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CNN Based Detection of Arrythmia and Normal Sinus Rhythm

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ABSTRACT: The Analysation of significant change of ECG signal in short term is not possible with the specific time intervals. Many misleads and misjudgements will happen when ECG signal was not extracted perfectly. We propose a Computer Aided Diagnosis system to classify different ECG signals very accurately. Discussion of problems and solutions will be presented after the experiment results.

KEYWORDS: Arrythmia Detection, Convolutional Neural Network, Electro Cardio Gram Signal, Sinus Rhythm, Signal Classification.

I. INTRODUCTION

In recent years, the World Health Organization's data on non-infections chronic disease (NCD) have indicated that NCD is the leading cause of global death to date. In 2016, NCD accounted for 71% (41 million) of the world's 57 million deaths. The main cause of these deaths is cardiovascular disease (17.9 million deaths, accounting for 44% of all NCD deaths and 31% of global deaths). The World Health Organization in 2010 has already suggested countermeasures for cardiovascular diseases. But the ground report shows, cardiovascular disease numbers has increased. This is showing the threat to public health stood by cardiovascular disease. Common cardiovascular diseases include, stroke, hypertensive heart disease, rheumatic heart disease, and atrial fibrillation (AF). ECG is the primary diagnostic tool for understanding arrhythmias; ECG signals contain information about different types of arrhythmias, but manual analysis of ECG signals is difficult. Arrhythmia signals are not always present, and may require long-term records and observations; these signals are complex and nonlinear.

The ECG related literature has shown that using machine learning and electrocardiogram diagnosis through computer aid diagnosis (CAD) system has good results. A research method proposed that integrated PCA and LDA to ECG signal features of 256 samples; they used KNN to classify, but not all of the data could be effectively classified. They used a weighted KNN (WKNN) for classification.

II.RELATED WORK

Most of the previous methodologies, classify the atrial fibrillation and normal sinusrhythm but with a less accuracy.In this paper, a Convolutional Neural Network function is used to convert 1D to 2D image dataset which provides high accuracy. The Proposing method will exist better accuracy and sensitivity compared to the existing method. Along with the Normal Heart Beat Rhythm, classification of Atrial premature beat, Premature Ventricular Contraction and Supraventricular Arrythmia signals are done using CNN.

[1] Pławiak P, Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system2018, In this paper they did to enhance the characteristic features of the ECG signal, the spectral power density was estimated. Genetic optimization of parameters and genetic selection of features were tested.[2] Maji U, Mitra M, Pal S, Automatic detection of atrial fibrillation using empirical mode decomposition and statistical approach2013. They Proposed The proposed algorithm can be applied to identify the instant of change in rhythm from normal to AF of a cardiac patient under observation. [3] Luz EJ, Schwartz WR, Camara-Chavez G, Menotti D, ECG-based heartbeat classification for arrhythmia detection 2016, In this work, current methods of ECG-based automated abnormalities heartbeat classification by presenting the ECG signal preprocessing, the heartbeat segmentation techniques, the feature description methods and the learning algorithms used. [4] Zubair M, Kim J. Yoon C, An automated ECG beat classification system using convolutional neural network 2016, In this paper, we proposed an ECG heart beat classifier using convolutional neural networks which have the ability to extract and learn suitable features from raw ECG data.

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III. PROPOSED WORK

The Proposed block diagram show below that gives an overview of out work graphically,

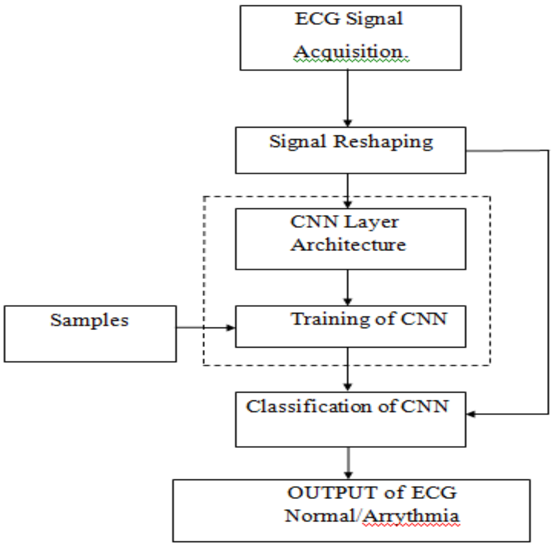

Fig. 1 Proposed Block Diagram

A. ECG Signal Acquisition:

Electrocardiogram (ECG) includes the graphical recording of the electrical activity of the coronary heart over the years. it's far the most identified biological signal, and with non-invasive technique; it is typically used for the prognosis of a few sicknesses through inferring the sign. Cardiovascular sicknesses and abnormalities modify the ECG waveform; every portion of the ECG waveform incorporates information that applies to the clinician in arriving at a proper prognosis. The electrocardiograph sign taken from a patient is typically get corrupted with the aid of external noises, for this reason necessitating the need for a proper noise-free ECG signal. A sign acquisition system includes several stages, inclusive of sign acquisition through hardware and software program instrumentation, noise or other characteristics filtering and processing for the extraction of information. Electrocardiography signals recorded on a long timescale (i.e., numerous days) for the reason of figuring out intermittently taking place disturbances within the coronary heart rhythm. simple ECG waveform has proven in Fig.1. it is a mixture of P, T, U wave, and a QRS complicated. The whole waveform is referred to as an electrocardiogram with labels P, Q, R, S, and T indicating itsone of a kind capabilities.

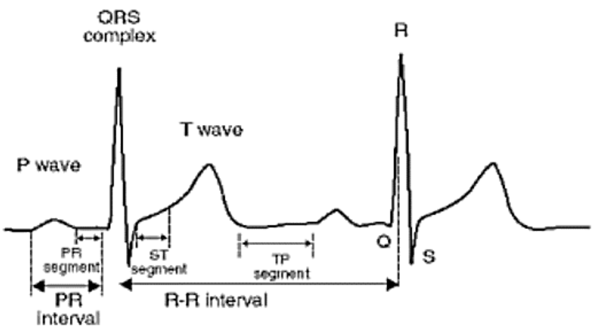

Fig 2. Schematic representation of ECG signal

B. ECG Signal Processing

signal processing is accomplished in the vast majority of systems for ECG evaluation and interpretation. it's far used to extract a few characteristic parameters. the sphere of biomedical sign evaluation or processing has advanced to the level of practical application of signal processing and pattern analysis techniques for efficient and progressed non-invasive prognosis, online tracking of vital ill patients, and rehabilitation and sensory aids for the handicapped. ECG evaluation issues resting ECG interpretation, stress testing, ambulatory monitoring, or intensive care monitoring, which bureaucracy a fundamental set of algorithms that situations the signal with appreciate to different kinds of noise and

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artifacts, stumble on heartbeats, extract fundamental ECG measurements of wave amplitudes and periods, and compress the information for efficient storage or transmission. It will become tough for the expert to diagnose the diseases if the artifacts are present inside the ECG signal.

The objectives of acquisition of ECG signal and signal processing system is to acquire the noise free signal. The major sources of noise are

1. Power line interference
2. Muscle contractions
3. Electrode contact noise
4. Motion Artifacts
5. Baseline wandering
6. Noise generated by electronic devices used in signal processing circuits
7. Electrical interference external to the subject and recording system
8. High-frequency noises in the ECG
9. Breath, lung, or bowel sounds contaminating the heart sounds (PCG).

There are various types of methods to extract the ECG parameters from the noisy ECG signal. First we need to analyze ECG signal to get which type of noise mesh up with the signal.

C. Create an image dataset

Two image datasets were created to be prepared using a CNN. The first one-dimensional digital ECG dataset was formed after signal filtering and segmentation for the filtered signal experiment, and the second one-dimensional digital ECG dataset was formed after signal segmentation for the non-filtered signal experiment. The 2D image indicates the ECG value of ECG signal at the corresponding time space by representing the amplitudes of the EEG signals as a function of time.

D. Convolution Neural Network Activation Function

The activation function converts the enter neurons right into a neuron output through an activation function. Activation functions are divided into linear functions and nonlinear functions. The sigmoid function is the maximum common activation function, defining the domain from positive infinity to negative infinity, with some value from zero to 1, and a slope symmetric to the y-axis. In nowadays's deep neural networks, getting to know the impact of the Sigmoid function is incredibly terrible, and the ReLU characteristic is regularly used as the activation function of the neural network. in this examine, the activation function become organized inside the CNN architecture of this observe after the convolutional layer and the fully-related hierarchy, and ultimately the SoftMax layer turned into an output.

IV. PSEUDO CODE

Training Using CNN80% of dataset are trained by the following steps

Step 1: Upload Dataset
Step 2: The Input layer
Step 3: Convolutional layer
Step 4: Pooling layer
Step 5: Convolutional layer and Pooling Layer
Step 6: Dense layer
Step 7: Logits Layer

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V. SIMULATION RESULTS

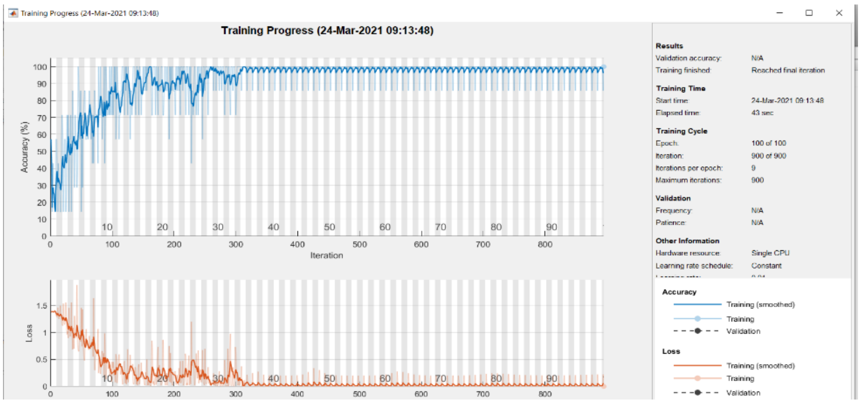

Fig 3. Training Process

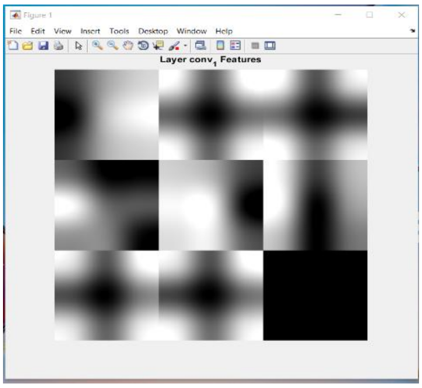

Fig 4. Layer Conv1 Features

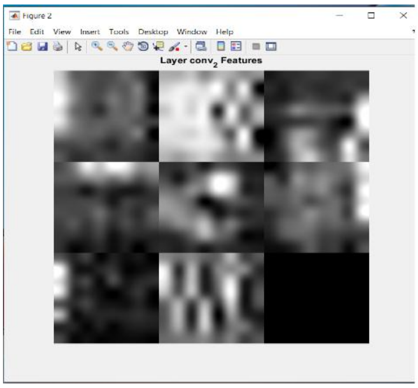

Fig 5. Layer Conv2 Features

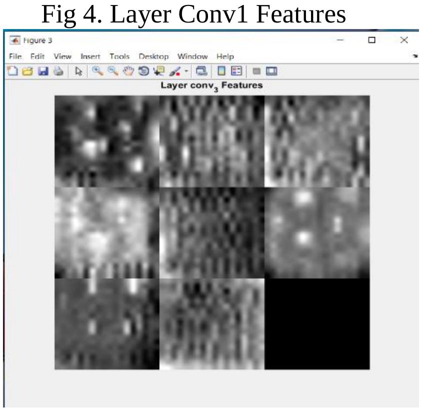

Fig 6. Layer Conv3 Features

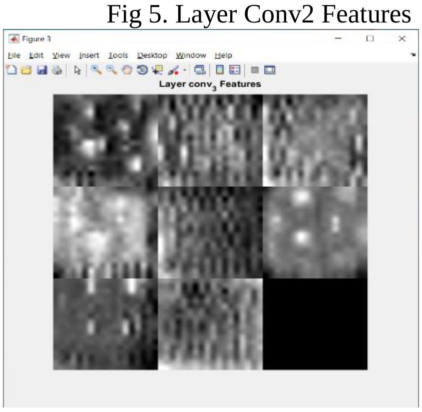

Fig 7. Layer Conv4 Features

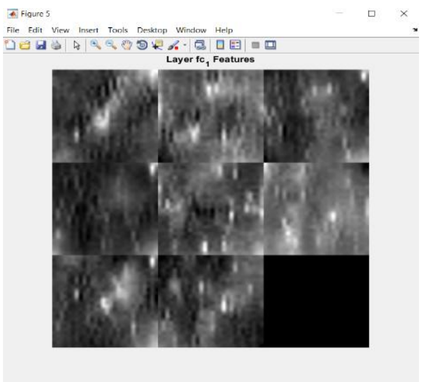

Fig 8. Layer fc1 Features

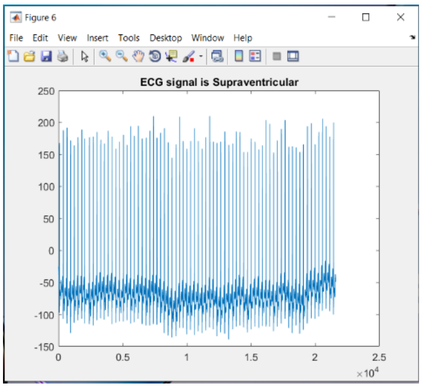

Fig 9. ECG Signal is Superventricular

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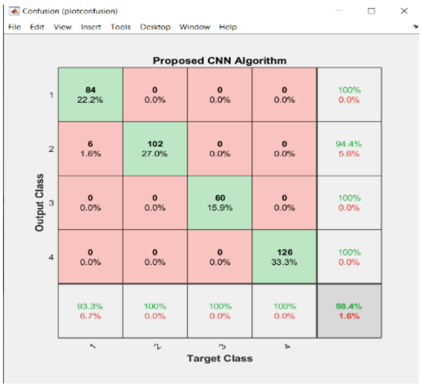


Fig 10. Proposed CNN Algorithm Confusion Matrix

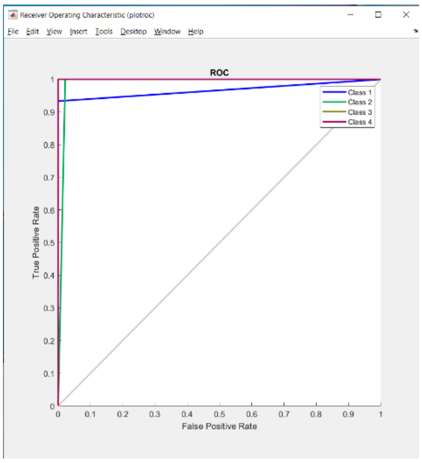


Fig 11. ROC

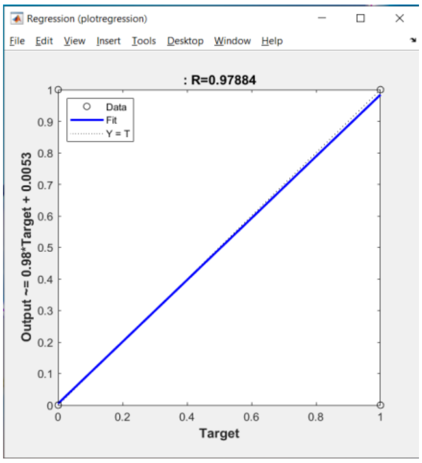


Fig 12. Regression

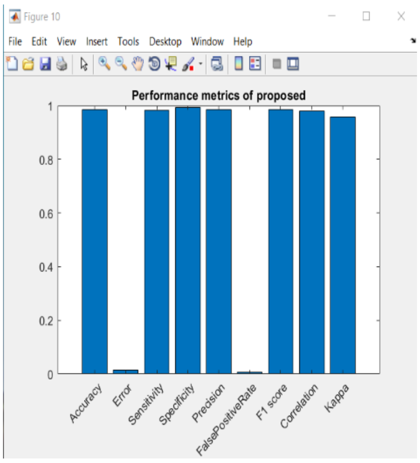


Fig 13. Performance metrics of proposed

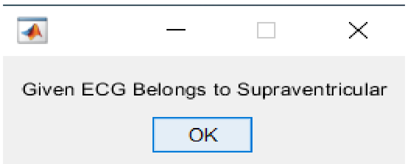


Fig 14. Output Results

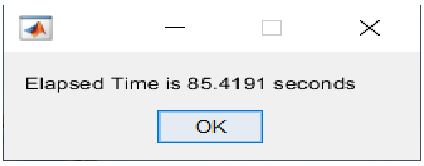
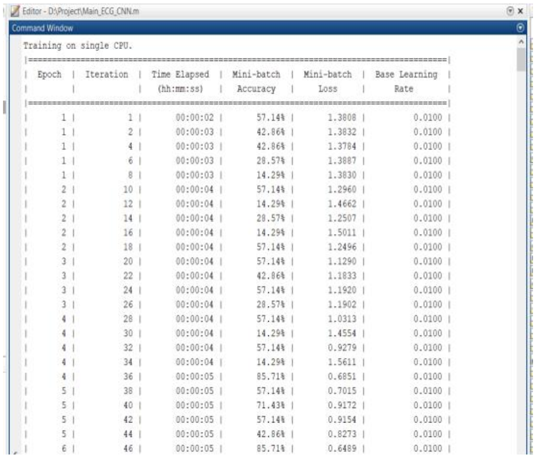
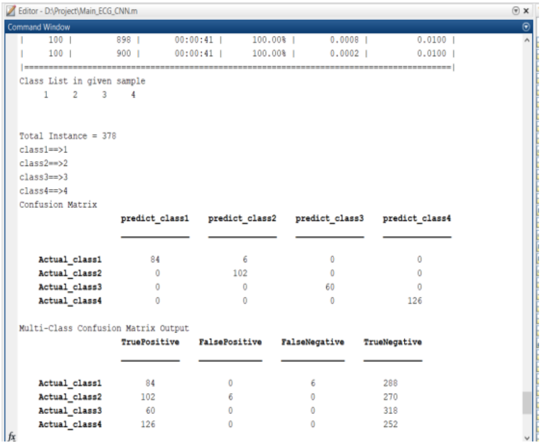


Fig 14. Elapsed time to compute algorithm


Training on single CPU.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:02	57.14%	1.3808	0.0100
1	2	00:00:03	42.86%	1.3832	0.0100
1	4	00:00:03	42.86%	1.3784	0.0100
1	6	00:00:03	28.57%	1.3887	0.0100
1	8	00:00:03	14.29%	1.3830	0.0100
2	10	00:00:04	57.14%	1.2960	0.0100
2	12	00:00:04	14.29%	1.4662	0.0100
2	14	00:00:04	28.57%	1.2507	0.0100
2	16	00:00:04	14.29%	1.5011	0.0100
2	18	00:00:04	57.14%	1.2496	0.0100
3	20	00:00:04	57.14%	1.1290	0.0100
3	22	00:00:04	42.86%	1.1833	0.0100
3	24	00:00:04	57.14%	1.1920	0.0100
3	26	00:00:04	28.57%	1.1902	0.0100
4	28	00:00:04	57.14%	1.0313	0.0100
4	30	00:00:04	14.29%	1.4554	0.0100
4	32	00:00:04	57.14%	0.9279	0.0100
4	34	00:00:04	14.29%	1.5611	0.0100
4	36	00:00:05	85.71%	0.6851	0.0100
5	38	00:00:05	57.14%	0.7015	0.0100
5	40	00:00:05	71.43%	0.9172	0.0100
5	42	00:00:05	57.14%	0.9154	0.0100
5	44	00:00:05	42.86%	0.8273	0.0100
6	46	00:00:05	85.71%	0.6489	0.0100

Fig 15. Training Iterations Process


100	898	00:00:41	100.00%	0.0008	0.0100
100	900	00:00:41	100.00%	0.0002	0.0100

Class List in given sample
1 2 3 4

Total Instance = 378
class1==>1
class2==>2
class3==>3
class4==>4
Confusion Matrix

	predict_class1	predict_class2	predict_class3	predict_class4
Actual_class1	84	6	0	0
Actual_class2	0	102	0	0
Actual_class3	0	0	60	0
Actual_class4	0	0	0	126

Multi-Class Confusion Matrix Output

	TruePositive	FalsePositive	FalseNegative	TrueNegative
Actual_class1	84	0	6	288
Actual_class2	102	6	0	270
Actual_class3	60	0	0	318
Actual_class4	126	0	0	252

Fig 16. Training Iterations Process

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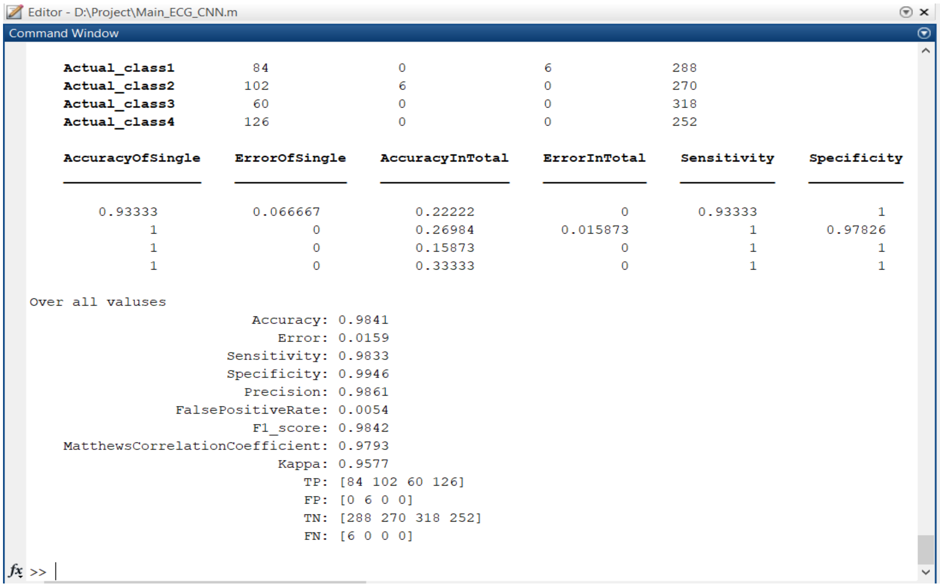

```
Editor - D:\Project\Main_ECG_CNN.m
Command Window

    Actual_class1        84           0            6            288
    Actual_class2       102           6            0            270
    Actual_class3        60           0            0            318
    Actual_class4       126           0            0            252

    AccuracyOfSingle    ErrorOfSingle    AccuracyInTotal    ErrorInTotal    Sensitivity    Specificity
    ________________    _____________    _______________    ____________    ___________    ___________

        0.93333           0.066667           0.22222                0         0.93333              1
              1                  0           0.26984         0.015873               1        0.97826
              1                  0           0.15873                0               1              1
              1                  0           0.33333                0               1              1

over all values
                     Accuracy: 0.9841
                        Error: 0.0159
                  Sensitivity: 0.9833
                  Specificity: 0.9946
                    Precision: 0.9861
            FalsePositiveRate: 0.0054
                     F1_score: 0.9842
 MatthewsCorrelationCoefficient: 0.9793
                        Kappa: 0.9577
                           TP: [84 102 60 126]
                           FP: [0 6 0 0]
                           TN: [288 270 318 252]
                           FN: [6 0 0 0]

fx >>
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Fig 17. Parameters measured for Detection

VI. CONCLUSION AND FUTURE WORK

In general, detecting atrial fibrillation involves the use of changes in the waveform of the ECG, notably the length and number of times. The proposed ECG system pre- processes, builds images, and predicts whether the wave- form has pattern of AF. The system can easily process a heartbeat data series into a single heartbeat, and converts the series of single heartbeats into an image without feature selection. The results delivered 99.18% accuracy, 99.31% sensitivity and 99.03% specificity for non-filtered ECG signals. With no cumbersome artificial settings, the results of this study are comparable to the related studies. The proposed system has high generalizability; it can help doctors to diagnose diseases effectively and reduce misdiagnosis. This can save considerable time, and finally the doctors can easily deliver the diagnosis for the patient.

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Preetha S, is currently pursuing Bachelor of Engineering in Electronics and Communication Engineering at GRT Institute of Engineering and Technology, Tiruttani, Anna University. Her Research Interest in classification of Medical signal Processing, Medical Image Processing, Classification of Digital Image Processing.

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