Cardiac Arrhythmia Classification using Hilbert Transform and CNN classifier

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Abstract: **The electrocardiogram (ECG) records the signal from our heart to know about the conditions of heart. Holter monitor is a portable ECG which records the electrical activity of the heart continuously over 24 hours or longer. This method is hard to analyze the functions of heart manually. So the automatic or computer aid method is needed to analyze and categorize each heartbeat. The Convolutional Neural Network (CNN) classifier is proposed to classify ECG signals automatically which provides better accuracy. The filtering of ECG signals are done in pre-processing step. The Hilbert transform is applied to extract the features from each of the ECG signals. Based on the MIT-BIH arrhythmia database CNN classifier achieves the overall accuracy of 99.43%**.

Keywords: electrocardiogram, Holter monitor, Hilbert transform, Convolutional Neural Network, arrhythmia.

I.INTRODUCTION

ECG test can detect heart disease, heart attack, an enlarged heart, or abnormal heart rhythms which may cause heart failure. Detection of heart conditions automatically by classifying ECG signals can be done by CNN classifier. Myocardial Infarction(MI) occurs when blood clot blocks blood flow to the heart. Without blood, tissue loses oxygen and dies.

Machine Learning (ML) can help predict MI before it occurs, thereby preventing irreversible damage to the heart. Imaging techniques used for MI detection are echocardiography, radionuclide angiography and Electrocardiography (ECG). In ECG electrodes are placed at certain spots of chest, arms and legs. These electrodes are connected to an ECG machine by lead wires. The electrical activity of the heart is measured and printed out. It indicates the rhythm of the heart and the weaknesses of different parts of a heart. The normal ECG waveform is shown in Fig. 1.

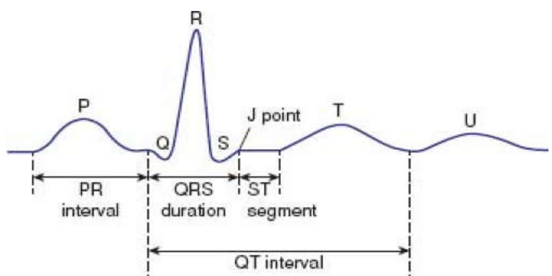

Fig.1 Normal ECG waves

There are three main components in ECG. They are the P wave, which represents the depolarization of the atria; the QRS complex, which represents the depolarization of the ventricles; and the T wave, which represents the repolarization of the ventricles.

The main components of ECG are P wave, QRS complex and T wave. P wave represents the depolarization of the atria, the QRS complex represents the depolarization of ventricles and the T wave represents the repolarization of the ventricles. Many machine learning techniques are used to detect the ECG signals automatically whether it is normal or abnormal such as SVM, decision trees, CNN. In our paper we proposed Convolutional Neural Network classifier to classify the ECG signals. This technique provides higher accuracy and optimized result than other machine learning methods.

In the existing work, ECG arrhythmia analysis based on "'hidden Markov modeling" (HMM). Many ventricular arrhythmias were classified by detecting and analyzing QRS complexes and determining R-R intervals. Model parameters were estimated from training data using an iterative, maximum likelihood re-estimation algorithm. The VEB detection performance was reported in terms of sensitivity and positive predictively as 97.25% and 85.67% respectively [5]. Neural networks designed for ECG compression and classification with optimum linear methods. A one hidden layer MLP was used in comparison with KLT. The work is more oriented towards compression of ECG from the point of view of reconstruction errors. It was found that one hidden layer ANN did not offer significant advantage over KLT [7]. In automated ECG classification using dual heart beat coupling based on CNN, they do not encode the position and orientation of the object and there will be lack of ability to be spatially invariant to the input data. The GLCM method is also used for arrhythmias classification and also hybrid deep learning which is named DELM-LRF-BLSTM for signal recognition but it has over fitting problem.

II. METHODOLOGY

The proposed method uses the Notch filter in pre-processing step and Hilbert transform for extracting morphological features. The Convolutional Neural Network is proposed for classifying any ECG signal normal or abnormal which produces high accuracy. The block diagram of proposed method is shown in Fig. 2.

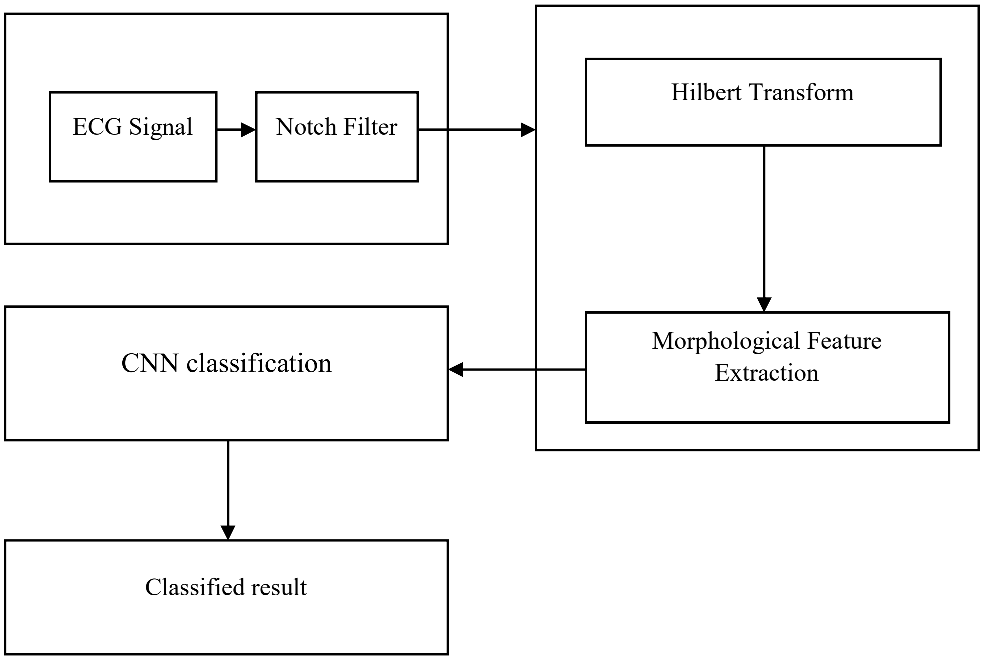

Fig. 2 Block diagram of proposed method

A. Notch Filter

A notch-reject filter attenuates frequencies in predefined neighborhoods about a center frequency of the 2-D Fourier transform. This filter can be used to reduce the periodic noise effects where the main frequencies of the periodic noises are known. Notch filter are used to remove repetitive spectral noise from an image. They are like a narrow high pass filter but they notch out frequencies other than the dc component. It attenuates a selected frequency, that is some of its neighboring frequency and leave other frequencies of the Fourier transform relatively unchanged.

B. Hilbert Transform

Hilbert transform is used to extract the morphological characteristics from each of the ECG signals. These morphological descriptors are represented in a lower dimensional space using PCA. The dynamic features are linked together to the morphological features, which are classified using CNN into 16 different classes of ECG signals. The Hilbert transform is a specific linear operator that takes a function, u(t) of a real variable and produces another function of a real variable H(u)(t). This linear operator is given by convolution with the function $1/(\pi t)$ .The Hilbert transform has a particularly simple representation in the frequency domain: It imparts a phase shift of ±90° ($\pi/2$ radians) to every frequency component of a function, the sign of the shift depending on the sign of the frequency. The Hilbert transform is important in signal processing, where it is a component of the analytic representation of a real-valued signal u(t). The Hilbert transform was first introduced by David Hilbert in this setting, to solve a special case of the Riemann–Hilbert problem for analytic functions. Some major important features will be extracted from ECG signals such as amplitude, duration, pre-gradient, post-gradient and so on. Hilbert transform makes the algorithm simpler and reduces the human effort since the machine has been trained to perform the workload.

C. CNN Classifier

CNN is an approach which is proposed to automatically detect the myocardial infraction using ECG signals. Convolutional neural network (CNN) algorithm is implemented for the automated detection of a normal and Abnormal ECG signals such as Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB), Atrial premature beat (APB) and Paced beat (PB)). A Convolutional Neural Network (CNN) is a multilayered neural network with a special architecture to detect complex features in data. CNNs represent a huge breakthrough in image recognition. They're most commonly used to analyze visual imagery and are frequently working behind the scenes in image classification. A convolutional neural network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels that scan the hidden layers and translation invariance characteristics. They have applications in image and video recognition, recommender systems, image classification, Image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series.

III. RESULT

MIT-BIH database is used based on CNN classifier to get output with better accuracy. The source of ECGs included in this database is a set of over long term Holter recordings. The configurations are used by BIH Arrhythmia Laboratory. The fig.3 shows the input ECG signal which is taken from BIT database. The notch filter removes repetitive spectral noise from an image which attenuates selected frequency and leave others. The filtered ECG signal using notch filter is shown in Fig.4.

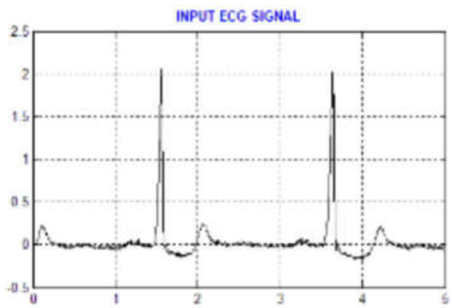

Fig. 3 Input ECG signal

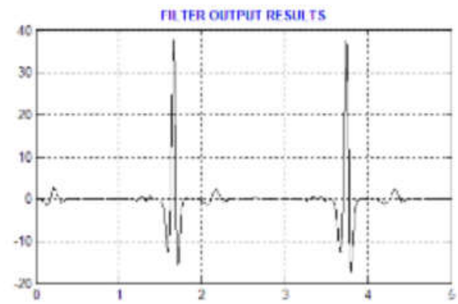

Fig. 4 Filtered ECG signal

The Fig. 5.a, 5.b, 5.c, 5.d shows the reconstructed waveform of input ECG signal using Hilbert transform. This transform used to get the amplitude of the signals. Hilbert transform is applied to extract the morphological characteristics from each of the ECG signals.

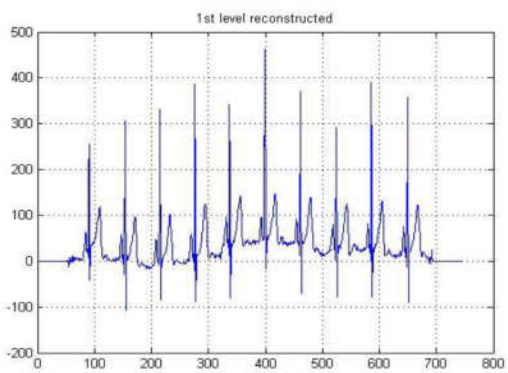

Fig. 5.a First level reconstructed waveform

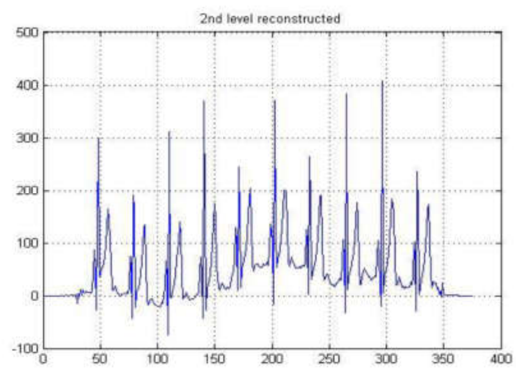

Fig. 5.b Second level reconstructed waveform

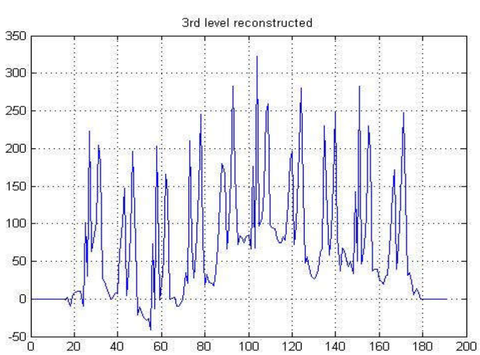

Fig. 5.c Third level reconstructed waveform

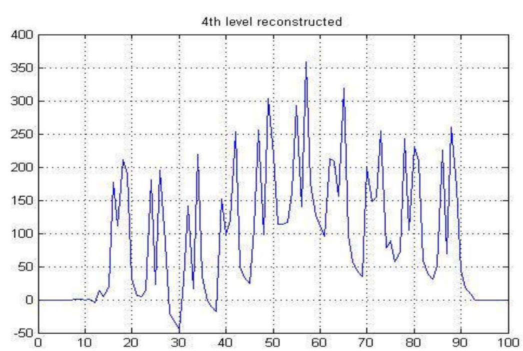

Fig. 5.d Fourth level reconstructed waveform

In this paper, each heartbeat segment consists of 110 samples before the R peak location and 146 samples after the R peak corresponding to the pre-R segment and post-R segment, respectively, i.e., a total of 256 samples are selected to determine the length of each event corresponding to 0.712s window size. The length of fragments is selected to incorporate most of the information regarding each cardiac event. The benefit of fixing the length of each cardiac event is to locate the R-peak accurately relative to the P and T waves because they have low amplitude and are noise sensitive. The disadvantage of such segmentation can be generation of false alarms due to the shortening of two consecutive signal intervals (i.e., during faster heart rate) and the ECG segment may contain the information from the neighboring one.

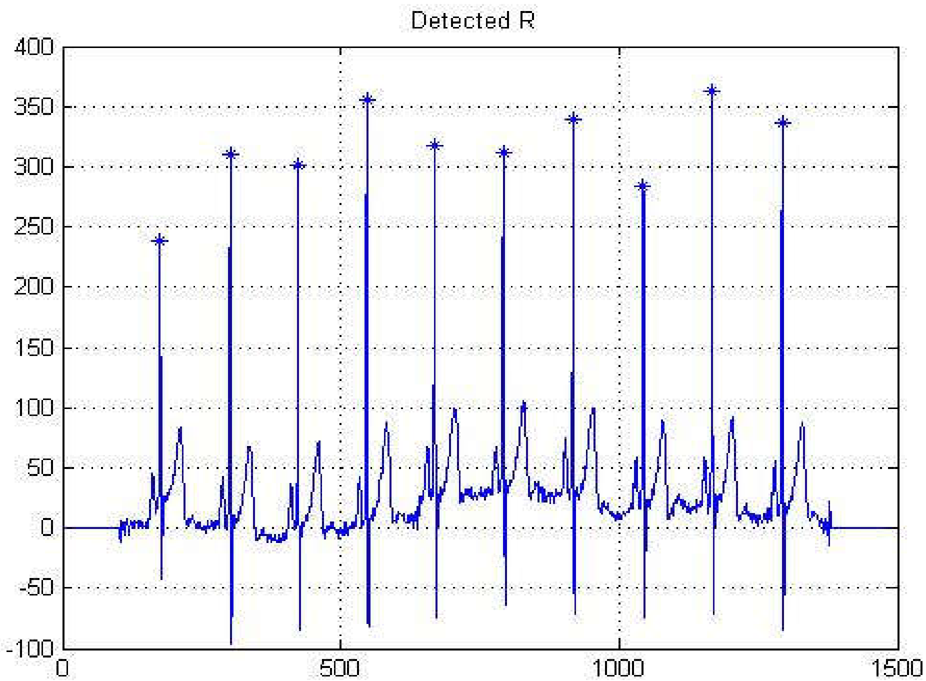

Fig 6. R-peak detection from ECG signal

The Fig.6 shows the R peak detection from the ECG signal. This is calculated using Hilbert transform. From this proposed CNN classifier classify the output signal. Finally, the patient has Arrhythmia ECG waveform. The classified output is shown in Fig. 7.

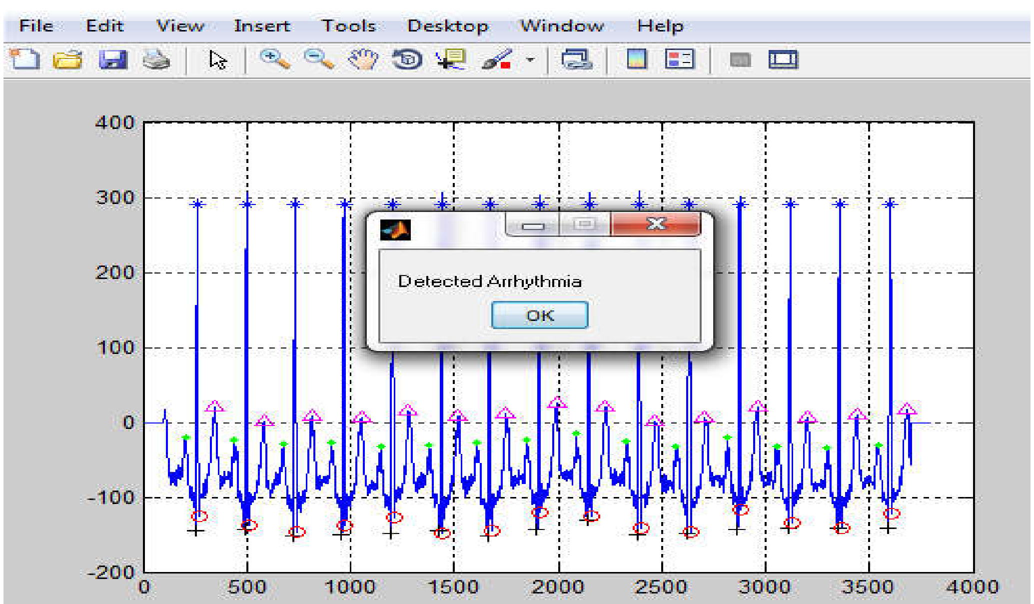

Fig.5. Detected Arrhythmia from ECG signal

The efficiency, training and validation of the developed technique is compared with the conventional methods, in which the efficiency of our developed method is better than other existing method. The accuracy comparison of the proposed classifier is given in the Table. 1

Accuracy Comparison			
Model	**Training**	**Validation**	**Test**
Baseline-CNN Baseline-Ann	67% 68.9%	66.6% 72.4%	65.8% 70%
Deep Residual-CNN	85%	75.6%	74.9%
Combined Unidirectional CNN Combined Bidirectional-Ann	83.6% 93.5%	77.9% 75%	79.8% 80%
CNN Using Hilbert Transform	99.3%	84.6%	98.7%

Table 1. Accuracy comparison of the proposed method

The comparison measure shows that the proposed technique provides better performance than the existing techniques. By the combined classification technique (CNN), the accurate irregularities of the heart are determined. The developed method provides the accuracy of about 98.8%, which is consistently higher than other existing techniques.

IV. CONCLUSION

Early diagnosis of myocardial infarction is crucial to reduce patient mortality. To diagnose different types of myocardial infarction, many researchers have focused on 12 lead ECG and Frank lead VCG and have achieved great performances. Due to advancements in technology, single-lead ECG devices are available for individual and home use for basic cardiac monitoring. This paper proposed a classification model of myocardial infarction ECG based CNN. The network structure had deep structural features, which could acquire the spatial and temporal characteristics of ECG signals. Without any handcrafted feature extraction, the model could obtain an accuracy of 98.7%.

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