Arrhythmia Detection Using One Dimensional Convolutional Neural Network

Mr. R. R. Karhe, Ms. Bhagyashri Badhe.

Head of Department, E&TC, SGDCOE, Jalgaon, Maharashtra, India
Student, E&TC, SGDCOE, Jalgaon, Maharashtra, India

---***---

Abstract - *Electrocardiogram signal is the basic signal in the age of computer and science for detection related with heart, there are also increasing Heart Disease Detection requirements, which indicates that the given ECG of a particular person is normal or abnormal (abnormality is like heart attack and arrhythmia (An arrhythmia is a problem with the rate or rhythm of your heartbeat.). Heart Disease Classification is a promising technology for automatic and accurate individual recognition, focusing on these challenges. Arrhythmia is categorized into 5 classes; here bradycardia, tachycardia, ventricular, contraction and normal ECG are detected with reference of CNN trained signal. By means of heart beat rate per minute ECG signal is detected in this paper in order to detect arrhythmia type using convolutional neural network.*

Key Words: ECG, wavelet transformation, convolutional neural network, Arrhythmia detection, data representation.

1. INTRODUCTION

Electrocardiogram signal is the basic signal in the age of computer and science for detection related with heart, there are also increasing Heart Disease Detection requirements, which indicates that the given ECG of a particular person is normal or abnormal (abnormality is like heart attack and arrhythmia(An arrhythmia is a problem with the rate or rhythm of your heartbeat.). Heart Disease Classification is a promising technology for automatic and accurate individual recognition, focusing on these challenges. Arrhythmia is categorized into 5 classes; here bradycardia, tachycardia, ventricular, contraction and normal ECG are detected with reference of CNN trained signal. By means of heart beat rate per minute ECG signal is detected in this paper in order to detect arrhythmia type using convolutional neural network.

Convolutional neural network (CNN), as one of the major deep learning algorithms, is now a day's gaining large attentions having maximum advantages, its powerfulness in automatically learning the intrinsic patterns from the data, which can both prevent time-consuming manual feature engineering and capture hidden intrinsic patterns more effectively. Inspired by signal processing of the electrocardiogram, CNN consists of multiple layers, each of which owns a small ECG beat consist of collection to process portions of the input ECG. These collections are tiled to introduce region overlap, and the process is repeated layer by layer to achieve a high level abstraction of the original ECG.

This paper propose a novel wavelet domain multiresolution convolutional neural network approach (MCNN) for ECG heart disease identification, which avoids data-dependent complicated heartbeat detection/ segmentation techniques and heavy manual feature engineering that are both time-consuming and of a limited generalization ability. Specifically, it allows for blind segmentation of both normal and abnormal ECG streams (i.e., system can randomly select an ECG segment for user identification purpose), provides a multiresolution data representation in the wavelet domain to achieve richer temporal and spectral characteristics, and leverages the self-learning ability of CNN to automatically adapt its internal parameters to wavelet-domain raw data. For algorithm evaluation, a one-lead ECG configuration is chosen, considering it is more convenient than the multilead ECG configuration in daily applications, and of course, it also poses more challenges to the identification algorithm. Moreover, to demonstrate the generalization ability of the proposed framework composed of blind segmentation, data representation enrichment, phase difference removal, parallel multiresolution feature self- learning and classification, eight diverse datasets are considered which include not only different electrode placement methods (chest and wrist) but also various heart health conditions (with and without cardiac abnormalities), which are much more challenging than other works.

2. SYSTEM OVERVIEW

The block diagram of the proposed approach is shown in Figure 1, below process is mainly divided into filtering, Segmentation/Coefficient Selection, CNN, Training process of all database ECG signal using CNN, arrhythmia monitoring.

2.1 Filtering

Different low frequency noises are affected by the ECG signal during its acquisition and transmission. Noises with low frequency include baseline wandering. The noises contaminated in the ECG signal may lead wrong interpretation. Baseline wander is a low-frequency noise component present in the ECG signal. This is mainly due to respiration, and body movement. Baseline wander have frequency greater than 1Hz. This low frequency noise, Baseline wander causes problem in detection and analysis of peak. This noise is removed by ZPLPF(Zero Pole Low Pass Filter). The value of alpha (α) should lies between 0.95 to 0.99. Here we use α=0.98. Common ECG signals used in prior art for heart disease come from either medical acquisitions or, more recently, off-the-person settings. Both of these contaminate the signal with noise, however, it is usually confined to 50/60 Hz (powerline interference) and 0–1 Hz (baseline wander from movement, breathing, and others. Noise in the acquired driving signals is noticeably more dominant and less predictable.

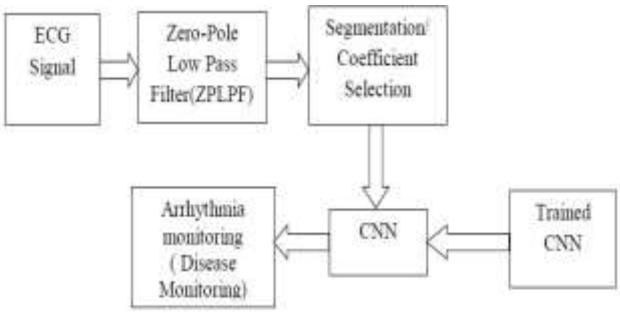

Fig.1 Basic block diagram of Arrhythmia detection using

2.2 Segmentation/Coefficient Selection

The raw ECG signal is first filtered sequentially using ZPLPF filters then the result is subtracted from the original ECG to obtain the baseline corrected ECG signal. Noise-reduced ECG is then arbitrarily divided into 3600 segments. The number of segments is optimized manually to obtain the highest accuracy. The coefficient is selected using DCT(Discrete Cosine Transform). We record signal for 10 second with sampling rate of 360, thus we get 3600 segments after segmentation

2.3 CNN algorithm

Numerous methods have been proposed for generic

heartbeat classification using ECG signal based on techniques such as discrete wavelet transform, feature selection, hidden Markov models (HMM) and mixture of experts method. In morphological features (wavelet and independent component analysis) and dynamic features (RR interval) are combined to give a set of more comprehensive features. These methods require certain amount of priori knowledge of the signals or they need expert input frequently. These limit the application of the method and higher variations may be encountered when classifying new subjects' ECG signals. Furthermore, integrity of ECG components, such as P, Q, R, S and T waves, may also be required for these algorithms. However, for arrhythmia, these ECG components may not always be well defined and their extraction becomes ambiguous.

To circumvent the limitation of these methods that require manual feature selection, some researchers turn their sight to convolutional neural network (CNN) and several CNN based approaches have been proposed for ECG classification recently. CNN has emerged as one of the most powerful machine learning approaches in recent years. Recent studies have also shown great potentials of CNN in dealing with biomedical applications, such as animal behavior classification, histo pathological diagnosis, protein structure prediction and electromyography (EMG) pattern recognition. CNN framework has a clear advantage of making use of large training dataset for improving classification performance. For instance, classifier for atrial fibrillation trained from 30,000 patient's ECG data that can outperform the average cardiologist performance. Even with a smaller training set (hundreds of beats), several recent studies have shown improved performance of cardiac arrhythmia detection with CNN.

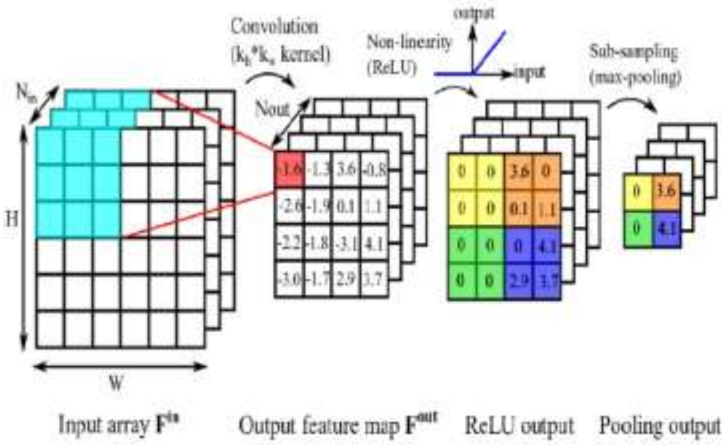

Fig. 2 The three main processing stages in a CNN.

This paper explored the 3-D approach for ECG classification with CNN. Using a 3-D encoded ECG inputs, not only the continuous waveforms, but also the relationships of various ECG components in adjacent heartbeats can be readily captured by the convolutiona l filters. Hence, as compared to these 1-D algorithms, the 2- D approach may boost the performance of the CNN classifier in terms of both network capacity and regularity. In this algorithm, we first used a 3-D CNN classifier for heartbeat classification. To supply a feature-rich input to the CNN network, three adjacent heartbeats in ECG were transformed into a 3-D coupling matrix that capture morphology of single heartbeat as well as temporal relationship in adjacent beats. Then, we proposed an automatic selection process to include the most representative beats into the training set to improve classifier performance, as opposed to a randomly selected set used in other studies. Our proposed method was tested using publicly accessible MIT-BIH arrhythmias database and compared with previous work following AAMI recommendations.

CNNs extract high-level features from input ECG signal using successive stages of convolutions, non-linearities, and sub sampling operations. The three stages are shown in Fig. 2. A typical vision application starts with 3 input feature map channels, corresponding to the red, green, and blue color channels of the signal. The convolution stage takes then as input a 3D array Fin with Nin 2D feature maps. Each filter in the filter bank connects an input feature map Fin to an output feature map Fout.

The convolution output is also a 3D array, Fout composed of Nout. A point-wise non-linearity is then applied to Fout. In current SOA CNNs, the ReLU is the most widely used nonlinearity and is computed by $f(x) = \max(0;x)$. In addition to being computationally cheap, using ReLUs empirically often yields better classification accuracy compared to saturating non-linearities, i.e, sigmoidal non- linearities. The pointwise non-linear transformation is usually followed by a subsampling operation. A common sub-sampling strategy with many empirical advantages is max pooling, where each pooling window is replaced by the maximum value in the window. An example of a 2x2 non-overlapping pooling stage is shown in Fig. 2.

When designing CNNs hardware accelerators, one major consideration is the energy consumption from the amount of memory access and the number of computes needed. Rounding a full precision pre-trained network to lower precision weights and activations will help to reduce hardware resources but the accuracy of the network is usually compromised. It is possible to increase the accuracy by also training deep networks using reduced bit precision methods.

In order to run reduced precision CNNs on the Null Hop accelerator, CNN developed a custom branch of Caffe1. It uses to train networks from scratch as well as to fine-tune existing 32-bit floating-point networks to any specified fixed point precision for both weights and activations using the power2quant algorithm. The average scarcity in the activations increased from 57% in floating precision to a remarkable 82% in reduced precision.

2.4 CNN algorithm with classifier

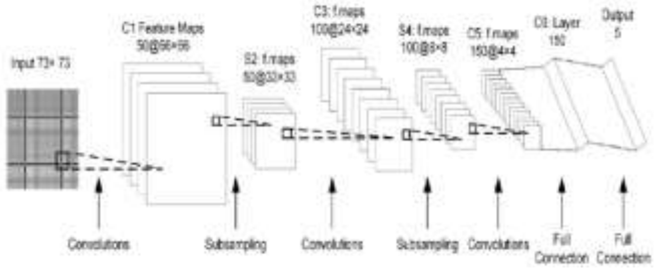

Fig. 3 Schematic for proposed CNN classifier.

Fig. 3 shows a schematic for our CNN classifier. This CNN classifier has a similar form to the one used for MNIST handwritten digit database. Our CNN model contains 3 convolutional layers, 2 sub-sampling layers (1 maximum sub-sampling layer and 1 average sub-sampling layer), 1 fully connected layer with dropout and a softmax loss layer. Rectified linear units (ReLU) is used as activation function.

Different input sizes were tested for the best performance.

The convolution filter sizes were adjusted accordingly. An open source MATLAB toolbox MatConvNet was used to implement the CNN classifier.

2.5 Training process of ECG using CNN

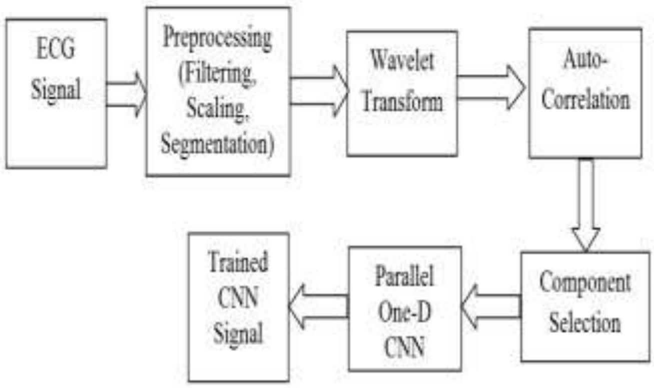

Fig. 4 Training process of all database ECG signal into One Dimensional ECG Signal

The system diagram of the proposed approach is shown in Fig. 4, including pre-processing, wavelet transform, autocorrelation, component selection and parallel 1D- CNN. This section gives detailed description of our approach according to the signal processing.

Specifically, the ECG stream is firstly blindly split up into signal segments with an equal length of two seconds without leveraging any heartbeat location information, which is not only immune to diverse morphological/beat- to-beat interval vairiabilities, but also tolerant to signal artifacts that are usually major challenges in non-blind segmentation approaches. Afterwards, the ECG segments are tansformed to the wavelet domain which is expected to reveal more detailed time and frequency characteristics in multiple resolutions than the original time domain. Then the auto-correlation operation is performed to each wavelet component to remove the blind-segmentation- induced phase difference. Finally, based on the enriched data representation, a 1D-CNN is applied to each wavelet component to learn the intrinsic patterns automatically, which allows for parallel feature self-learning in various wavelet scales, avoiding time consuming manual feature engineering.

3. Experimental Result and Discussion

3.1 Result of Heart Disease Classification

The resultant Graphic User Interface(GUI) for heart Disease Identification is shown in figure 5. The GUI allows the user to identify type of heart disease that may be arrhythmia having 3 types or normal patient. The GUI consists of buttons and that buttons are enabled sequentially with each step is completed satisfactorily.

Figure 5 Basic GUI(Graphic User Interface) The GUI consists of :

1. TRAIN: For every ECG sample/signal CNN is trained for

21 times, because CNN have 7 layers and 3 iterations,

that's why signal is trained with 7*3=21 iterations .

2. TEST: It load the particular ECG signal on display. For that it open file which contains signal with .mat format

3. CNN TEST: It apply the ZPLPF to remove noise from signal and extract filtered signal and shows normality or abnormality(here bradycardia, tachycardia and ventricular are detected.) of heart disesase.

4. DISPLAY:It display ECG Signal, pole zero plot for ZPLPF, original and filtered ECG.

5. STATUS VIEWER: It shows the status of CNN training , normality or abnormality(here bradycardia, tachycardia and ventricular are detected.) of heart disesase. When there is nothing is loaded on all 3 buttons, status viewer shows wait notation.

First step is to acquire ECG signal using the "TEST" button. The GUI shows the chosen ECG signal from database in figure 6. The ECG signal of .mat format is selected as a input signal , these input signal are classified using CNN classifiers.

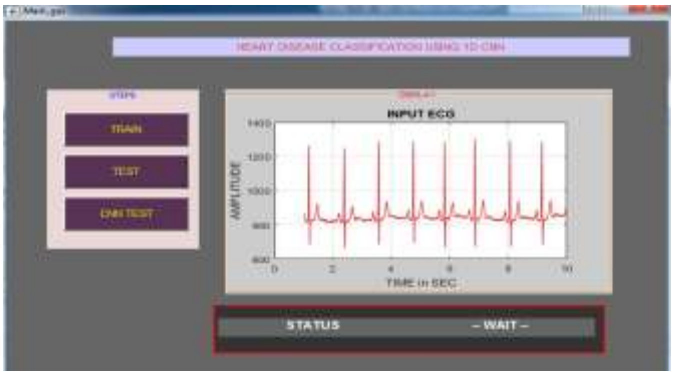

Figure 6 GUI with displayed acquired signal

Once the signal is acquired the TRAIN button is enabled. The second step is to perform training operation on the ECG signal to extract layer information for CNN. For every ECG samples/signals CNN is trained for 21 times as indicated in figure 7. Signal is trained 21 times because CNN have 7 layers with 3 epoch having 21 iterations. After this STATUS VIEWER shows that CNN TRAINING is COMPLETE as shown in figure 8. After this step CNN TEST button becomes active.

```
Command Window
>> Main_gui
Epoch 1: Cost on iteration 1 is 2.173875
Epoch 1: Cost on iteration 2 is 1.327682
Epoch 1: Cost on iteration 3 is 1.251828
Epoch 1: Cost on iteration 4 is 1.262965
Epoch 1: Cost on iteration 5 is 0.958969
Epoch 1: Cost on iteration 6 is 1.179353
Epoch 1: Cost on iteration 7 is 0.966960
Epoch 2: Cost on iteration 8 is 0.866337
Epoch 2: Cost on iteration 9 is 1.042696
Epoch 2: Cost on iteration 10 is 1.098549
Epoch 2: Cost on iteration 11 is 1.025537
Epoch 2: Cost on iteration 12 is 0.912214
Epoch 2: Cost on iteration 13 is 0.951671
Epoch 2: Cost on iteration 14 is 0.816962
Epoch 3: Cost on iteration 15 is 0.968962
Epoch 3: Cost on iteration 16 is 0.812616
Epoch 3: Cost on iteration 17 is 0.779444
Epoch 3: Cost on iteration 18 is 0.991796
Epoch 3: Cost on iteration 19 is 0.947538
Epoch 3: Cost on iteration 20 is 1.055523
Epoch 3: Cost on iteration 21 is 0.906916
fx >>
```

Figure 7 21 times Trained Signal having 7 CNN layers and 3 epoch

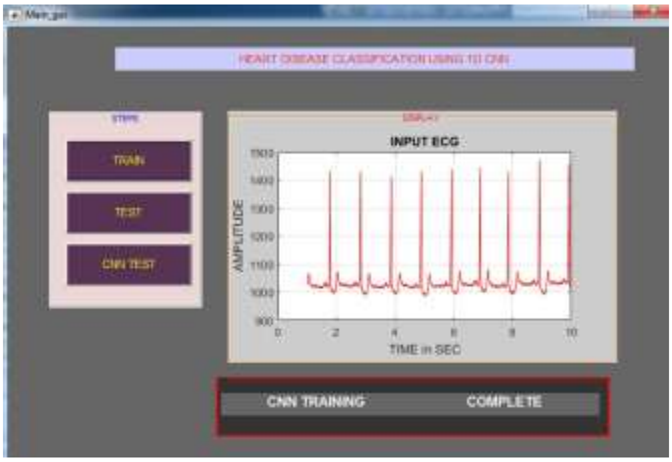

Figure 8 CNN training complete status showed by GUI. After training is done the CNN TEST button is enabled. The third step is to perform filtering operation on the signal to improve the signal quality by reducing the low frequency noise and determine the filter is stable. CNN TEST button is used to perform filtering using ZPLPF as indicated in figure 9 (If the pole lies between and on circle within 1 real and imaginary part then we can say that it is stable filter) and it also shows filtered and original ECG with amplitude variations indicated in figure 10.

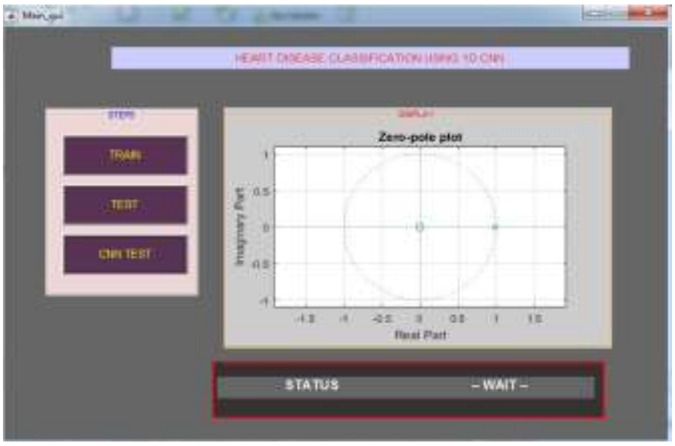

Figure 9 GUI with displayed stable zero-pole plot for ZPLPF

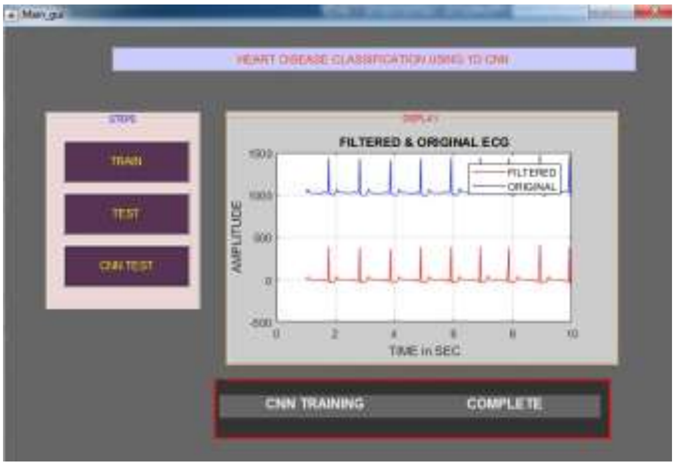

Figure 10 GUI with displayed filtered and original signal

3.2 Result of normal ECG signal

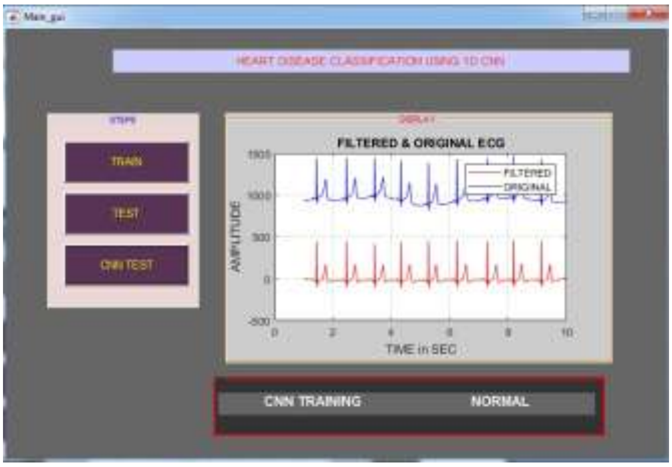

Figure 11 GUI displays normal ECG

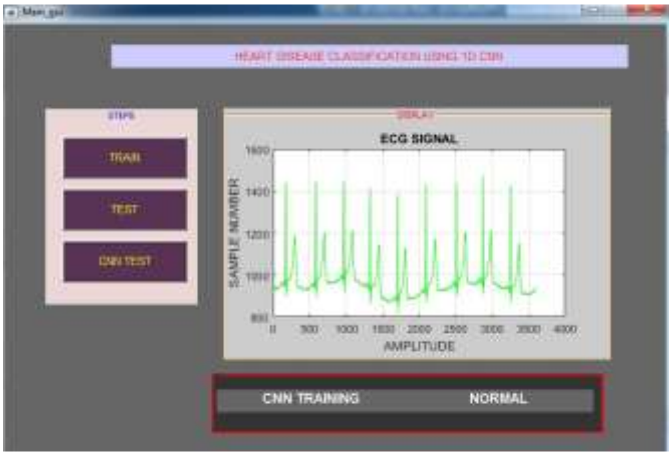

Figure 12 Normal ECG with Filtered and original signal

Figure 11 and 12 GUI displays normal ECG output with Filtered and original signal. Normal ECG fulfills the criteria for Heart rhythm and the heart rate is lies between 60 to 100 beats per minute (heart rate= 60-100bpm). ECG criteria follows: Regular rhythm with normal rate of 60 to 100 beats per minute.

3.3 Result of Bradycardia disease

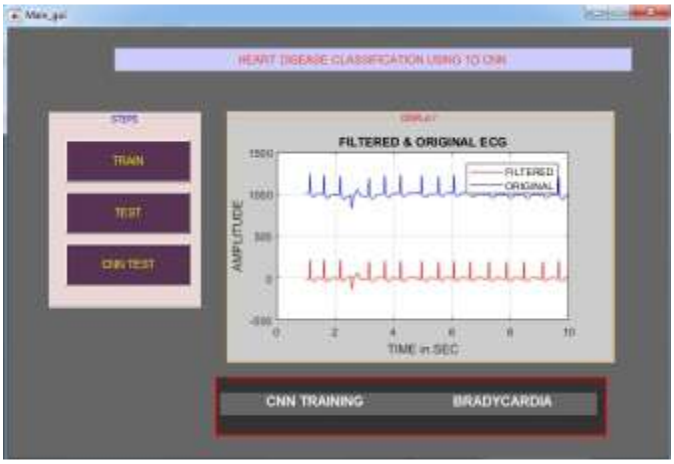

Figure 13 GUI displays Heart Disease Bradecardia

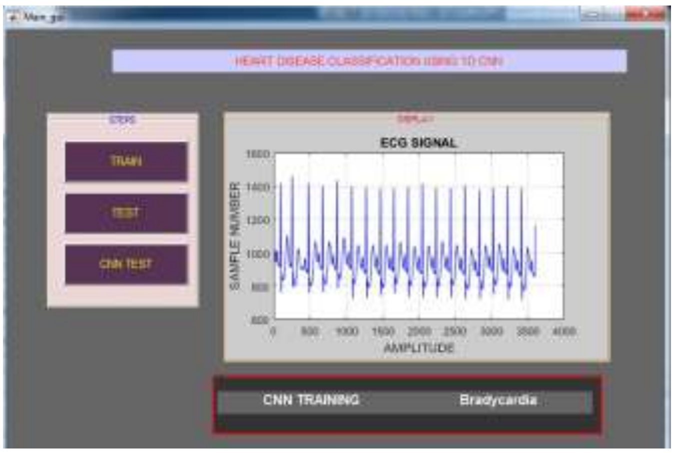

Figure 14 Heart Disease Bradecardia with Filtered and original signal

Figure 13 and 14 displays GUI displays Heart Disease Bradecardia with Filtered and original signal. bradycardia fulfills the criteria for Heart rhythm but the heart rate is slower than 60 beats per minute (heart rate< 60bpm). ECG criteria follows: Regular rhythm with ventricular rate slower than 60 beats per minute. P-waves with constant morphology preceding every QRS complex.

3.4 Result of ventricular disease

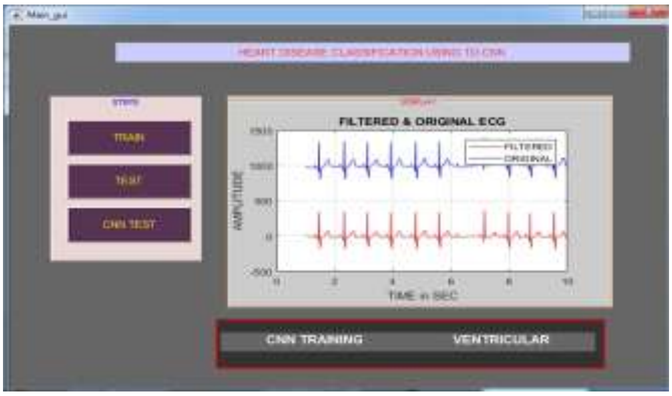

Figure 15 GUI with displayed Heart Disease Ventricular

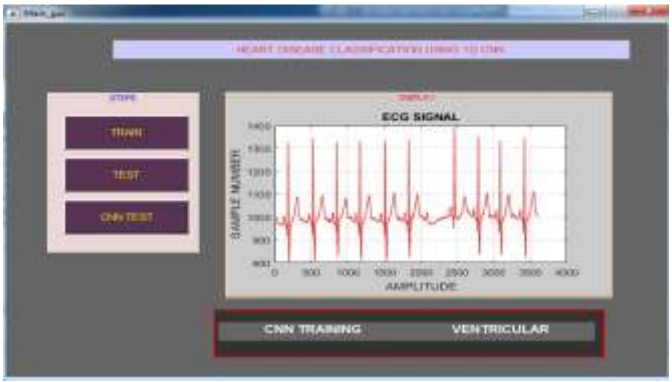

Figure 16 Heart Disease Ventricular with Filtered and original signal

Figure 15 and 16 displays GUI with displayed Heart Disease Ventricular with Filtered and original signal. Ventricular arrhythmias: Abnormal rapid heart rhythms (arrhythmias) that originate in the lower chambers of the heart (the ventricles) having 20-40 bpm. Ventricular arrhythmias include ventricular tachycardia and ventricular fibrillation.

3.5 Result of tachycardia disease

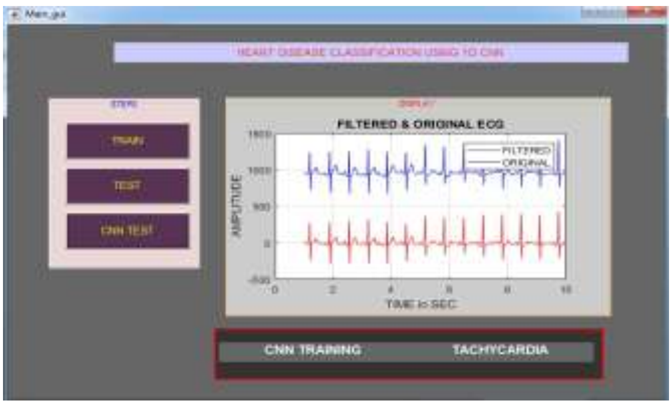

Figure 17 GUI with displayed Heart Disease Tachycardia

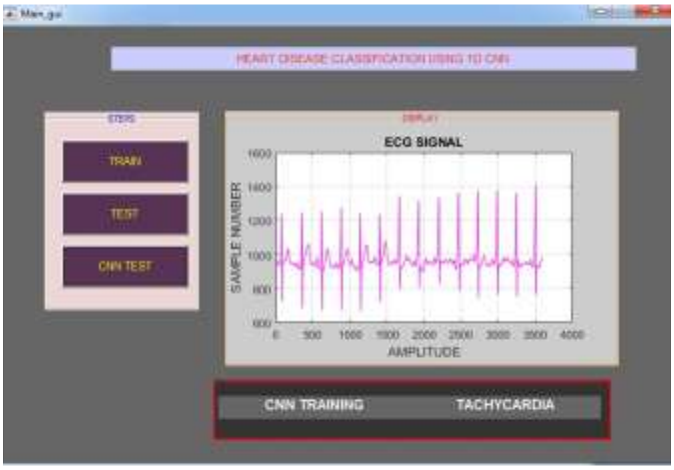

Figure 18 Heart Disease Tachycardia with Filtered and original signal

Figure 17 and 18 GUI with displayed Heart Disease Tachycardia with Filtered and original signal Tachycardia is a common type of heart rhythm disorder (arrhythmia) in which the heart beats faster than normal while at rest. Tachycardia occurs when an abnormality in the heart produces rapid electrical signals that quicken the heart rate (heart rate > 100bpm), which is normally about 60 to 100 beats a minute at rest.

3.6 Result Analysis for normal and different arrhythmias

Table 1 Result Analysis

File Name	Status of Disease	CNN training status display	Display on command window
3.Mat	Normal	Complete	Ecg Is Normal Having 60 - 100bpm
12.Mat	Bradycardia	Complete	Ecg Is Abnormal With Bradycardia Disease Having Beat
19.Mat	Tachycardia	Complete	Ecg Is Abnormal With Tachycardia Disease Having Beat Rate Is Greater Than
21.Mat	Ventricular	Complete	Ecg Is Abnormal With Ventricular Disease Having Beat Rate Is Lies Between 20

4. CONCLUSIONS

This work contributions include novel multiresolution convolutional neural network for Heart Disease Identification applications. Focusing on existing challenges, we have introduced convolutional neural network algorithm and CNN training and segmentation techniques for heart disease identification and fetched data of all the ECG signal database from MIT-BIH with convolutional neural network algorithm and training of ECG signal to compare that trained signal with original ECG Signal, which indicates that the given ECG of a particular person is normal or abnormal Heart Disease Identification system is becoming increasingly important in arrhythmia identification and its accuracy is upto 90% than manual detection by doctor which conclude that Normal ECG fulfills the criteria for Heart rhythm and the heart rate is lies between 60 to 100 beats per minute (heart rate= 60-100bpm). ECG criteria follows: Regular rhythm with normal rate of 60 to 100 beats per minute.

Bradycardia fulfills the criteria for Heart rhythm but the heart rate is slower than 60 beats per minute (heart rate< 60bpm). ECG criteria follows: Regular rhythm with ventricular rate slower than 60 beats per minute Ventricular arrhythmias: Abnormal rapid heart rhythms (arrhythmias) that originate in the lower chambers of the heart (the ventricles) having 20-40 bpm.

Tachycardia is a common type of heart rhythm disorder (arrhythmia) in which the heart beats faster than normal while at rest. Tachycardia occurs when an abnormality in the heart produces rapid electrical signals that quicken the heart rate (heart rate > 100 beats per minutes)

REFERENCES

[1] I. Odinaka, P.-H. Lai, A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag, and J. W.Rohrbaugh, ``ECG biometric recognition: A comparative analysis,'' *IEEE Trans. Inf. Forensics Security*, vol. 7, no. 6, pp. 1812 1824, Dec. 2012.

[2] M. K. Bashar and H. Yoshida, "Robust Human Recognition using Heartbeat Feature", Abstract, the 37th Int. Conf. of the IEEE Engineering in Medicine and Biology Society (EMBC 2015), pp. 107, August 25–29, 2015, Milan, Italy.

[3] S. I. Sa e, J. J. Soraghan, and L. Petropoulakis, ``ECG biometric authentication using pulse active width (PAW),'' in *Proc. IEEE Workshop Biometr. Meas. Syst. Secur. Med. Appl. (BIOMS),* Sep. 2011, pp. 1 6.

[4] M. Oquab, L. Bottou, I. Laptev, and J. Sivic, ``Learning and transferring mid-level image representations using convolutional neural networks,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 1717 1724.

[5] C. Ye, M. T. Coimbra, and B. V. K. Vijaya Kumar, ``Investigation of human identification using two-lead electrocardiogram (ECG) signals,'' in *Proc. 4th IEEE Int. Conf. Biometrics, Theory Appl. Syst. (BTAS)*, Sep. 2010, pp. 1 8.

[6] Q. Zhang, C. Zahed, V. Nathan, D. A. Hall, and R. Jafari, ``An ECG dataset representing real-world signal characteristics for wearable computers,''in Proc. IEEE Biomed. Circuits Syst. Conf. (BioCAS), Oct. 2015, pp. 1 4.

[7] M. Tantawi, K. Revett, A.-B. Salem, and M. F. Tolba, ``ECG based bio-metric recognition using wavelets and RBF neural network,'' in *Proc. 7th Eur. Comput. Conf. (ECC)*, 2013, pp. 100 105.

[8] J. Yao and Y. Wan, ``A wavelet method for biometric identification using wearable ECG sensors,'' in *Proc. 5th Int. Summer School Symp. Med. Devices Biosensors (ISSS-MDBS)*, 2008, pp. 297 300.

[9] A. Lourenço, H. Silva, and A. Fred, ``Unveiling the biometric potential of nger-based ECG signals,'' *Comput. Intell. Neurosci.*, vol. 2011, Jun. 2011, Art. no. 720971.

[10] C.-M. Ting and S.-H. Salleh, ``ECG based personal identification using extended Kalman lter,'' presented at the IEEE 10th Int. Conf. Inf. Sci., Signal Process. Appl., Kuala Lumpur, Malaysia, 2010, pp. 774 777.

[11] Q. Zhang, D. Zhou, and X. Zeng, ``A novel machine learning-enabled framework for instantaneous heart rate monitoring from motion-artifact- corrupted ECG signals,'' *Physiol. Meas.*, vol. 37, no. 11, pp. 1945 1967, 2016.

[12] S. Mukhopadhyay, S. Biswas, A. B. Roy, and N. Dey, ``Wavelet based QRS complex detection of ECG signal,'' *Int. J. Eng. Res. Appl.*, vol. 2, no. 3, pp. 2361 2365, 2012.

[13] M. A. García-González, A. Argelagós, M. Fernández- Chimeno, and J. Ramos-Castro, ``Differences in QRS locations due to ECG lead: Relationship with breathing,'' in *Proc. 13th Medit. Conf. Med. Biol. Eng. Comput.*, 2014, pp. 962 964.