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Convolution Neural Network Model based ECG classifier

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ABSTRACT:
Cardiovascular diseases (CVDs) are commonly diagnosed by inspecting ECG image, ECG demonstrate the electrical activity of the heart. The abnormality of the heart is called arrhythmia. The arrhythmia is divided into three categories normal, abnormal, noisy. The goal of our research is to design a Deep learning based convolution neural network which can carry out the task of feature extraction, classification. Our experiments with these Algorithm achieved overall accuracy above 98.0%, precision above 91.0%, specificity above 98.4%, and sensitivity above 98.7%. The performance of the proposed algorithm is tested on ECG images that are taken from Experimental database.
Keywords— ECG Arrhythmia Images, Deep Learning (DL), Convolution Neural Networks (CNN), ECG images.

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I. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are the number one cause of death today. Over 17.7 million people died from CVDs which is an about 31% of all deaths , and over 75% of these deaths occur in low- and middle-income countries[1]. Arrhythmia is a representative type of CVDs that refers to any irregular change from the normal heart rhythms. There are several types of arrhythmia including atria fibrillation, premature contraction, ventricular fibrillation, and tachycardia.

The graphical recording of the electrical signals generated by the heart is known as ECG which provides diagnostic information about the cardiac condition of a patient. P wave is the first electrical positive signal in the normal ECG. It has positive polarity and duration is less than 120 milliseconds. The largest part of the ECG signal is the QRS complex which is the result of contraction of the ventricles where: a. Q wave is the first negative or downward deflection. b. R wave is always the first positive deflection, c. S wave is the negative deflection followed by the R wave [2]. The difference in amplitude and interval of different wave provides a measure for detecting various cardiac abnormalities. The most distinguishable time domain features of ECG signal are QRS-complex, RR interval, ST segment etc . Disturbance of this electrical function is common in cardiac disease. The abnormalities in heart is found by the doctors by observing the deviation of P, QRS and T signal from the normal signal in terms of time duration and amplitude[4]. ECG is a bipolar low frequency weak signal and the normal range of this signal is 0.01-150Hz. Its amplitude ranges from 0.05-3mV and normal heart rate is 60-100 BPM [2].

The literature has reflected that the arrhythmia detection and classification are well-known methods used in the diagnosis of cardiovascular disease [3-5].

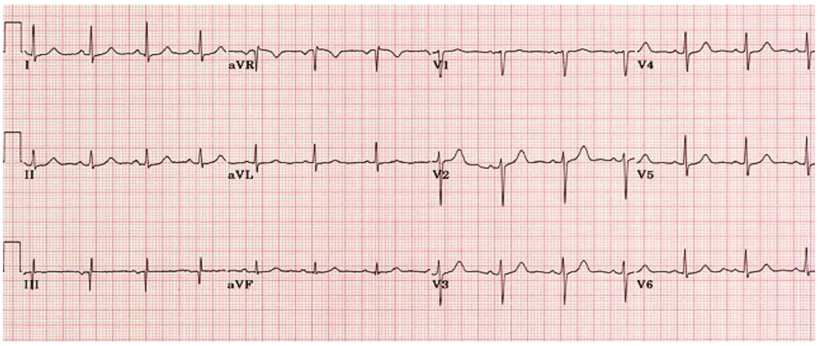

Fig: Normal ECG Image

In this paper, we propose a frame work for ECG classification using deep neural networks. For this to happen we describe a deep learning and Convolution Neural Network. This network has been trained on the task of arrhythmia detection for learning which it is possible to assume that the model need to learn most of the shape related feature of the ECG Images. Also we have a large amount of labeled data with classes for this task, which makes it easy to train a model with convolution neural network and multiple hidden layers, Activation layers and the result in the form of accuracy.

The remaining paper is organized as follows. The related work is introduced in Section II, the details of our proposed method are given in Section III, and the performed experiments and resulting discussions are presented in Section IV. Finally, several concluding remarks are given in Section V.

II. RELATED WORK

U Rajendra Acharya et al, In this work a CNN was trained using the augmented data and achieved an accuracy of 94.03% and 93.47% in the diagnostic classification of heartbeats in original and noise free ECGs, respectively. When the CNN was trained with highly imbalanced data (original dataset), the accuracy of the CNN reduced to 89.07%% and 89.3% in noisy and noise-free ECGs. When properly trained, the proposed CNN model can serve as a tool for screening of ECG to quickly identify different types and frequency of arrhythmic heartbeats [6].

The goal of this research was to design a method based on one Dimensional Convolution Neural Networks (1-D CNN) for the classification of ECG Signal which is able to accurately classify three different arrhythmias, like N-Non-ecotic beats or normal beat , V -Ventricular ectopic beats , Q -Unknown Beats. The present research is based on 60,000 ECG signals fragments from the PhysionNet's MIT-BIH Arrhythmia database. The database is divided into two categories, that is train set and test set. The 1-D CNN is applied to the database and the obtained result gives the accuracy of 97.44%[8].

Yıldırım et al, The recent findings show that deep neural networks (DNNs) extract representative features directly from input data and classify them with the aid of hidden layers (convolutional and max-pooling layers). DNNs, convolutional neural networks (CNNs), recurrent neural networks (RNNs) long short-term memory (LSTM) and combinations of these networks and pattern recognition algorithms were used as deep learning approaches on ECG arrhythmic heartbeat classification. DNNs models are sent to ECG signals as 1D data form of features.. [8]

Yao et al, proposed deep bidirectional LSTMs network-based approach with wavelet-based layers that obtained the frequency sub-bands of ECG signals which is achieved 99.39% for five different arrhythmia classification on MIT-BIH database.. [9]

Acharya et al, Discussed the attention-based time-incremental convolutional neural network (ATI-CNN) that preserve both spatial and temporal information of ECG signals with classification accuracy of 81.2% on classification of paroxysmal arrhythmias.[10]

Rahhal et al, proposed that combining of topological data analysis, features and deep learning approach which is achieved 99.00% on MIT-BIH arrhythmia benchmark database.. [11]

Hannun et al, proposed a novel approach based on DNNs with using stacked denoising autoencoders (SDA) for ECG signal classification which is obtained high accuracy values on three different databases.. [12]

III. PROPOSED METHOD

A] The Block Diagram of CNN

The proposed Block Diagram is consists of Data Acquisition, Classification Model, Training data, Testing data and output classifier. The Data (ECG images) are taken from data Acquisition and divided into two categories Training data and testing data. This data is fed to classification model with

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respect to algorithms it classify and it gives output result to output classifier.

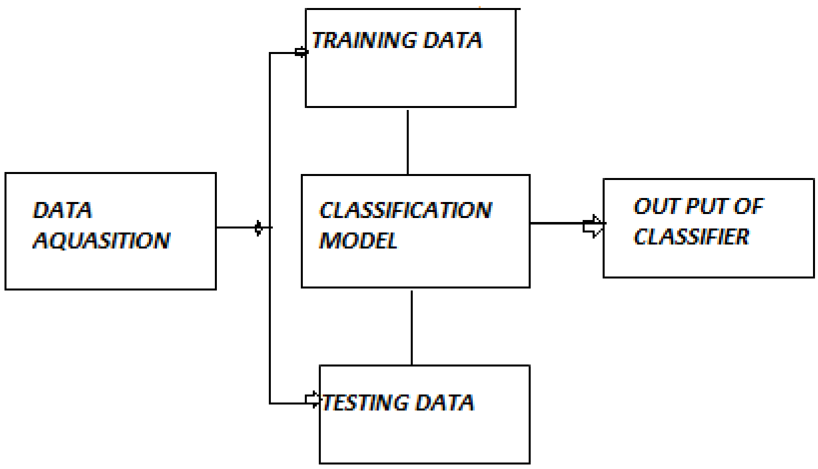

Fig 1: Block Diagram of CNN

B] Flow of CNN

The proposed method is consist of data acquisition, classification model(CNN) training data and testing data and out put. for gaining the necessary data parameters from the ECG is carried out. To classify heart disease we train a Convolutional Neural Network (CNN) model using experimental ECG images. The model involves the following steps [17].

Convolution neural network is a subset of artificial intelligence . CNN acts as a camera to ANN and CNN is used for image recognition .

The flow of Convolution neural network are :

STEP 1 – convolution layer (input , feature detector , feature map)

STEP 2 – max pooling layer (feature map , pooled map)

STEP 3 – flattening (convert the feature map into vertical form)

STEP 4 – full connection with ANN (output of CNN is connect ed to input of ANN)

C] Architecture of Convolution Layer

This is the first layer. The image of each ECG is considered as an input to layer. Then the image is converted into matrix of pixels. After that the matrix is reduced into the smaller matrix by applying some filters(rules). The value of filters is multiplied by original pixel values when filters displaces in line with the image grid [18].

The summing of multiplication is done to give one final number at last, since the filter reads the image from top to bottom and left to right. So, in this format the filters are applied and we get a reduced matrix.

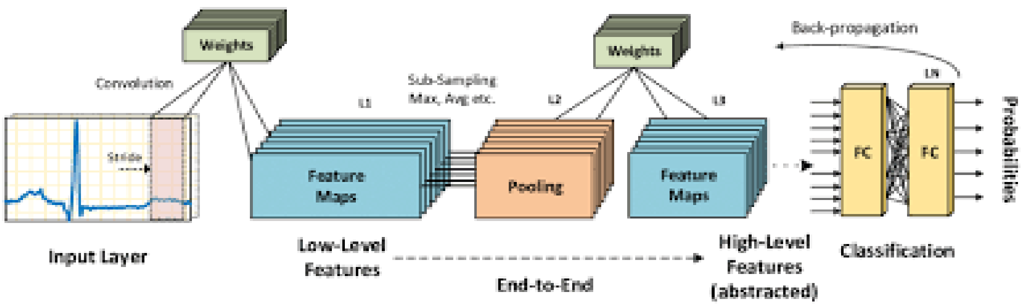

Fig 2: Architecture of CNN

ELU Layer

This layer is the activation function layer which is the modified version of ReLU activation function to produce more accurate results known as Exponential Liner Unit. The layer tends to coverage cost to zero

$$ELU \quad \begin{cases} x & for\ x \geqslant 0 \\ \alpha(e^x - 1) & for\ x < 0 \end{cases}$$

Pooling Layer
This layer is used to reduce dimensions of the feature map and computations. It uses down sampling method. They can Max, Average from rectified and downsized feature map.

Fully Connected Layer
This portion is responsible for taking output from convolution networks. The fully connected layer at end of the network results in N dimensional vector, where N is the number of classes from which the softmax activation function layer selects the class having greater probability.

Softmax Layer
This is activation function layer which is responsible for multi-class classification. The layer converts outputs from Fully Connected Layer into probability distributions and the class having greater probability of occurrence than other classes is selected as the final classification output. The output from this layer ranges from [0,1] as the sum of probabilities for the outcomes of an event is one. This is the last layer of the model for the final classification and its equation is shown below

$$\text{softmax}(z_j)= \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \text{ for j = 1,...,K}$$

where z is the inputs as vectors to output layer and j indexes the output units from 1,2,3…., K.

D] ECG data(Samples)
In this Study, ECG database are collecting from hospital. Real experiment dataset are used for performance evaluation of the proposed patient-specific ECG approach. 6000 images are collected from the hospital. This ECG images have supported our own research into arrhythmia analysis and related subjects. The database is divided in three categories Normal, Abnormal, Noisy ECG images.

IV. PERFORMANCE MEASURES

We have evaluated the performance of the classification algorithms using six measures; sensitivity, specificity, classification accuracy. These measures are defined using True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP decision occurs when an arrhythmia detection of the classifier coincided with a decision of the physician. TN decision occurs when both the classifier and the physician suggested the absence of arrhythmia. FP occurs when the system labels a healthy case as an arrhythmia one. Finally, FN occurs when the system labels an arrhythmia case as healthy.

Classification Accuracy
Classification accuracy is defined as the ratio of the number of correctly classified cases and is equal to the sum of TP and TN divided by the total number of cases N.
FPR = $(TP + TN)/\ \mathrm{T}N$ or
FPR=1-TNR

Classification Sensitivity
Sensitivity refers to the rate of correctly classified positive and is equal to TP divided by the sum of TP and FN. Sensitivity may be referred as a True Positive Rate.

TPR = $TP/\ (TP + FN)$

Classification Specificity
Specificity refers to the rate of correctly classified negative and is equal to the ratio of TN to the sum of TN and FP. False Positive Rate equals (100-specificity).
TNR= $TN/\ (FP + TN)$

V. EXPERIMENTAL RESULT

The database used was Experimental Images Arrhythmia, includes Normal, Abnormal, Noisy Images. Deep neural networks can carry out the task of feature extraction, classification directly from the experiment data itself. Here we use Convolution Neural Network(CNN) a Deep Learning algorithm, The database is divided into two categories, that is train set and test set. Our experiments with these Algorithm achieved overall accuracy above 98.9%, precision above 91.8%, specificity above 98.4%, and sensitivity above 98.7%. The performance of the proposed algorithm is tested on python platform. The 6000 Experiment ECG Images are collected from Jaydeva Cardiac Centre, Kalaburagi, Karnataka, India.

Method	Accuracy	sensitivity	specificity
CNN	98.9	98.7	91.8

Table: Result of CN

VI. CONCLUSIONS

This paper proposed CNN networks. The proposed had high accuracy and had low complexity of implementation. This model had Accuracy is 98.9%, sensitivity is 98.7 %and specificity is 91.8% . By comparing and contrasting various methods in the "Discussion" section, we could affirm that the method applied in the present paper yielded considerably better performances than those of the state-of-the-art

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