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# A Review on ECG Classification Methods

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**ABSTRACT**

Arrhythmia is a main group of illnesses in cardiovascular disorder and it can occur on its own or with different cardiovascular diseases. The diagnosis of arrhythmia especially depends on the ECG (electrocardiogram). ECG is an important contemporary medical device that records the process of cardiac excitability, transmission, and recovery. The purpose of this study is to classify ECG signal using different methods.
**Keywords:** Arrhythmia, ECG classification, Convolutional neural network, DCT, QRS, ICA, PVC

## I. INTRODUCTION

Cardiovascular disease is one of the foremost diseases that threaten human existence. So, regular monitoring of heart rhythm has become a more and more important and necessary matter on the way to manage and keep away from the CVDs. Arrhythmia is a primary group of diseases in cardiovascular disease. It can arise on its own or with other cardiovascular illnesses. It is a set of circumstance in which the heart beat is irregular that is, too slow or too fast. The analysis of arrhythmia mainly depends on the ECG (electrocardiogram). ECG is an essential modern medical device that records the process of cardiac excitability, transmission, and recovery. Automatic detection of irregular heart rhythms from ECG signals is a important task for the automatic diagnosis of cardiovascular disorder. The electrocardiogram (ECG) is the bioelectrical activity signal of the heart which represents the cyclic rhythm of contraction and relaxation of the heart muscles. Arrhythmia is an abnormal heartbeat; it reasons abnormal rhythms consisting of slow or rapid heartbeat [1].

Arrhythmia forms the basis of heart disorder analysis, which may point to the severe problems in the heart. The problem faced using ECG for heart disease diagnosis is that the normal ECG analysis differs from individual to individual and likewise the arrhythmia also differs, thus complicating the heart disease diagnosis. Diagnosis of certain arrhythmia by visual examination takes time and is a boring process. Thus, automatic classification of heartbeat is useful and helps medical specialists for quick and precise diagnosis of heart beat. Use of pattern classifier techniques can improve ECG arrhythmia diagnoses.
The ECG signal is acquired via number of electrodes. The ECG recordings contain noise and the amplitude of the beats varies from person to person. Thus pre-

processing of the signal is necessary for beat detection and feature extraction. The P, Q, R, S and T waves of the ECG signal consist of all main features [2]. A sample ECG waveform is shown in Figure 1. The features of these waves are used to categorize distinct types of arrhythmia. The ECG signals can be separated into vital and plain parts. The most significant information in the ECG signal is concentrated in the P wave, QRS complex and T wave [3].

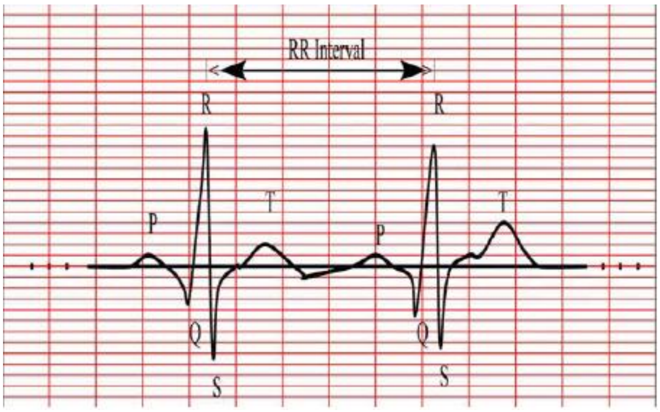


**Figure 1.** A Sample ECG Waveform

Arrhythmia is mainly determined by the QRS complex wave. ECG signal analysis includes QRS waveform detection, feature selection and heartbeat classification. There are various studies analysing the ECG signal for cardiac arrhythmia. Studies based on QRS pattern [4, 5], automatic detection of discerning arrhythmia using Hidden Markov models [6], wavelet transform [7], Hermite function [8] and Neural networks [9,10]. Feature selection is crucial for efficient automatic classification of ECG. The features are either selected from the time domain or frequency domain. The wavelet transform methods are widely used for denoising of the ECG signal [11, 12]. The wavelet transforms decompose the ECG signal into various components of different scales. The phase information is maintained due to the linear operation of the transforms. Wavelet functions support symmetry and compactness and have shown to achieve high accuracy for ECG signals.

The organization of this document is as follows. In Section 2 (Classification Methods), I'll give detail of any modifications to equipment or equipment constructed specifically for the study and, if pertinent, provide illustrations of the modifications. In Section 3 (Comparison). In Section 4(Conclusion)

## II. ECG CLASSIFICATION METHODS

### A. Investigating Cardiac Arrhythmia in ECG using Random Forest Classification

Here, ECG classification for arrhythmic beat classification is done using RR interval. The method is based on discrete cosine transform (DCT) conversion of RR interval. The RR interval of the beat is extracted from the ECG and used as characteristic. DCT conversion of RR interval is applied and the beats are categorized using random tree. Experiments had been performed using MIT-BIH arrhythmia database. ECG signal is divided into 154 samples.

In this work, it is proposed to examine the classification accuracy of random forest classifier on ECG data. The time series data obtained from MIT-BIH is transformed to frequency domain using Discrete Cosine Transform (DCT) for feature extraction. Two types of arrhythmia namely LBB and RBB are measured in this work.

**Methodology**

The QRS complex along with the RR interval plays an vital role in arrhythmia identification [13]. The peaks are detected as follows:

- The moving average of the signal is calculated using n number of records.
- New signal is derived by subtracting the moving average from the original signal.
- Peak of the signal' R' is found.

- Peaks of P, Q, S and T are found by relative position.

Growing an ensemble of random trees for classification using a probabilistic scheme is called random forest of trees. Classification accuracy is high as the trees vote for the most popular class. Trees drawn at random from a set of possible trees is called random tree. Random tree is a decision tree that considers *K* randomly chosen attributes at each node. The class probabilities on each node are based on back fitting with no pruning [14]. The steps involved in growing a random tree are:

- The training set for growing the tree is obtained by selecting N cases at random but with replacement from the original dataset.
- A random number of attributes m are chosen for each tree. These attributes form the nodes and leafs using standard tree building algorithms. The best split on m is used to split the nodes and m is held constant.
- Each tree is grown to the fullest extent possible without pruning.

The extracted beats contain 68 instances of left bunch bundle block, 30 instances of right bunch bundle block and 56 normal instances. In this paper, it was proposed to implement a frequency domain method using Discrete Cosine Transform (DCT) for feature extraction. Two different arrhythmia conditions were investigated along with normal ECG. ECG data for this investigation was obtained from phyiobank website. The average classification accuracy obtained by the proposed method is over 90%.

### B. Integration of independent component analysis and neural networks for ECG beat classification

Here the system use a scheme for ECG beat classification by merging independent component analysis (ICA), RR interval, and neural network classifiers. ICA is used to extract relevant factors from ECG signals. The ICA based features together with the RR interval then serve as input feature vector for the following neural network classifiers. Two neural networks, including probabilistic neural network (PNN) and back-propagation neural network (BPNN), were used in the study. Eight types of ECG samples were selected from the MIT-BIH arrhythmia database for experiments. Both neural network classifiers demonstrated high classification accuracies of over 98% with relatively small number of ICs.

The block diagram for ECG beat is depicted in Figure. 2. The method is divided into three steps: (1) ECG sampling and pre-processing, (2) calculation of feature vector, and (3) classification by neural networks, which are described, separately, as follows

- ECG sampling and pre-processing

The ECG signals are taken from the MIT-BIH arrhythmia database for recognition. Since the majority of the diagnostic information lies around the R peak of the ECG signal, hence a portion of signal before it and a portion of signal after it are selected for processing.

- Calculation of feature vector

Two sets of features are to be extracted from the data files. One set is the ICA-based features and the other is the RR interval. To estimate the ICA-based features, the independent components (ICs) should be calculated as bases for signal decomposition.

- Classification by neural networks

The probabilistic neural network (PNN) used in this study has a two-layer structure, including a radial basis layer and a competitive layer The radial basis layer contains the same number of neurons as that of the classes to be classified. Each neuron is responsible to calculate the probability that an input feature vector is associated with a specific class.

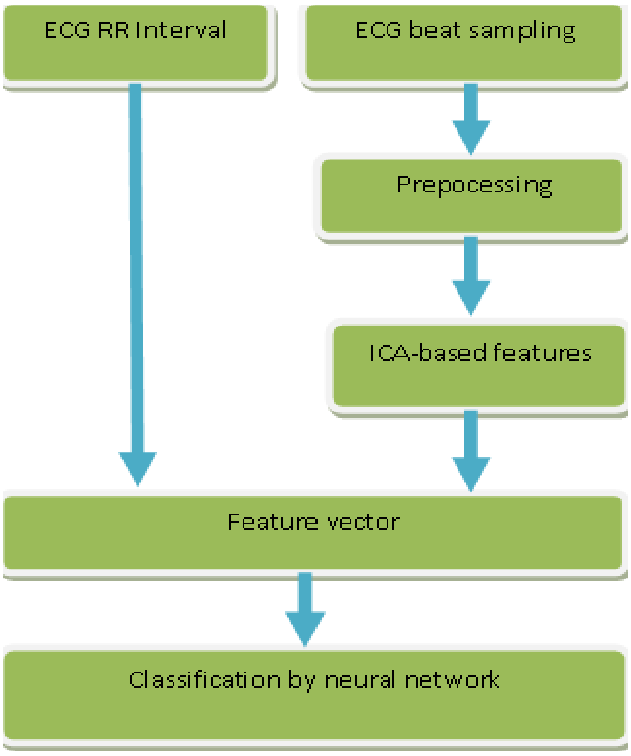


**Figure 2.** Block Diagram for ECG Beat

The block diagram for ECG beat is shown in Figure 2. Eight ECG beat types were selected from the MIT-BIH arrhythmia database for experiments. Signal is divided into 4900 samples for ECG classification. The eight beat types employed in the study were normal beat (NORM), left bundle branch block beat (LBBB), right bundle branch block beat (RBBB), artial premature beat (APB), premature ventricular contraction (PVC), paced beat (PB), ventricular flutter wave (VFW), and ventricular escape beat (VEB).

### C. Arrhythmia Detection from Heartbeat using K-Nearest Neighbor Classifier

Here the system classifies heartbeat into 17 types. This system consists of two parts, the detection and classification of heartbeats. The system detects heartbeats through repetitive features and classifies them using a k-nearest neighbor algorithm. Features such as the QRS complex and P wave were accurately extracted using the PanTompkins algorithm. For the classifier, the distance metric is an adaptation of locally weighted regression. The system was validated with the MIT-BIH Arrhythmia Database. The system achieved a sensitivity of 97.22 % and a specificity of 97.4 % for heartbeat detection. The system also achieved a sensitivity of 97.1 % and a specificity of 96.9 % for classification. We used the well-known MIT-BIH Arrhythmia Database to train and test the classifier. The database contains 48 half-hour recordings each containing two ECG lead signals. Thus, the database can also provide a basis for comparison with other methods. The database contains approximately 109,000 heartbeats. All recordings have an annotation associated with each heartbeat. The annotation provides the location of the QRS complex and the types of the heartbeats. The annotation types can be used to determine the truth of classification. Our system considers 17 annotation types. The 17 types include normal (NOR), left bundle branch blocks (LBBB), right bundle branch block (RBBB), atrial premature (APC), aberrated atrial premature (AP), nodal premature (NP), supraventricular premature (SP), premature ventricular contraction (PVC), fusion of ventricular and normal (VFN), atrial escape (AE), ventricular escape (NE), ventricular escape beat (VE), paced (PACE), fusion of paced and normal (FPN), ventricular flutter wave (VF), non-conducted P wave (NCP) shown in Table 1.Signal is classified into10972 samples.

In this study, the system classifies heartbeats into 17 types for a reliable and automatic decision support system. The system consists of two parts: heartbeat detection and classification. This method uses a well-known Pan-Tompkins algorithm [15] to accurately detect heartbeats and extract features. Also a *k*-NN algorithm is used for locally weighted regression (LWR) to classify heartbeats according to their extracted features. The effectiveness of this system by means of extensive experiments using the MIT-BIH Arrhythmia Database [16].

**Table 1.** Different Types of Heartbeat and Annotation

| Heartbeat Type | # of heartbeats | Annotation |
|---|---|---|
| Normal beat (NOR) | 74976 | N |
| Left bundle branch block beat (LBBB) | 8068 | L |
| Right bundle branch block beat (RBBB) | 7250 | R |
| Atrial premature beat (APC) | 2544 | A |
| Aberrated atrial premature beat (AP) | 138 | A |
| Nodal (junctional) premature beat (NP) | 84 | J |
| Supraventricular premature beat (SP) | 2 | S |
| Premature ventricular contraction (PVC) | 7120 | V |
| Fusion of ventricular and normal beats (VFN) | 802 | F |
| Atrial escape beat (AE) | 16 | E |
| Nodal (junctional) escape beat (NE) | 230 | J |
| Ventricular escape beat (VE) | 106 | E |
| Paced beat (PACE) | 7024 | / |
| Fusion of paced and normal beat (FPN) | 982 | F |
| Unclassifiable beat (UN) | 32 | Q |
| Ventricular flutter wave (VF) | 324 | ! |
| Non-conducted P wave (NCP) | 4 | X |

### D. ECG Classification using STFT Based Spectrogram and Convolutional Neural Network

In this system ECG arrhythmia classification method is based on a deep two-dimensional convolutional neural network on classification of five different rhythms. The input one-dimensional ECG signals in the time domain signals are transformed into two-dimensional time-frequency spectrograms. Nevertheless, in this step noise filtering and manual feature extraction are no longer required. In addition, training data are obtained through augmenting of the derived ECG images, which can result in higher classification accuracy. The segmented 2D time-frequency spectrograms are fed as input of the convolutional neural network. The 2D CNN model can automatically suppress the measurement noises and extract relevant feature maps throughout the convolutional and pooling layer intelligently. Thus, the method can be applied to the ECG signals from various ECG acquisition devices with different sampling rates, and it is beneficial in precise identifications of ECG arrhythmia. In all, the ECG arrhythmia classification method consists of the following steps, e.g., ECG signals data acquisition, ECG signals pre-processing, and 2D-CNN classifier.Average accuracy of this model is 99.00%

## Methodology

The overall procedure of the ECG arrhythmia classification model is shown in Figure .3. The original ECG signals were shared by the MIT-BIH arrhythmia database [17]. The input ECG signals were divided into data recordings with an identical duration of 10 seconds. The one-dimensional ECG time domain signals, there are five different classes of arrhythmia, based on the recordings annotations which made by two or more cardiologists independently. Afterward, each ECG signal record is transformed into an image of time-frequency spectrogram by using the short time Fourier transform (STFT). The ECG spectrogram images are fed into the proposed deep two-dimensional convolutional neural network (CNN) model. With these obtained ECG spectrogram images, classification of the five ECG types is performed in the 2D-CNN classifier automatically and intelligently. The five ECG types are normal beat (NOR), left bundle branch block beat (LBB), right bundle branch block beat (RBB), premature ventricular contraction beat (PVC), atrial premature contraction beat(APC).The signal is divided into 2520 samples for ECG classification.

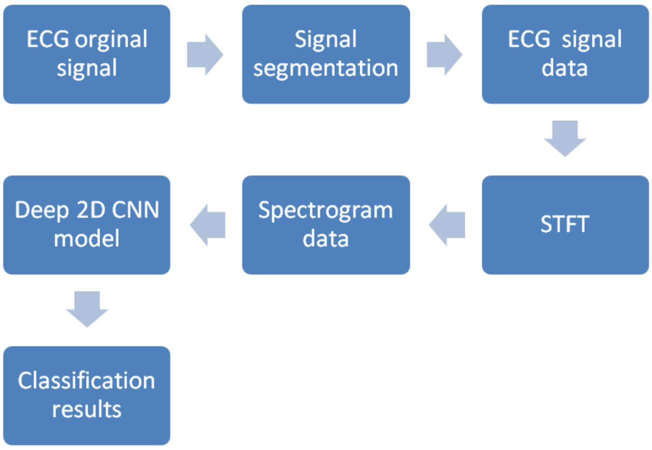


**Figure 3.** ECG Arrhythmia Classification Model

Figure 4 shows the structure of 2D CNN. First, each ECG data recording was transformed into an ECG spectrums images which size is 256×256 pixel. In the first hidden layer, the Convolution2D layer with 8 convolution kernels and the kernels size of 4×4 was applied, and the activation function we choose is RELU (Rectified Linear Unit). Afterwards, a MaxPooling2D which pool size is (2, 2) was added. Then, the output shape of the first Layer is 32×8×1024. In the second hidden layer, the Convolution2D layer with 13 convolution kernels and the kernels size of 2×2 was applied, and the activation function is RELU. Then, a MaxPooling2D with the pool size of (2, 2) was added, and the output shape of the second layer is 64×8×512. In the third hidden layer, the Convolution2D layer with 13 convolution kernels and the kernels size of 2×2 was applied, and the activation function is RELU. Next, a MaxPooling2D with the pool size of (2, 2) was added, and the output shape of the third Layer is 64×8×512 finally.

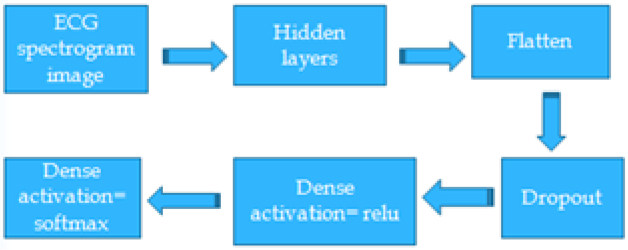


**Figure 4.** Structure of the 2D-CNN

## III. COMPARISON

Compared to the performance of the 2D-CNN model with previous ECG arrhythmia classification works, including FFNN (Feed Forward Neural Network), RFT(Random Forest), K-NN(K Nearest Neighbor). Since these works have a different number of the test set and types of arrhythmia, it is unfair to directly compare with accuracy itself. However, the CNN model achieved successful performance compared to other previous works while introducing the different approach of classifying ECG arrhythmia using STFT-based spectrogram and convolutional neural network. The comparison between different models is shown in Table 2.

**Table 2.** Comparison Table

| Model | Type | Test set | Average accuracy |
|---|---|---|---|
| 2D-CNN | 5 | 2520 | 99.00% |
| FFNN | 8 | 4900 | 98.71% |
| RFT | 3 | 154 | 92.16% |
| K-NN | 17 | 10972 | 97.00% |

## IV. CONCLUSION

From the comparison it is clear that ECG signal can be classified efficiently and more accurately by using 2D-CNN. ECG arrhythmia classification method is based on deep learning techniques. The comparison table 2 shows that the classification of ECG signals based on two dimensional convolution neural network can reach an averaged accuracy of 99.00%. Therefore it is better than the existing RFT, FFNN and K-NN methods.

## V. REFERENCES


[1] Sandoe E, Sigurd B. Arrhythmia – A Guide to Clinical Electrocardiology. Bingen: Publishing Partners Verlags GmbH, 1991.

[2] J. Pan and W. J. Tompkins, ―A Real-time QRS detection algorithm,‖ IEEE Trans. Biomed. Eng., vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[3] R.M. Rangayyan, Biomedical Signal Analysis: A CaseStudy Approach, Wiley–Interscience, New York, 2001.

[4] I. Christov, G. Gómez-Herrero, V. Krasteva, I. Jekova, A. Gotchev, K. Egiazarian, Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification, Med. Eng. Phys. 28 (2006) 876– 887.

[5] P. Chazal, M. O'Dwyer, R.B. Reilly, Automatic classification of heartbeats using ECG morphology and heartbeat interval features, IEEE Trans. Biomed. Eng. 51 (2004) 1196–1206.

[6] A. Koski, Modelling ECG signals with Hidden Markov Models, Artif. Intell. Med. 8 (1996) 453–471, International Journal of Computer Applications (0975 – 8887) Volume 37– No.4, January 2012.

[7] C.W. Li, C.X. Zheng, C.F. Tai, Detection of ECG characteristic points using wavelet transform, IEEE Trans. Biomed. Eng. 42 (1995) 21–28.

[8] P. Laguna, R. Jane, S. Olmos, N.V. Thakor, H. Rix, P. Caminal, Adaptive estimation of QRS complex wave features of ECG signal by the Hermite model, Med. Biol. Eng. Comput. 34 (1996) 58–68.

[9] Z. Dokur, T. Olmez, ECG beat classification by a novel hybrid neural network, Comput. Methods Program Biomed. 66 (2001) 167–181.

[10] Y.P. Meau, F. Ibrahim, S.A.L. Narainasamy, R. Omar, Intelligent classification of ECG signal using extended EKF based neural fuzzy system, Comput. Methods Program Biomed. 82 (2006) 157–168.

[11] J. P. Martinez, S. Olmos, and P. Laguna, ―Evaluation of a wavelet-based ECG waveform detector on the QT database,‖ Comput. Cardiol., vol. 27, pp. 81–84, Sep. 2000.

[12] P. M. Agante and J. P.Marques de Sa, ―ECG noise filtering using wavelets with soft-thresholding methods,‖ Comput. Cardiol., vol. 26, pp. 535–538, Sep. 1999.

[13] M. Engin, ―ECG beat classification using neuro-fuzzy network,‖ Pattern Recognition

[14] Frederick Livingston: Implementation of Breiman's Random Forest Machine Learning Algorithm, inECE591Q Machine Learning conference, Fall 2005.

[15] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," IEEE Transactons on Biomedical Engineering, vol. BME-32, no. 3, pp. 230-236, Mar. 1985.

[16] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," IEEE Engineering in Medicine and Biology Magazine, vol. 20, no. 3, pp. 45-50, May/Jun. 2001.

[17] G. B. Moody, Mark R G . The impact of the MIT-BIH Arrhythmia Database. IEEE Engineering in Medicine and Biology Magazine, 2002, 20(3): 45-50.


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