

# ECG Analysis for the detection of cardiac arrhythmia

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**Abstract**— A heart arrhythmia is a problem of irregular rhythm of the heartbeat and the effective detection of them require lot of time and expensive for expertise clinicians. This paper Proposes 2-D convolutional neural network (CNN) approach for the Classification of arrhythmia types. The MIT- BIH arrhythmia is a freely available dataset which has been Extensively used for Evaluation of the ECG signal. The proposed architecture converts each of the heartbeat into 2- D grayscale image which is taken as input for the CNN Classifier. The proposed architecture achieved high accuracy.

**Keywords**— Arrhythmia, ECG signal, Convolutional Neural Network, CNN Classifier.

## 1. INTRODUCTION

Arrhythmia, also known as cardiac arrhythmia is the problem with rhythm of the heartbeat. An Electrocardiogram(ECG) is a tool that records the Electrical conduction of the heart. The ECG consist of the components such of P wave, QRS Complex consist of Q wave, R wave and S wave, it represents ventricular depolarization. T wave represents the ventricular repolarization. ECG analysis helps to find various health problems. The most common heart problem is arrhythmia, arrhythmia may cause the dysfunction of the heart muscle and not to pump enough blood to the organs. Single arrhythmia beat might lead to a serious impact on our life. Continuous arrhythmia beat can lead to the fetal circumstance. In the last decade classical machine learning techniques was used for the classification of the heartbeat. They used classical machine learning Techniques such as wavelet transform, support Vector machine, multilinear Single Value decomposition and hidden Markov Model. The success of this approach was mainly affected by selection of feature extraction algorithm. The drawbacks of this approach are 1) Good performance only on carefully selected ECG signal Recordings. 2) The ECG beat loss in noise filtering and the feature extraction schemes. 3) Low Classification performance. 4) Limited number of arrhythmia type machine learning based approach requires feature extraction engineering. It is tedious and increases the complexity of the System.

In this paper, we proposed the new approach for the classification of the arrhythmia, a 2-D CNN based Image classifier. CNN use the data in form of 2-D images that represent the attributes of the ECG signals. The proposed methodology uses the MIT-BIH database. This model has achieved high

accuracy in measurements for the classification of different types of arrhythmias.

## 2. RELATED WORK

The proposed paper discusses various techniques and transformations proposed for extracting feature from an Arrhythmia Analysis and interpretation of ECG signal. In addition, this paper also provides a comparative study of various methods purpose.

Multi-model Deep Learning Ensemble for ECG Heartbeat Arrhythmia Classification introduced a novel deep learning system for classifying the electrocardiogram (ECG) signals. The heartbeats are classified into different arrhythmia types using two proposed deep learning models. The first model is integrating the convolutional neural network (CNN) and long short-term memory (LSTM) network to extract useful features within the ECG signal. The second model combines several classical features with LSTM in order to effectively recognize abnormal classes. These deep learning models are trained using a bagging model then aggregated by a fusion classifier to form a robust unified model[1].Cardio Net: An Efficient ECG Arrhythmia Classification System Using Transfer Learning presents a novel method of heartbeat classification from ECG using deep learning. An automated system named 'CardioNet' is devised that employs the principle of transfer learning for faster and robust classification of heartbeats for arrhythmia detection. It uses pre-trained architecture of DenseNet that is trained on ImageNet dataset of millions images. The weights obtained during training of DenseNet are used to fine-tune CardioNet learning on the ECG dataset,

resulting a unique system providing faster training and testing[2].

**ECG Arrhythmia Classification By Using Convolutional Neural Network And Spectrogram** proposed approaches operates with a large volume of raw ECG time-series data and ECG signal spectrograms as inputs to a deep convolutional neural networks (CNN). Heartbeats are classified as normal (N), premature ventricular contractions (PVC), right bundle branch block (RBBB) rhythm by using ECG signals obtained from MIT-BIH arrhythmia database. The first approach is to directly use ECG time-series signals as input to CNN, and in the second approach ECG signals are converted into time- frequency domain matrices and sent to CNN. The most appropriate parameters such as number of the layers, size and number of the filters are optimized heuristically for fast and efficient operation of the CNN algorithm. The proposed system demonstrated high classification rate for the time- series data and spectrograms by using deep learning algorithms without standard feature extraction methods [3]. **Arrhythmia Classification Techniques Using Deep Neural Network** primary goal of this research is to review the development of arrhythmias classification techniques over time, i.e., January 2010 to January 2020, using the machine and deep learning approach. The primary objectives of this research study is to examine the arrhythmia classification techniques as practically implementable[4]. **Classification of Arrhythmia in Heartbeat Detection Using Deep Learning** paper presents Automatic exposure to ECG-based arrhythmia is very convenient since it eliminates physicians' need to personally interpret the signs and allows people to track their cardiac symptoms using handheld devices[5].**Auto-encoder and bidirectional long short-term memory based automated arrhythmia classification for ECG signal** proposed AE-biLSTM method contains an encoder that extracts higher level feature from the Electro cardiogram arrhythmias signals using bidirectional long short-term memory (biLSTM) network, then a decoder output reconstruct Electro cardiogram arrhythmias signals from higher level features using biLSTM network. Finally, the proposed method accurately classifies the 6 heartbeats types, such as normal

(N) sinus beat, atrial fibrillation (AFIB), ventricular bigeminy (B), pacing beat (P), atrial flutter (AFL), sinus brady cardia (SBR). The simulating process is activated in MATLAB. Lastly, the AE-biLSTM method utilize 2 extra databases: (i) new N beat (ii) AFIB beat, which is self-determining of the network's training database[6].

### 3 METHODOLOGY

#### A. Data

The study aims to find the accurate arrhythmia detection based on 2-D ECG images and deep learning technique .Our proposed system consist of data, image generation and deep neural network. ECG arrhythmia database (MIT-BIH database) consist of ECG signals obtained from 47 with patients. It consists of records with approximate duration of 30 minutes. MIT-BIH database consist of 17 classes of heartbeat. Based on the advanced medical instrumentation the heart beat is categorized into five different types.

#### B. QRS Peak Detection

QRS peak detection is a difficult task, because of the various types of noise could be present in the ECG signal. To perform QRS peak detection we use the famous Pan - Tompkins algorithm. Fig. 1 shows the various steps of the Pan-Tompkins algorithm. The signal is passed through the band pass filter. Fig. 2 shows the output of the filter.

The ECG signals are differentiated using filtering process. This process enhances the slope of the QRS complex of the signal. Fig. 3 shows the output of the derivative process. Next process after differentiation is squaring, the signals are squared so that the components of the signal display the positive values. The output of this process is given in Fig. 4. The moving window integration produces a signal that includes information about both the slope and the width of the QRS complex. Fig. 5 show the output of the moving window integration. Fig. 6 shows the final output marking the R peaks of the QRS complex.

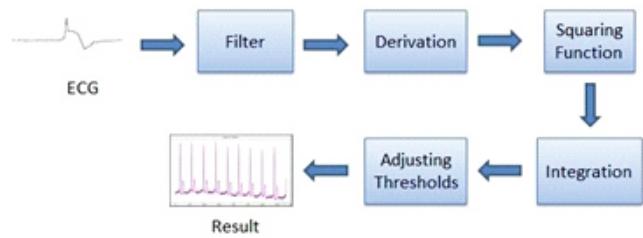


Fig. 1 Pan-Tompkins Algorithm

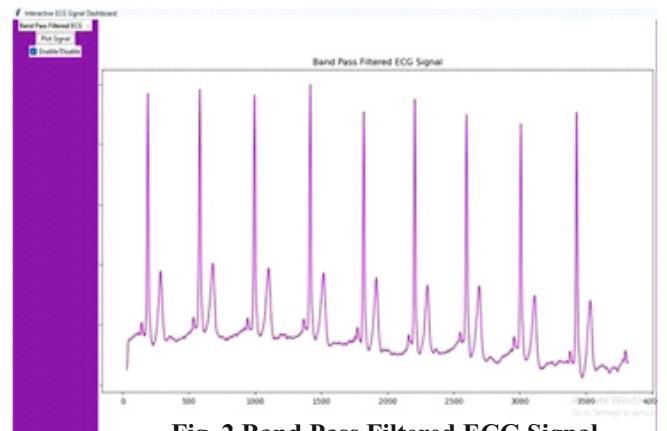
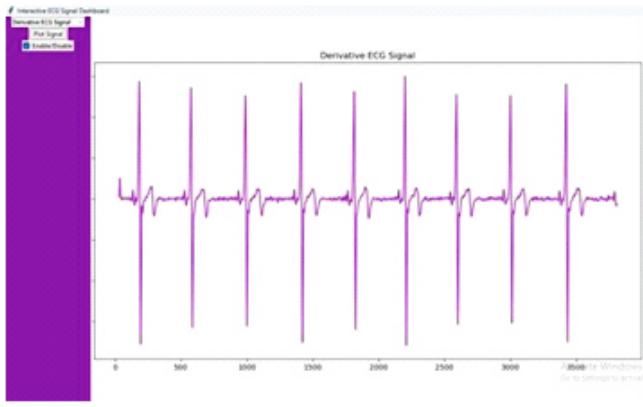
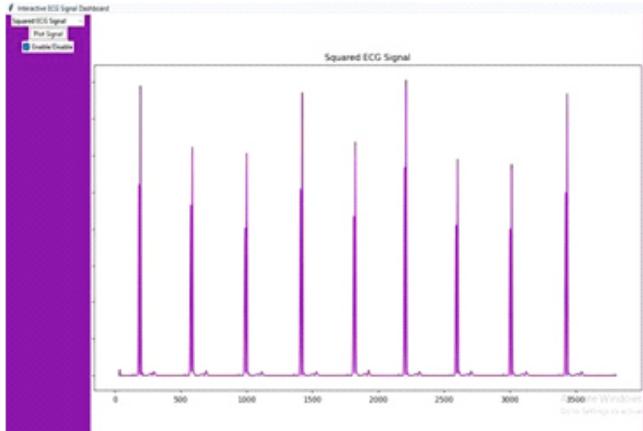


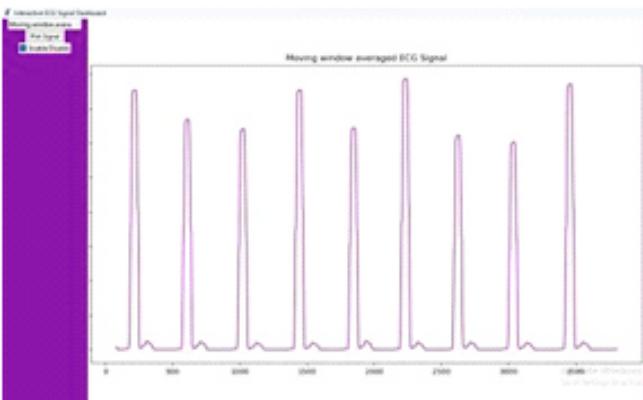
Fig. 2 Band Pass Filtered ECG Signal



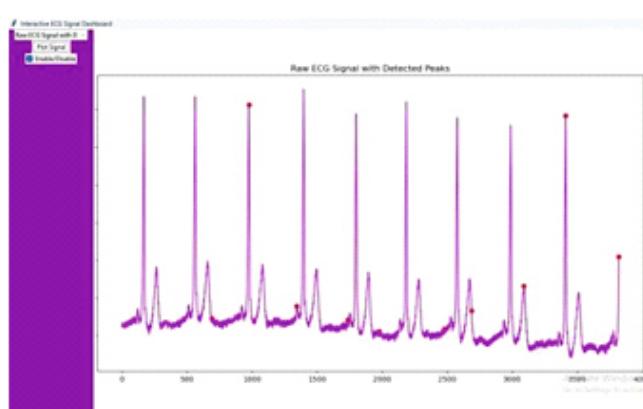
**Fig. 3 Derivative ECG Signal**



**Fig. 4 Squared ECG Signal**



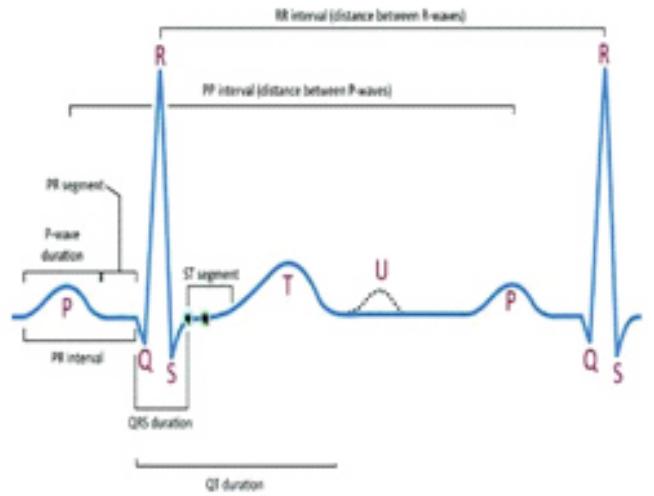
**Fig. 5 Moving Window ECG signal**



**Fig. 6 ECG Signals with Detected Peaks**

### C. Segmentation and image generation

ECG Signals are examined. The segmentation of wave was performed were the heartbeat were extracted as given in fig 7. After the segmentation each heartbeat was converted into 2-D grayscale image This transformation lead to the easy analysis of the data.

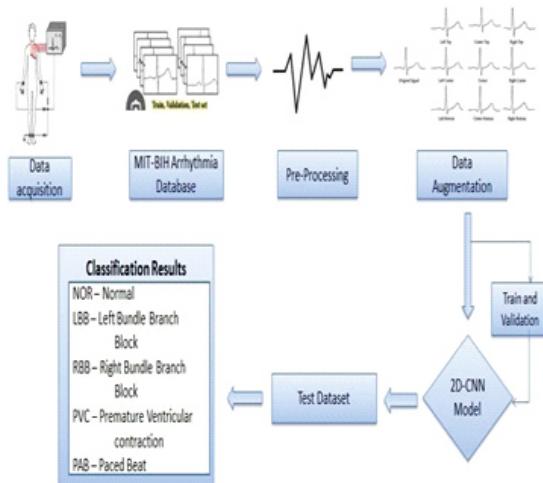


**Fig. 7 Segmentation of heartbeat**

### D. Proposed Model

The architecture of proposed model given in fig 8.CNN is a type of deep learning algorithm Which is commonly used for image analysis. It includes more than 3 layers with many hidden layers. The kernel size is  $[n,n]$  where  $[n=2]$ . The size of input layer is  $[15 \times 15]$ . In the CNN architecture consist of the layers such as Convolution layer, Batch, Relu etc. These are arranged in sequence. Fully connected layer is followed by dropout layer and it is followed by softmax layer [Activation function and the final layer is classification layer. In The training of the model the Size, Regularization factor

,maximum number of Epochs, dropout factor Parameters are considered. The performance of the training will be Evaluated using validation set.



**Fig. 8 Architecture diagram of proposed system**

## I. RESULTS AND DISCUSSION

### A. Performance

The evaluation of model is done using metrics such as accuracy, sensitivity, specificity, precision are given in equation 1,2,3,4.

$$Accuracy = \frac{1}{17} \sum_{c=1}^{17} \frac{T_p^c + T_n^c}{T_p^c + T_n^c + F_p^c + F_n^c} \quad (1)$$

$$Sensitivity = \frac{1}{17} \sum_{c=1}^{17} \frac{T_p^c}{T_p^c + F_n^c} \quad (2)$$

$$Specificity = \frac{1}{17} \sum_{c=1}^{17} \frac{T_n^c}{T_n^c + F_p^c} \quad (3)$$

$$Precision(p) = \frac{1}{17} \sum_{c=1}^{17} \frac{T_p^c}{T_p^c + F_p^c} \quad (4)$$

$T_p^c$  denotes the true positives (for all c instances that are classified as c)

$T_n^c$  denotes true negatives (all non-c instances that are not classified as c);

$F_p^c$  denotes the false positives (all non-c instances that are classified as c);

$F_n^c$  denotes false negatives (all c instances that are not classified as c).

### B. Comparison

Different Technique have been compared based on computational complexity given in equation 5.

$$O(\sum_{l=1}^d n_{l-1} \times s_l^2 \times n_l \times m_l^2) \quad (5)$$

Computational Complexity of SVM in the form of Big O notation can be given as:

$$O(m^3)$$

d :The number of convolutional layer.

$n_l$  : The filter's width in a given l-th layer

$s_l$  : size of the filter

$m_l$  : The and output feature map

SVM and other Machine learning algorithm needs to undergo the process of feature Extraction' and optimization of weights while the CNN perform automatic feature extraction with proper parameter selection.

**TABLE 1: COMPARISION WITH PRIOR RELATED WORK**

Algorithm	Accuracy(%)
2-DCNN	90
Logistic Regression	74
SVM	70
Random Forest	76
KNN	73

## 5. CONCLUSION

By The analysis of proposed model and by comparing the 2D-CNN Architecture with prior related work, 2-D CNN architecture is more Effective than traditional Machine learning methodologies yielding with accuracy of 90%.

The advantage of CNN-Architecture is it can eliminate pre-processing thereby increasing the accuracy. The 2-D CNN architecture with Signal to image transformation is most effective method for detection of arrhythmia. The application of this proposed System can be implemented in app for real-time monitoring.

## REFERENCES

- [1] Ehab Essa, Xianghua xie, "Multi-model Deep Learning Ensemble for ECG Heartbeat Arrhythmia Classification", IEEE Conference :2020 28<sup>th</sup> European Signal Processing Conference(EUSIPCO). 2020.
- [2] Anita Pal, Ranjeet Srivastva, Yogendra Narain Singh," CardioNet: An Efficient ECG Arrhythmia Classification System Using Transfer Learning", Science direct Journal, 2020.
- [3] Sena Yağmur Şen, Nalan Özku, "ECG Arrhythmia Classification By Using Convolutional Neural Network And Spectrogram", IEEE Journal, 2019 Innovations in Intelligent Systems and Applications Conference (ASYU),2019.
- [4] Muzammil Hussai and Muhammad Kamran Malik, "Arrhythmia Classification Techniques Using Deep Neural Network", Hindawai journal,2021.
- [5] Wusat Ullah, Imran Siddique, Rana Muhammad Zulqarnain., "Classification of Arrhythmia in Heartbeat Detection Using Deep Learning", Hindawai journal,2021.
- [6] M. Ramkumar , R. SarathKumar , A. Manjunathan M Mathankumar , Jenopaul Pauliah , "Auto-encoder and bidirectional long short-term memory based automated arrhythmia classification for ECG signal",The Elsevier Journal of Knowledge-Based Systems,2021.
- [7] Mehmet Akif OZDEMIR, Onan GUREN, and Ozlem KARABIBER CURA, Aydin AKAN,Aytug ONAN " Abnormal ECG Beat Detection Based on Convolutional Nutral Networks", 2020 Medical TechrologiefNational conference

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