Classification of ECG using convolutional neural network (CNN)

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***Abstract*-. Electrocardiogram (ECG) gives the clear record on electrical activities of heart. This record can be used to diagnose various heart diseases. An approach is proposed to automatically detect the myocardial infraction using ECG signals. In this work, a convolutional neural network (CNN) algorithm is implemented for the automated detection of a normal and Abnormal ECG signals (Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB), Atrial premature beat (APB) and Paced beat (PB)). The feature extraction and signal classification both are carried in a single CNN unit. MIT-BIH arrhythmia database is used to obtain the five different classes of ECG signals. This proposed classifier accurately classifies the signals with reduced classification time. So, in clinical settings this method can be implemented to help the clinicians in the diagnosis of myocardial infarction.**

Keywords: Electrocardiogram (ECG), Cardiovascular diseases (CVDs), Convolutional neural network (CNN)

I. INTRODUCTION

Cardiovascular disease (CVD) is a very significant cause of death worldwide. It is the condition of affecting the heart or blood vessels. Figure 1 shows an illustrates of myocardial infraction due to the blockage in the heart. It can be prevented by leading a healthy lifestyle.

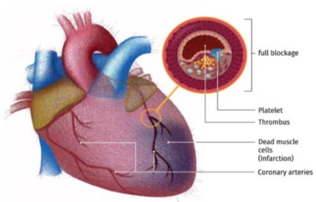

Figure 1. An illustration of myocardial infraction

In this paper, we have proposed a convolutional neural network classifier to classify ECG signal into normal and abnormal classes. The single lead ECG signals are used for this classification which is tested on MIT-BIH database. The proposed classifier achieves good classification performance with other classifiers in terms of accuracy and computing time.

Deep learning consists of an input layer, hidden layers, and an output layer. The term deep learning refers to two or more hidden layers in the architecture. It is an automatically learning algorithm which learn the necessary features from the given input signals used for classification. The Convolutional neural network is a class of deep learning technique. Convolutional neural network [1], [2] mostly used in analysing image.

II. PROPOSED WORK

The block diagram of proposed work is shown in the following figure 2. The abnormalities in the input ECG signals are classified using Convolutional neural network classifier.

A. Database

The MIT-BIH Arrhythmia Database [3] is taken in this classification method. It has 48 recorded signals which are recorded from 47 person. The records are extracted from two leads namely leadII and leadV1. The duration of each record is half an hour. The records from 25 men who is 32 to 89 years old and the 22 women who is 23 to 89 years old (two records are collected from the same male). The sampling rate is 360 samples per second. ECG signal extracted from lead II is used in this classification method.

B. Segmentation

Segmentation is carried outto analyse the signal properly. The input ECG signal is segmented into number of heartbeats. Since each heartbeat is different from each other.

C. Scalogram

A time–frequency representation (TFR) view the signal in both time and frequency. The different form of representing the signal in time and frequency are the smoothed Pseudo-Wigner distribution, the spectrogram

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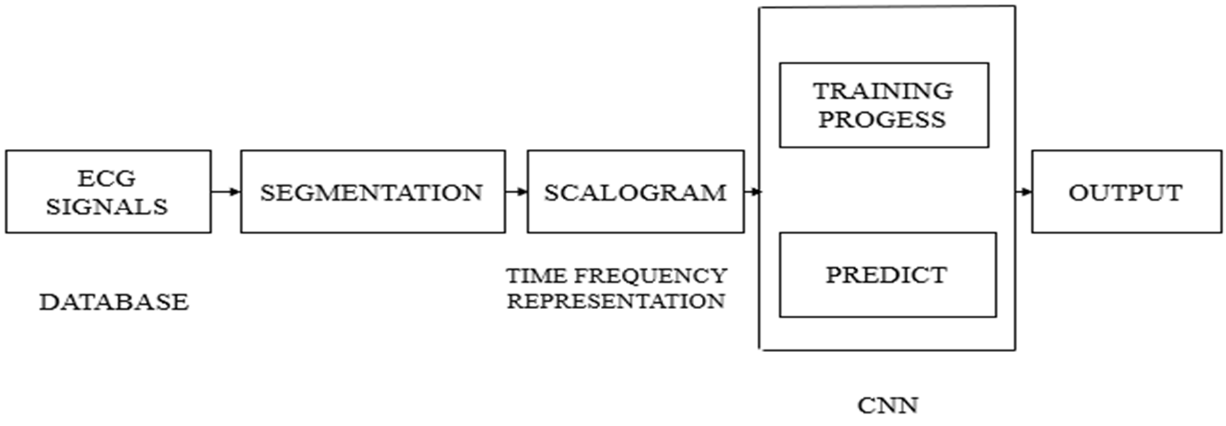

Figure 2. Block diagram of proposed method of ECG analysis

(Squared magnitude of short-time Fourier transform), and the scalogram (squared magnitude of Wavelet transforms).

Time frequency representation of signals using spectrogram which uses Fourier transform does not help to identify the difference between the signals, even though each segmented heartbeat has different meaning. So, in the proposed method scalogram [4] time- frequency representation is used which uses wavelet transform.

In wavelet transform the time and frequency are well localized. So, it gives sharp time frequency picture. The wavelet transform greatly enhances the spectral information present as a function of time in the signal.

D. Convolutional neural network

The convolutional neural networks (CNNs) [5] technique has two components namely feature identifier and fully connected layer.The feature identifier is carried out using convolutional layers and pooling layers, where the features are learned automatically. The fully connected component carries out signal classification using the features learned from the feature's identifier component.

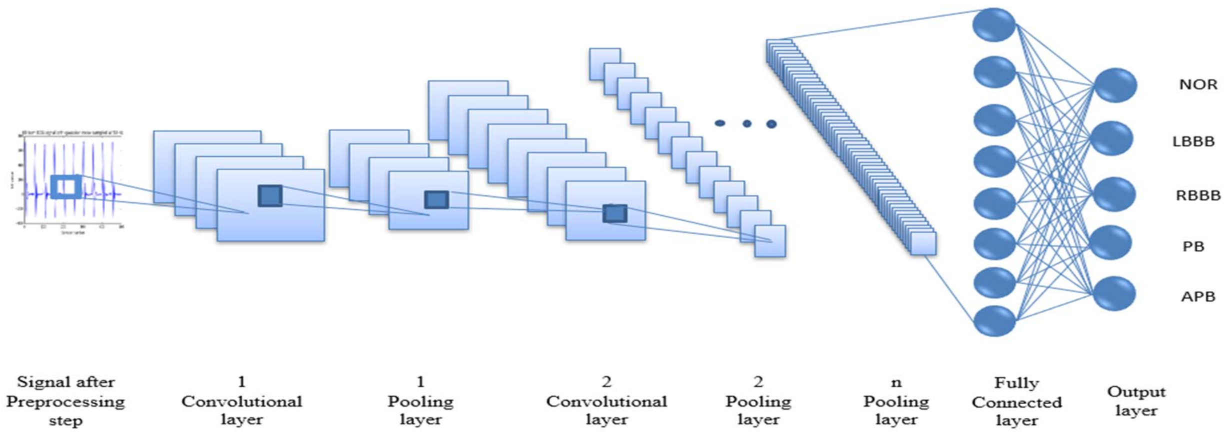

Figure 3. Basic Deep convolutional neural network

Convolution layer

The convolution layer is the main building block of a CNN [6]. Let $x_i^0=(x_1, x_2 \ldots, x_n)$ be the data input vector.

Where,

n - total number of samples in the ECG segment.

The convolutional layer output is computed as,

$$C_i^{l,k}=\sigma(b_k+\sum_{n=1}^{N} w_n^k\, x_{i+n-1}^{0k})$$

Where,

l - layer index,

σ-activationfunction producing nonlinearity

b - bias for the activation map

N - size of the filter

w_n^k - Weight for the n^{th} filter index and k^{th}activation map.

Pooling Layer

The pooling layer [7] performs down sampling. The commonly used pooling strategiesare max pooling and mean pooling. Here maximum pooling is employed, which is experimentally determined.

The Pooling layer output is computed as,

$$P_i^{l,k} = \max_{t \in T}(C_{i \times s}^{l,k})$$

Where,

T - window size of the pooling

S - Pooling stride

Fully connected layer

Fully-connected layersummarizes the features and gives the output.

The last fully connected layer of feature map is reduced as 1-D feature vector to provide the output layer. It is computed as,

$$V_k = p_1^{l,K}, p_2^{l,k}, p_3^{l,K}, \ldots\ p_i^{l,K}$$

Where,

V_k - feature vector of k^{th} feature branch

K - the last layer of the feature branch

E. Output

All the output elements are summed up to one for predicting the target categories. The output is classified into 5 heartbeat classes Normal beat (NOR), Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB),Paced beat (PB), Atrial premature beat (APB)

III. RESULTS AND DISCUSSION

A.Database

Database used is "MIT-BIH Arrhythmia database". For this analysis, five records 103,109, 118, 107 and 232 are used. The total number of beats in the record is given in Table 1. The input signals from those five records namely 103, 109, 118, 107,232 are shown in Figure 4.

Table 1. Number of Beats in each record from MIT-BIH.

Record	Subject	Normal	LBBB		RBBB	PB	APB	Other beats	Total
103	Male, age not recorded	2084	-		-	-	2	-	2084
109	Male, 69	-	2492		-	-	-	40	2532
118	Male, 64	-	-		2166	-	96	26	2288
107	Male, 64	-	-		-	2078	-	59	2137
232	Female, 76	-	-		397	-	1382	1	1780

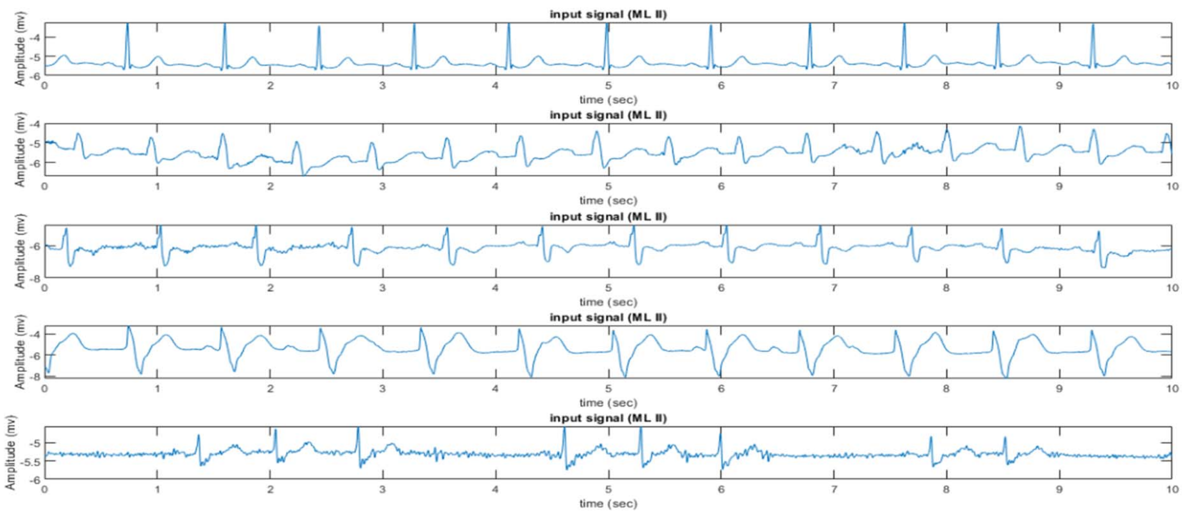

Figure 4. Five input signals from MIT-BIT database 103,109, 118, 107 and 232

B. Segmentation

The input signals are now segmented into individual heartbeats. The five-input signals are individually segmented into 10 heartbeats. Each individual heartbeat consists of 300 sampling points and it corresponds to 0.83 s on time scale. Figure 5 shows the 10 individual heartbeats of normal ECG signal.

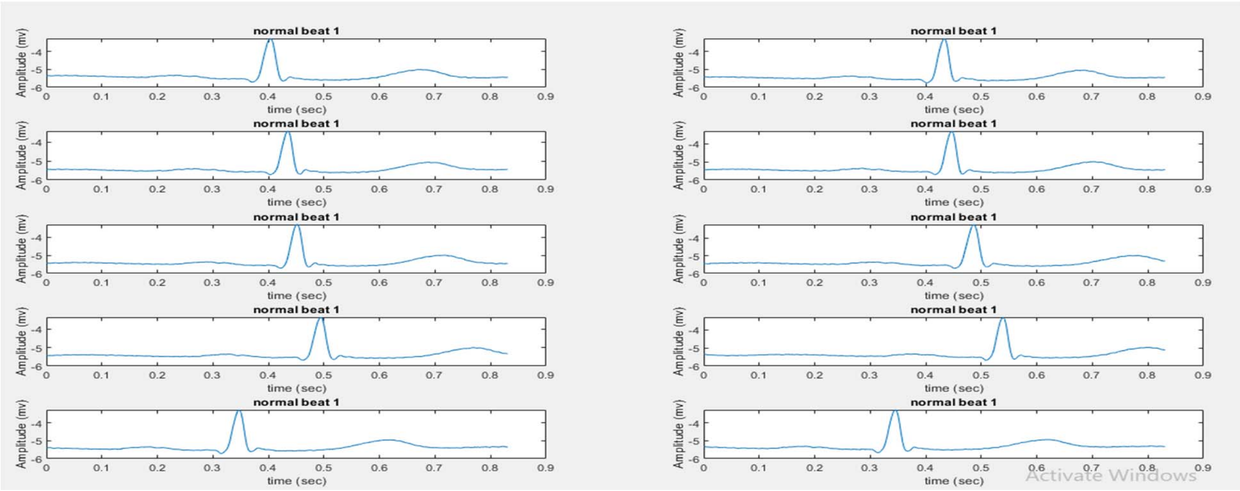

Figure 5. Segmented heartbeats of normal ECG signal

C. Scalogram

Scalogram the each individually separated beats of 5 input signals. Figure 6 shows the scalogram of 10 segmented beats in normal ECG signal.

In the scalogram representation the signals have,

- Well separated peak
- The normal and abnormal signal are clearly distinguishing from the irregularly separated yellow bars.

These representations are saved as images(.jpg) and train a convolutional neural network.

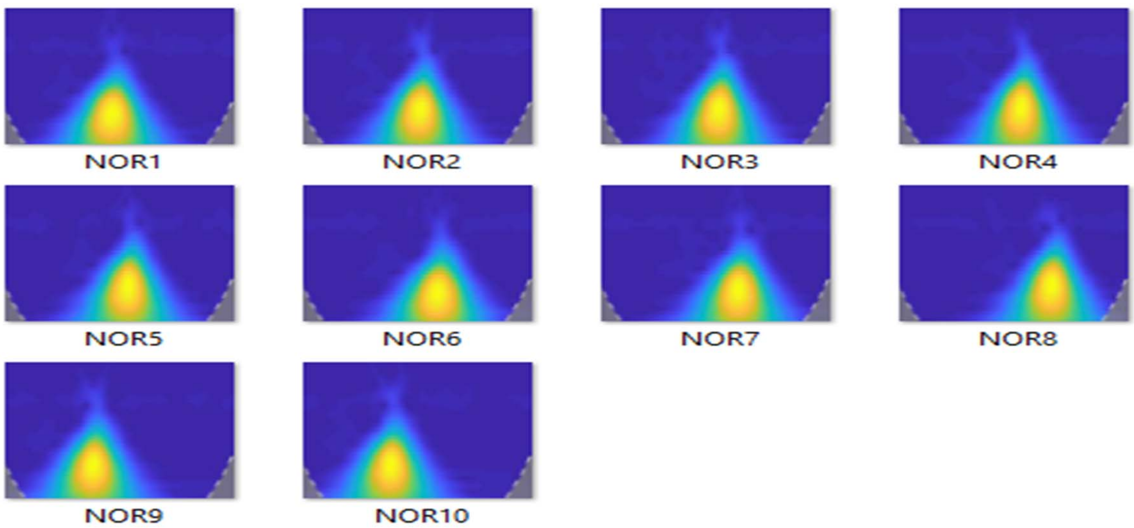

Figure 6. scalogram of 10segmented beats of normal ECG signal

D. Convolutional neural network

The saved images are given input to CNN network. The network is trained using 4 convolutional layer and pooling layer. The training progress is shown in figure 7.

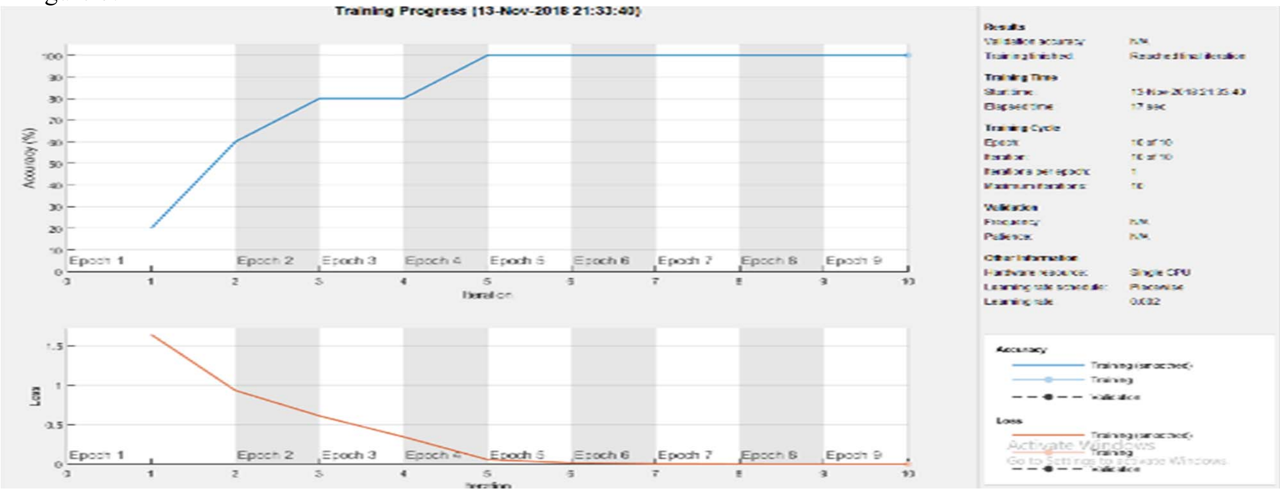

Figure 7. Training progress of convolutional neural network.

Table 2. Comparison of various classification techniques

Classifier	Feature Extraction technique	Classes	Classification accuracy (%)
KNN [8]	EMD+singular values	4	95.83
FS-SVM [9]	EMD+Statistical features	5	96.13
ANN [10]	DTCWT+Morphological Features	5	94.64
Navies Bayes [11]	Multivariate maximal time series motif	2	93.33
Hybrid Bees Algorithm - radial basis function [12]	Temporal + statistical feature	5	95.79
CNN	-	5	98.8

The performance of proposed system is comparaedwith the performances exisiting methods in Table 2. In this work, deep learning convolutional neural network is tested with MIT-BIH database. The CNN can perform both the feature extraction and the classification process in signal unit. So, in the classification method need not required any other technique to perform the feature extraction process. Also manually need not required to develop an optimum set of features to be fed into the classifiers. This is the advantage of convolutional neural network. The proposed method performance can be improved with the large number of sample data.

IV. CONCLUSION

The electrocardiography signal from MITBIH database is used to classify the signal using deep convolutional neural network. In this work, proposed method used to diagnose the abnormalities using deep CNN. Wavelet transform is used to generate a time frequency representation of an input signal. Wavelet transform greatly enhances the spectral information present as a function of time in the signal and this information is saved as image. Image is given as input to CNN, then the network trained with segmented heartbeats which is used to classify the signal. Classification accuracy of 98.8% achieved and processing time is reduced.

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