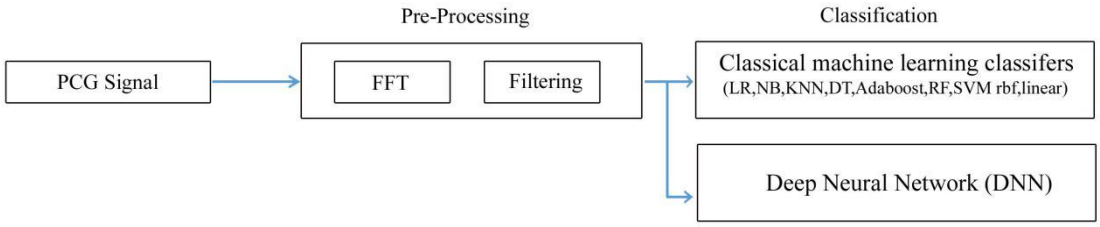

Fig1. Schematic illustration of heart beat classification using classical machine learning and Deep Neural Network (DNN) algorithm

3.1Processing

The database sound signal is taken for analysis for easy processing and the signal is sampled with a frequency of 2 kHz. The obtained frequency has more noise and some hidden units, which are difficult to obtain a perfect output. So, FFT is helpful in noise removal [2]. The PCG signal is fed to a pre-processing level, where the features of the signal are extracted. The extracted signal features contains frequency domain, which is filtered by Butterworth band pass filter at specified frequency range [2]. The obtained data signals are trained using CML and DNN algorithms to classify as normal or abnormal sound of heartbeat.

3.2 Classification

Classical Machine Learning Approach (CML)

In Classical machine learning approach, the obtained filtered signal is passed to all the 7 classifier algorithms where, each algorithm possesses different functionality parameters. So, the training is done by setting epoch values and validation parameters. Since the algorithm differs, the results are obtained accordingly to the application of each algorithm. CML is basically a shallow network to which, data is fed and a model is created.

Proposed Deep Neural Network Approach (DNN)

As DNN is a parameterized, the performance relies on the optimal parameters. Thus, identifying optimal parameter is considered as an essential objective in the present work. Initially, to determine the number of units in a DNN layer, we ran three trails of experiments with number of units in the range [256-512-1024, 2048, 3072] with a moderately sized DNN. DNN network with 3072 gave good performance as shown in table 1. Thus, we decided to set the number of neurons as 3072. To identify the learning rate, two trails of experiments are run in the range [0.01-0.5]. Among the experimental range, DNN network has performed well with the learning rate 0.01. By setting parameters and learning rate, the input is passed through the DNN network layers with each layers are possessed with set of neurons associated with specific weight. These weights are trained using backpropagation method and weights are optimized [10]. During the weight optimizing process, some neurons posses with error, which is known as gradient loss function. The error is rectified by passing the weight into activation function [3]. Rectified linear unit(ReLu) function is used to calculate the gradient loss. The function propagate over each hidden layers and target the loss function on the neurons and update the bias and the weight at each layer [11].

Table-1 Parameters of the DNN architecture.

Layer (type)	Output Shape	Parameters
dense_1(Dense)	(None, 3072)	1846272
dropout_1 (Dropout)	(None, 3072)	0
dense_2 (Dense)	(None, 2048)	6293504
dropout_2(Dropout)	(None, 2048)	0
dense_3 (Dense)	(None, 1024)	2098176
dropout_3 (Dropout)	(None, 1024)	0
dense_4(Dense)	(None, 768)	787200
dropout_4 (Dropout)	(None, 768)	0
dense_5 (Dense)	(None, 512)	393728
dropout_5 (Dropout)	(None, 512)	0
dense_6 (Dense)	(None, 256)	131328
dropout_6 (Dropout)	(None, 256)	0
dense_7(Dense)	(None, 128)	32896
dropout_7 (Dropout)	(None, 128)	0

We created 6 hidden layers with updated bias and weights. During this weight update, network posses with over-fitting problem. To overcome over-fitting, regularization is done over the network. The regularization is done by applying dropout. Dropout is applied at the first hidden layer of the network, where loss is dramatically high, by which every node in the hidden layer is trained according to the weights over-fitted to the node and updated with new weights. Likewise, every layer is processed with dropout [10].

IV.Dataset Description

The objective of the proposed framework is to categorize the recorded heart sound signal into two categories namely, normal and abnormal. The normal sounds recorded were of the healthy people and abnormal sounds were of the people suffering from different cardiovascular problems. The obtained data from PhysioNet 2016 challenge contains six different data sets classifying normal and abnormal. From the entire dataset, 70% is taken for training and 30% for testing [1]. The detailed description of the dataset is given in Table 1. The total numbers of training instances are 1803 and 466 for normal and abnormal classes respectively. The total numbers of testing instances used for both the classes are 772 and 199 respectively.

Table-2 Description of the PCG dataset available in PhysioNet 2016 Challenge [1]

	Normal			Abnormal		
Data	**Total**	**Train**	**Test**	**Total**	**Train**	**Test**
Set-a	117	82	35	292	204	88
Set-b	386	270	116	104	73	31
Set-c	7	5	2	24	17	7
Set-d	27	19	8	28	20	8

Set-e	1958	1371	587	183	128	55
Set-f	80	56	24	34	24	10
Total	2575	1803	772	665	466	199

V.Result Analysis

Using Classical machine learning algorithm (CML), several outputs are obtained in which the highest value obtained in RF with accuracy-0.822, precision-0.866 and Fl-score-0.911 as shown in table-3. To get better results, DNN is implemented. We ran various trails within the epochs of 600. These epochs helps to learn the complexity of the data over the network. First, we formed 3 layer DNN network and the result obtained from the network is well at the first layer of DNN compared to CML. To increase the performance of the network, we proceeded to 5 layer followed by 7 layer network. We obtained accuracy- 0.931, precision-0.968, recall-0.944 and Fl-score-0.956 using seven layers. We repeated the process by increasing the network layer. But there was no better result observed, so we formed the network with 7 layers.

Table-3: Performance assessment obtained for different classical machine learning algorithms (Logistic Regression (LR), Naive Bayes (NB), K-Nearest Neighbors, Decision Tree(DT), Ada Boost,Random Forest(RF),Support Vector Machine-Radial Basic Function (SVM-rbf), Support Vector Machine Linear(SVM -L)) for PCG signal classification.

Classification Algorithms	Accuracy	Precision	Recall	Fl-score
LR	0.763	0.837	0.872	0.854
NB	0.328	0.861	0.185	0.305
KNN	0.808	0.860	0.907	0.883
DT	0.783	0.855	0.877	0.866
Ada Boost	0.841	0.866	0.918	0.902
RF	**0.850**	**0.866**	0.961	**0.911**
SVM rbf	0.822	0.834	**0.970**	0.897
SVM Linear	0.759	0.838	0.864	0.851

Table-4: Performance assessment obtained for different number of hidden layers using the proposed DNN architecture for PCG signal classification

Proposed Architecture	Accuracy	Precision	Recall	Fl-score
DNN 1 Layer	0.846	0.863	**0.958**	0.908
DNN 2 Layer	0.842	0.890	0.914	0.902
DNN 3 Layer	0.853	0.873	0.955	0.912
DNN 4 Layer	0.850	0.895	0.920	0.907
DNN 5 Layer	0.853	0.891	0.930	0.910
DNN 7 Layer	**0.931**	**0.968**	0.944	**0.956**

VI.Conclusion

In this paper, deep neural network (DNN) architecture is proposed for classification of PCG signal. The signal is analyzed using classical machine learning algorithms. But, DNN gave better performance results when compared to CML algorithms. DNN is more effective, when compared to CML algorithms. The performance rate of proposed DNN is higher in comparison with CML algorithms. The proposed DNN architecture can be performed with the real time data, which will be helpful in various fields especially in the medical field, as assistive tool for monitoring health condition of patients.

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