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Neural Network Classifiers for Cardiac Arrhythmiya From Scanned ECG Documents

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ABSTRACT

In this paper Neural Networks have been implemented for categorizing the beats in an ECG into normal and abnormal. This paper intends towards the enabling of automatic detection and classification of various Arrhythmia types. The MIT-BIH Arrhythmia database has been implemented. This database is referred for classify the ECG image in to Standard Arrhythmia CU Ventricular Tachyarrhythmia, Supraventricular Arrhythmia and Ventricular Tachyarrhythmia. During the process, the scanned ECG images have been preprocessed to remove noise. After cropping the ROI, the Dijikstraw's shortest path algorithm is employed for detection and digitization of ECG signal. A wide Variety of Harris corner features are drawn out from the digitized ECG signal. Using these features ECG signals are classified into different categories. The real time scanned ECG images are also used for disclosure and classification of ECG images. The dataset is divided as training and testing sub-data. The accuracy and abilities of investigating the concepts of ECG arrhythmia detection is explained with practical and comparisons with various network models have been implemented.

Key words: Neural networks, MIT-BIH, Dijikstraw's shortest path algorithm, Harris corner.

1.INTRODUCTION

Human heart is a four chambered muscular organ which pumps blood into arteries and circulates oxygen throughout the body. Hence the pulsation of the heart called heartbeat is extremely important. An electrical signal is engendered from the Sinoatrial node at top of the right chamber of the heart [1]. This signal stimulates heart beat. However the heart may experience abnormal increase or decrease in its beat rate. Such abnormality is known as arrhythmia [2].Arrhythmia is classified into two categories: Bradycardia and Tachycardia. When the heart rate falls down 60 BPM, its Bradycardia and when its rises higher than 100 BPM, its Tachycardia. Both types show different effect on the human body. Bradycardia causes drowsiness, fainting, sleepiness and rare chances of cardiac arrest. However, Tachycardia affects the pumping capability of the heart and generates the symptoms like chest pain, problem of breathing and may cause heart attack. It implies not all arrthymias are dangerous but most can damage heart and cause death. Hence sudden cardiac death is growing concern in the world.

In order to detect such abnormality in heart rate, an electrocardiogram (ECG) device is used. This device measures the variation in the electrical signals of heart. As per the reports by the American Heart Association (AHA) about 295,000 emergency cases of cardiac arrests in the United States are taken out of hospital [2]. An automated system that is able to diagnose heart beats and offer an early detection of arrhythmia would greatly assist in preventing cardiac arrests and save thousands of lives. It would also benefit cardiologists in monitoring the heart beat rates and deciding on the specific types of arrhythmia from the two categories as mention above.

A heart beat can be symbolized as QRS, T and P wave as shown in figure1 below. As shown in the diagram, beat morphology (Normal and abnormal pattern) of different waves of ECG signals will be considered for the arrhythmia detection. Hence, wavelet decomposition operation is performed. In that operation, signals are down sampled. If there is reduction in detailed feature of ECG signals, fourth level decomposition can be used and a pattern matching to the original one is chosen. Value of ECG signal from second order decomposition can be identified. Getting the R peaks, few more features can be determined with respect to the location of R, T, S waves and their respective amplitude.

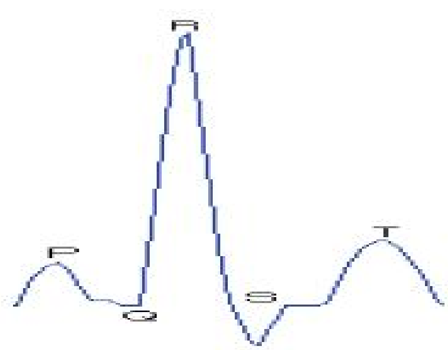

Figure 1: ECG Signal

This research heads towards the enhancement in arrhythmia analysis and detection by using neural network classifiers. This analysis is dedicated to the results concerned with identifying and classifying the pattern showing abnormality in electrical signals produced in the heart. The ECG images are scanned and digitized using Dijikstraw's shortest path algorithm. The Harris croner features are extracted from the digitized ECG signal. This work pulls together different kinds of neural network models and weighs their performance against another. The training and testing of samples drawn using the eminent MIT-BIH arrhythmia database serves as the basis for simulation results. The performance is also evaluated for the real time scanned ECG images to detect the Arrhythmia ECG images. This paper is structured as follows. Section II briefly evaluates works related to ECG Arrhythmias disease detection and classification. Whereas, this implemented method for integrating ECG digitization and different neural network taxo mical models is mention and elaborated in Section III. A MATLAB based system for ECG images classification with arrhythmia detection has been presented in Section IV. In Section V, reports the evaluation results of the different suggested classification models. Finally, Section VI concludes the research.

2. RELATED WORK

Remarkable works and related research have been done in analyzing the time domain features of ECG signal. This includes RR intervals, QT segments, QRS complexes and other morphological features [2–4]. On the other hand, the spectral domain offers a different insight and its parameters give a distinctive representation of signal which can be used for better diagnosis. Besides the precise time-domain changes of some arrhythmias will have an apparent impact on the ECG spectrum. The most well-known tool for investigating a signal in frequency domain is the Fourier Transform (FT), which in spite of detailed frequency information provides no link to the time domain. Meaning, one wouldn't know when different frequencies of signal occur. Each arrhythmia is triggered in a specific part of the heart's conduction system and each part of the ECG signal corresponds to a specific part of depolarization or repolarization, FT can't provide the sufficient information for an accurate detection. This problem can be overcome with assistance of time– frequency (TF) techniques. Short-time Fourier transform (STFT) is a popular TF technique could be used to reckon the energy distribution of the ECG signal; the features are then extracted from the energy distribution and used in classification algorithms. There is a tradeoff in time and frequency resolutions in STFT, limiting authenticity of the features [5]. Wavelets resolve this issue by employing a time-scale resolution scheme for signal analysis. Papers adopting STFT and wavelet techniques for ECG signal processing and arrhythmia classifications report significant improvements compared to single domain studies [6–9]. As a supervised classification problem, many machine learning algorithms have been proposed in literature. Support vector machine (SVM) [7, 10, 11], self-organizing map (SOP) [12], artificial neural networks (ANNs) [6, 13], linear discriminate analysis (LDA) [2, 14], conditional random filed (CRF) [15], decision trees [16]. Using the same dataset and exploring various features and dimensionality reduction algorithms helps in forming a fast evolving field for ECG arrhythmia classification.

3. DETECTION AND CLASSIFICATION OF ARRHYTHMIYA FROM SCANNED ECG IMAGES

Various steps for classification and detection of arrhythmia disease from scanned ECG images as follows:

A. Database Gathering and Preprocessing
- Obtaining the Arrhythmia and Normal ECG Images Data from MIT-BIH laboratory
- Prepare the Data of scanned ECG Documents
- Scanning the real time ECG images and preparation of the database.

B. Preprocessing of scanned ECG images using Median Filter.

C. Design a method digitization of scanned ECG images using Dijikstraws Shortest Path Algorithm

D. Feature Extraction: Harris Corner Detection

E. Design and development of neural network classifier for classification of the ECG signal data as normal or Arrhythmia

F. Evaluate the performance of neural network classifiers
- Patternnet
- Feedforwardnet
- Cascadednet
- Layercnet (Recurrent Neural Network)

A. Database preprocessing

The ECG signals are downloaded and recorded from the PhysioBank database using MIT-BIH Arrhythmia Database which is generally recognized as a standard test bench for the evaluation of arrhythmia detectors and basic research of cardiac dynamics to investigate the ECG signal by patient monitors in real ICU settings.

The various ECG signals considered are as follows. These ECG signals are converted to image format.

1. MIT BIH Images (Total 55 ECG Images)
   a. Arrhythmia ECG Images: 45
   b. Normal ECG Images: 10

2. Types of Arrhythmia ECG Images Data (Total 175 ECG Images)
   a. Standard Arrhythmia ECG Data: 45 ECG Images
   b. CU Ventricular Tachyarrhythmia Database: 35 ECG Images.
   c. Supraventricular Arrhythmia Database: 18 ECG Image
   d. Ventricular Tachyarrhythmia Database: 77 ECG Images

3. Real Time Scanned Images
   a. Arrhythmia ECG Images: 32
   b. Normal ECG Images: 10

ECG paper recordings need to be scanned. Scanning resolution can be 300 dpi (dots per inch). Preferred algorithm for the image compression is JPEG. Figure 2 represents a scanned ECG paper recording.

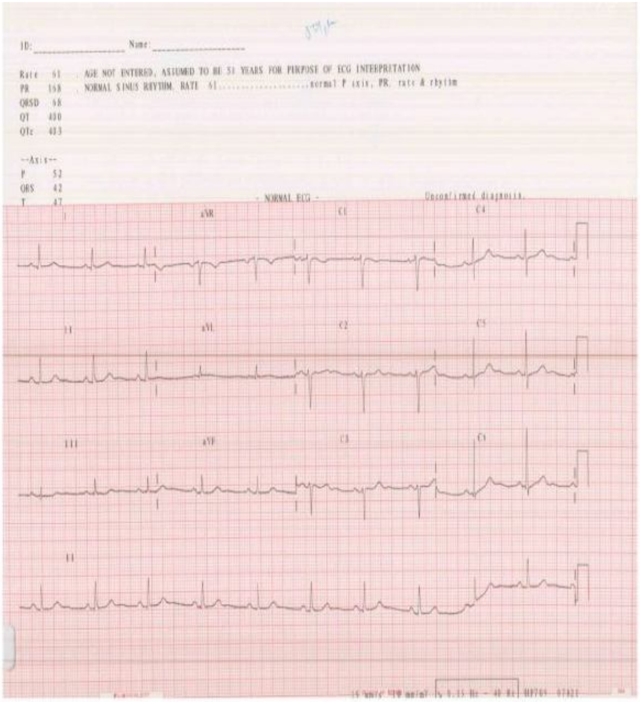

Figure 2: Scanned ECG Document

- The first step is carried out to select and crop one of the 12-lead ECG signals as shown in the figure 2 for cropping III lead

Figure 3: Cropped ECG Image.

- **Oversampling the ECG**

The ECG image is over sampled 8 times in horizontal direction. Amount to oversample is determined by maximum slope, e.g. if max slope is 16%, oversample by 16. The MATLAB function interp2 is used for oversampling. The interp2 function returns interpolated values of a function of two variables at specific query points using linear interpolation. The results always pass through the original sampling of the function. X and Y contain the coordinates of the sample points. V contains the corresponding function values at each sample point. Xq and Yq contain the coordinates of the query points.

- **Median Filter For Noise Removal**

The scanned and cropped ECG image is preprocessed to remove noise using well known median filter.

Digitization of ECG Images

- Shortest Path Calculation

The shortest path is computed using 255 **-** image intensity as energy function. The Dijikstraws Shortest path algorithm is used for finding the shortest path.

- Down sample

The computed shortest path is downsampled 8 times to account for oversampling.

- Plot the Curve

The shortest path found is the ECG curve traced in the ROI image. The curve is plot on the original image for accuracy as shown in figure 4.

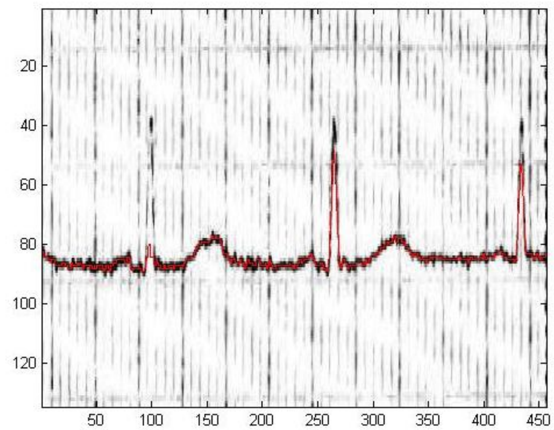

Figure 4: ECG curve plot on the original ECG image

All ECG images from the dataset are digitized.

Features Extraction

Feature extraction is one of the important steps for classification since even the best classifier may perform poorly if the features are not well chosen. Followed by ECG digitization, Harris corner features have been extracted from the digitized signal. Harris Corner Detector is a corner detection operator that is commonly used in computer vision algorithms to extract corners and infer features of an image. It was first introduced by Chris Harris and Mike Stephens in 1988 upon the improvement of Moravec's corner detector.[17] Compared to the previous one, Harris' corner detector takes the differential of the corner score into account with reference to direction directly, instead of using shifting patches for every 45 degree angles, and has been proved to be more accurate in distinguishing between edges and corners.[18]

Neural Networks for Classification

Artificial neural networks are relatively crude electronic networks of neurons based on the neural structure of the brain. They process records one at a time, and learn by comparing their classification of the record (i.e., largely arbitrary) with the known actual classification of the record. The errors from the initial classification of the first record is

fed back into the network, and used to modify the networks algorithm for further iterations.
A neuron in an artificial neural network is

1. A set of input values (xi) and associated weights (wi).
2. A function (g) that sums the weights and maps the results to an output (y).

Neurons are organized into layers: input, hidden and output. The input layer is composed not of full neurons, but rather consists simply of the record's values that are inputs to the next layer of neurons. The next layer is the hidden layer. Several hidden layers can exist in one neural network. The final layer is the output layer, where there is one node for each class. A single sweep forward through the network results in the assignment of a value to each output node, and the record is assigned to the class node with the highest value.
The Harris corner features are used for training neural networks. Various neural network architectures are considered such as

- Patternnet
- Feedforwardnet
- Cascadednet
- Layercnet (Recurrent Neural Network)

4.PROPOSED SYSTEM

Matlab-based GUI-driven tool is developed for effective detection and classification of arrhythmia using ECG images. Figure 5 shows graphical user interface (GUI) developed for proposed algorithm before execution.

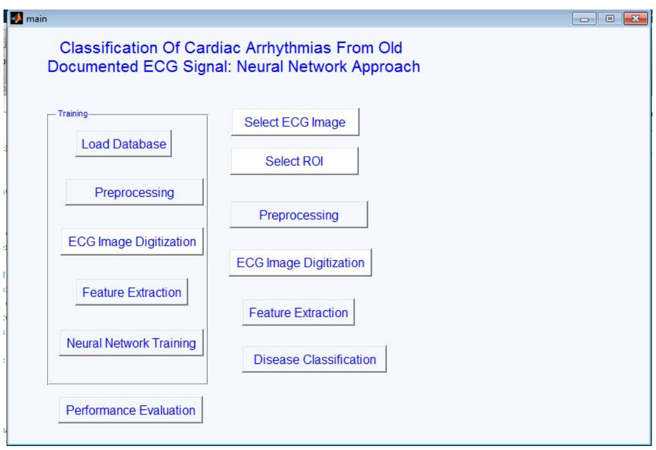

Figure 5: MATLAB based proposed system

GUI for this software is divided into number of subgroups according to their functionality. This software module not only detects arrhythmia but also helpful in analyzing scanned ECG images for analysis and classification of Arrhythmia.

Database Selection and Preprocessing:

ECG images in database are selected. The ECG images are oversampled 16 times. The ROI from the scanned ECG image is selected. Then for preprocessing, median filter is used for noise removal.

ECG Image Digitization:

In this the digitization toolbox is implemented for digitization of ECG signal from the scanned ECG image. The Dijikstraw's shortest path is used for digitizing the ECG image.

C. Features Extraction

Harris corner features are extracted from the digitized ECG signals.

Neural Networks for Training and Classification

Neural networks are trained with various features for Arrhythmiya disease detection and classification. This module deals with disease detection : if the patient is suffering with disease or not, if yes then what type of arrhythmia he's suffering with, can be found by "Disease Classification" push button then arrhythmia is displayed in box.

5.RESULTS AND PERFORMANCE EVALUATION

Three different datasets have been evaluated for the performance.

- The ECG images dataset have been prepared from real time ECG documents. The database Contains 32 images of Arrhythmiya and 10 Normal ECG images.
- The MIT-BIH data of ECG signals is converted to ECG images data for performance evaluation. The data contains 45 Arrhythmiya images and 10 normal images.
- For classification of the Arrhythmia ECG images four Arrhythmiya have been considered as:
  Standard Arrhythmia (45 ECG Images),
  CU Ventricular Tachyarrhythmia (35 ECG Images),
  Supraventricular Arrhythmia (18 ECG Images)
  And
  Ventricular Tachyarrhythmia (77 ECG Images).

The database contains approximately 109,000 beat labels. ECG signals MIT-BIH Database are described by- a text header file (.hea), a binary file (.dat), a binary annotation file (.atr) and (.mat) a mat lab file.
To evaluate the performance for all cases 70 % training data is used.

Performance Measure

The performances of various neural network architectures have been evaluated by considering different number of hidden nodes. Four parameters are used for evaluating performance of the algorithm. Those are accuracy, precision, recall and execution time. These parameters are defined using 4 measures True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)
True Positive: arrhythmia detection coincides with actual labeled data
True Negative: both classifier and actually labeled absence of arrhythmia

False Positive: system labels a healthy case as an arrhythmia one

False Negative: system labels an arrhythmia as healthy

Accuracy: Accuracy is the ratio of number of correctly classified cases, and is given by

Accuracy= (TP+TN) / N

Total number of cases are N

Precision is the fraction of retrieved documents that are relevant to the query. Precision takes all retrieved documents into account, but it can also be evaluated at a given cut-off rank, considering only the results returned by the system

Precision is defined as

Precision = TP/ (TP+FP)

Recall is the fraction of the relevant documents that are successfully retrieved. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

It is trivial to achieve recall of 100% by returning all documents in response to any query. Therefore, recall alone is not enough but one needs to measure the number of non-relevant documents also, for example by also computing the precision.

Recall is defined as

Recall= TP / (TP+FN)

Performance Evaluation for MIT BIH data

To classify the ECG images as normal and Arrhythmiya MIT-BIH data is used.

Distribution of records of MIT-BIH NSR & arrhythmia database.

Table 1: Distribution of records of MIT-BIH NSR & Arrhythmia database.

Class	Records Number
Normal Class	16272-16420-16483-16773-16795-17052-17453-18184-19088-19830
Arrhythmia Class	100-101-102-103-104-105-106-107-108-109-111-112-113-114-115-116-117-118-119-121-122-123-124-200-201-202-203- 205-207-208-209-210-212-213-214-215-217-219-220-221-222-223-228-230-231-232-233-234

Table 2. Accuracy mit-bih data

Number of Hidden Nodes	*5*	*10*	*15*	*20*	*25*	Average
Feedforward Neural Network	85.56	**100**	85.56	81.11	81.11	86.668
Patternnet	**85.56**	81.11	81.11	85.56	85.56	83.78
Cascaded Forward Net	91.11	**95.56**	76.67	76.67	87.78	85.558
LayrecNet	85.56	**92.22**	85.56	50	81.11	78.89

For almost neural networks the accuracy is better for 10 hidden nodes. The average accuracy of feedforward neural network is 86.668 which are better as compared with other neural network architectures.

Table 3: Precision mit-bih data

Number of Hidden Nodes	*5*	*10*	*15*	*20*	*25*
Feedforward Neural Network	0.8879	1	0.8879	0.8629	0.8629
Patternnet	0.8879	0.8629	0.8629	0.8879	0.8879
Cascaded Forward Net	0.7222	0.9592	0.8409	0.8409	0.9018
Layercnet	0.8879	0.9327	0.8879	0.5	0.8628

Table 4: Recall mit-bih data

Number of Hidden Nodes	*5*	*10*	*15*	*20*	*25*
Feedforward Neural Network	0.8556	1	0.8556	0.8111	0.8111
Patternnet	0.8556	0.8111	0.8111	0.8556	0.8556
Cascaded Forward Net	0.9111	0.9556	0.7667	0.7667	0.8778
LayrecNet	0.8556	0.9222	0.8556	1	0.8111

Table 5: F Measure mit-bih data

Number of Hidden Nodes	*5*	*10*	*15*	*20*	*25*
Feedforward Neural Network	0.8525	1	0.8525	0.8041	0.8041
Patternnet	0.8789	0.8555	0.8789	0.8556	0.8556
Cascaded Forward Net	0.9104	0.9555	0.7532	0.7532	0.8759
LayrecNet	0.8525	0.9217	0.8525	0.6667	0.8041

Table 6: Execution time in seconds for mit-bih data

Number of Hidden Nodes	*5*	*10*	*15*	*20*	*25*
Feedforward Neural Network	10.425	3.813	9.046	15.155	32.176
Patternnet	1.49	5.888	12.751	37.520	69.769
Cascaded Forward Net	18.78	6.443	17.885	25.967	60.482
LayrecNet	9.883	38.327	37.226	93.719	150.949

Performance Evaluation for Classification of Arrhythmiya Types

Objective of the module is to classify the ECG image. ECG digitized signal into cases of various arrhythmias. Harris Corner features approach with neural network classification is used to derive key parameters of the sampled ECG signal. Various types of Arrhythmias used for classification are

- Standard Arrhythmia ECG Data
- CU Ventricular Tachyarrhythmia Database
- Supraventricular Arrhythmia Database
- Ventricular Tachyarrhythmia Database

The MIT-BIH Arrhythmia Database directory of ECG signals is selected from physionet.

Table 7: Classification accuracy for types of Arrhythmiya

Number of Hidden Nodes	5	10	15	20	25	Average
Feedforward Neural Network	90.38	100	92.31	92.31	86.54	92.308
Patternnet	82.05	89.74	92.31	100	92.31	91.282
Cascaded Forward Net	86.54	86.54	82.69	94.87	84.62	87.052
LayrecNet	92.31	84.62	86.54	76.92	82.05	84.488

The average accuracy of feedforward neural network is 92.308 which are better as compared to other neural network architectures.

Table 8:. Classification precision for types of Arrhythmiya

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	0.8272	1	0.839	0.839	0.8011
Patternnet	0.7875	0.8382	0.839	1	0.839
Cascaded Forward Net	0.8011	0.8011	0.7971	0.946	0.8283
LayrecNet	0.839	0.8053	0.8011	0.6328	0.7476

Table 9: Classification recall for types of Arrhythmiya.

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	0.8077	1	0.8462	0.8846	0.7308
Patternnet	0.7308	0.8462	0.8846	1	0.8846
Cascaded Forward Net	0.7308	0.7308	0.6538	0.9231	0.6923
LayrecNet	0.8846	0.6923	0.7308	0.6538	0.7308

Table 10: Classification F Measure for types of Arrhythmiya.

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	0.8936	1	0.9167	0.9388	0.8444
Patternnet	0.8444	0.9167	0.9388	1	0.9388
Cascaded Forward Net	0.844	0.844	0.7907	0.96	0.8182
LayrecNet	0.9388	0.8182	0.8444	0.07907	0.8444

Table 11: Classification execution time in seconds or types of Arrhythmiya

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	2.202	8.273	31.139	62.71	135.59
Patternnet	5.393	13.83	34.262	46.54	212.97
Cascaded Forward Net	33.346	19.404	44.676	81.71	267.78
LayrecNet	26.308	60.011	41.377	402.84	603.18

The lower number of hidden nodes, lower will be the execution time. By considering the average performance, the number of hidden nodes should be chosen as 5 or 10.

Performance measures for real time scanned ECG images

The performance is evaluated on real time scanned 42 ECG images. The image ROI is cropped and after digitization, Harris Corner features are extracted. These features are used for classification of ECG images as Normal or Arrhythmiya using neural networks.

Table 12: Accuracy real time scanned database.

Number of Hidden Nodes	5	10	15	20	25	Average
Feed forward Neural Network	87.5	84.38	87.5	89.06	89.06	87.5
Patternnet	87.5	87.5	87.5	73.44	87.5	84.688
Cascaded Forward Net	82.8	87.5	87.5	81.2	87.5	85.3
LayrecNet	**87.5**	**89.06**	**90.6**	**87.5**	**89.06**	**88.744**

The average accuracy of layercNet is better for Real time scanned data which is 88.75. The numbers of hidden nodes to be chosen are 15.

For almost neural networks the accuracy is better for 10 numbers of hidden nodes.

Table 13: Precision real time scanned database

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	0.881	0.9	0.9	0.9	0.9
Patternnet	0.9	0.9	0.9	0.826	0.9
Cascaded Forward Net	0.836	0.9	0.9	0.817	0.9
LayrecNet	0.9	0.9103	0.921	0.9	0.9103

Table 14: Recall real time scanned database

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	0.875	0.8438	0.875	0.8906	0.8906
Patternnet	0.875	0.875	0.875	0.7344	0.875
Cascaded Forward Net	0.8281	0.875	0.875	0.8125	0.875
LayrecNet	0.875	0.8906	0.9063	0.875	0.8906

Table 15: F Measure real time scanned database

Number of Hidden Nodes	5	10	15	20	25
Feedforward Neural Network	0.873	0.8424	0.873	0.8893	0.8893
Patternnet	0.873	0.873	0.873	0.7142	0.873
Cascaded Forward Net	0.8271	0.873	0.873	0.8118	0.873
LayrecNet	0.873	0.8893	0.9054	0.873	0.8893

Table 16: Execution time in seconds for real time scanned database

Number of Hidden Nodes	*5*	*10*	*15*	*20*	*25*
Feedforward Neural Network	2.102	9.9167	31.491	61.514	133.60
Patternnet	3.5592	8.5091	24.081	39.302	74.551
Cascaded Forward Net	15.4231	8.2387	32.163	69.053	116.84
LayrecNet	11.2978	21.209	46.146	65.273	131.77

6.CONCLUSION

In this paper, neural network classification framework is used for classification of ECG images into different arrhythmiya types. A Harris corner is used as a feature extractor and the extracted features are fed into a neural network to carry out the final classification. Different neural networks are evaluated for performance. Main focus of this study is to implement a simple, reliable and easily applicable ECG digitization technique for the digitization of scanned ECG images. After digitization, classification of the selected four different cardiac conditions is performed. For the MIT-BIH data and for the classification data the feed forward neural network with 10 hidden gives better accuracy in terms of precision, recall, F measure and execution time. For the real time scanned ECG data although the performance of layrecNet is better, the feed forward neural networks also gave the better performance. Hence we can conclude that feed forward neural network architecture with 10 hidden nodes is the appropriate neural network architecture for classification of cardiac arrhythmia from scanned ECG images.

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