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PCA and SVD based Feature Reduction for Cardiac Arrhythmia Classification

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***Abstract*: Automatic electrocardiogram (ECG) beat classification is essential to timely diagnosis of dangerous heart conditions. A good system depends heavily upon the accurate and reliable detection of QRS complex as well as the T and P wave. Here, first the noise is removed from the digitized ECG signal. Then Stationary Wavelet Transform (SWT) is applied to the de-noised signal. After that QRS complex, T and P waves are detected and also delineated using different amplitude threshold values. This algorithm allows delineation of wide variety of QRS complex, P and T wave. The PQRST properties from the recorded ECG are used to analyze the type of arrhythmia. In this project, Myocardial Infarction, Premature Ventricular Contraction, Ventricular Tachycardia, Supra ventricular arrhythmias, ST deviation, Ischemia Change are classified using Feed Forward Artificial Neural Network Classifier. The databases are extracted from MIT-BIH (Massachusetts Institute of technology/ Beth Isrel Hospital), EURO (European ST-T Database), VFDB (Malignant Ventricular Arrhythmia database) and SVDB (Supra Ventricular Database), MIT ST Change database, Long term ST Change database. Wavelet transform algorithm is used for extracting the features. The dataset is first trained, validated and tested after which it is analyzed by using the Pattern Recognition Toolbox in MATLAB and for better efficiency the features are reduced by using Principal Component Analysis. The Artificial Neural Network achieved 94.4% accuracy in its test dataset before feature reduction and 100% after feature reduction.**

Keywords: ECG, Artificial Neural Network Classifier, SVD, PCA.

I. INTRODUCTION

A. *Electrocardiogram*

ECG is the recording of the electrical activity of the heart conducted through ions in body to surface. The information obtained from the ECG signals is used to identify different types of heart diseases. An ECG is the representative signal of cardiac physiology, which can be used in diagnosing cardiac disorders [1] [2]. ECG is a main way of gathering information from a body in order to better analyze the hearts activities [3]. This paper deals with the detection of QRS Complexes using wavelet transform based algorithm. MIT/BIH (Massachusetts institute of technology / Beth Isrel hospital) Data bases [4] are used to verify the various algorithms using MATLAB software. Leads are used to record the ECG signals with 3-12 electrodes. Multilead systems with more than 12 electrodes are also available.

Several approaches to Classification were reported in this topic which includes Bayesian approach [7], heuristic approach [8], Expert systems [9] and Markov models [10]. In general these approaches seem to suffer from common drawbacks according to previous publications, which depends on high sensitivity to noise and unreliable in dealing with new patterns. Artificial neural Networks have often been used as a tool for realizing classifiers that are able to deal even with non-linear discrimination between classes and to accept incomplete or ambiguous input patterns [11]. Back Propagation algorithm is used which performs gradient descent algorithm to minimize the mean square error between the actual output and the desired output by adjusting the weights [12]. In our study, the Wavelet algorithm and Neural network is used to detect and classify Myocardial infarction, Premature Ventricular Contraction, ventricular Tachycardia, Supra Ventricular Arrhythmia, ST deviation, Ischemia Change.

II. PROBLEM FORMULATION

A. *Cardiovascular Diseases*

Cardio vascular disease (CVD) causes the death of over 17 million people worldwide each year. The cause of CVD is due to heart attacks, strokes heart valve problems and arrhythmia. Myocardial Infarction, Premature Ventricular Contraction, Ventricular Tachycardia, Long Term Supra Ventricular arrhythmias are the life threatening cardiac disorders. The classification of ECG into these different cardiac diseases is a complex task. Therefore the characteristic shapes of ECG have to be found for the successful classification. By using the magnitude, area and duration typical heart beats are analysed by using ECG and the PQRST wave properties. Therefore ECG abnormality detection should be reliable in an ECG monitoring system or a defibrillator, if not the patient will lose the chance of treatment. Therefore for this analysis Wavelet transform algorithm is efficient rather than Discrete Fourier Transform (DFT). There are hundreds of different types of cardiac arrhythmias like atrial flutter, atrial fibrillation, ventricular flutter, ventricular fibrillation etc. There are many databases out there for personal use that make project like this possible. So finding the quality ECG signal, which does not require filtering and relatively clean signals are desired. The signals are then analyzed using Artificial Neural Networks (ANN).

Using an ECG is a non-invasive technique that is simple to analyze. A patient is attached to few leads and then every single beat is analyzed by the equipment that makes up the ECG. To understand better about ECG, knowledge about the signal outputted by the leads that are analyzing the heart are to be known. Each heart beat signal is analyzed by the ECG. Certain properties help us to determine which cardiac arrhythmias, if any is occurring in the heart. For the arrhythmias in this paper most of them can be analyzed due to differences in the QRS part of the signal. The difference in the heart is determined by the width and height.

Myocardial Infarction (MI) is a type of heart arrhythmia which occurs when part of the heart muscle, called myocardium, is deprived of oxygen and nutrients. Common causes of ischemia are Narrowing or obstruction of a coronary artery and a rapid arrhythmia, causing an imbalance in supply and demand for energy. The heart muscle cells die when the episode of ischemia lasts for a longer period of time. This is called a heart attack or myocardial infarction. This is the reason why it is critical to recognize ischemia on the ECG in an early stage. Within in few minutes severe ischemia results in ECG changes. While the ischemia lasts, several ECG changes will occur and disappear again. Therefore, it may be difficult to estimate the duration of the ischemia on the ECG, which is crucial for adequate treatment [13]. Ischemia episodes have been performed on the ST-T European database [14].

PVCs are premature heart beats that originates from the ventricles of the heart. They are premature because they occur before the regular heart beat. This early heart beat can happen in the upper (atria) or lower chamber (ventricles).The pattern is normal beat, the extra beat (PVC),a slight pause then a stronger than a normal beat. The heart is filled with more blood during the pause following the PVC giving the next beat with extra force. This pattern may occur randomly or at regular intervals. It is caused by an ectopic cardiac pacemaker located in the ventricle. It is characterized by premature and bizarrely shaped QRS complexes usually wider than 120 msec on with the width of the ECG. Many studies have shown PVCs, when associated with myocardial infarction, can be linked to mortality. Consequently their immediate detection and treatment is essential for patients with heart diseases. PVCs are performed with MIT-BIH Arrhythmia database [15].

Ventricular Tachycardia (VT) is a fast heart rhythm that occurs in one of the ventricles of the heart. It has a pulse rate of more than 100 beats per minute. It is a difficult problem for the physicians as it often occurs in life threatening situations. The symptoms of VT are angina, palpitations, shortness of breath etc [16].

Supra Ventricular Tachycardia (SVT) is also a rapid heart rate with a heart rate above 100 beats per minute. It starts and ends quickly. It originates above the heart's ventricle. It is also called Paroxysmal Supra ventricular Tachycardia. The symptoms of SVT are palpitations, Dizziness etc.

ST Segment depression is determined by measuring the vertical distance between the patient's trace and the isoelectric line. It is a sign of myocardial ischemia.

Long term ST is to detect the transient ST segment changes in the Electrocardiograms.

B. MATERIALS AND METHODS

1) Materials

a) MIT-BIH arrhythmia database

In this paper, ECG database from MIT-BIH and EURO [17] database were used. MIT-BIH database is comprised of 48 files, each containing 30-min ECG segments selected from 24-hour.recordings of 47 different patients. Of the 48 files, 28 were randomly chosen and 25 were chosen to include arrhythmic heart beat samples [18]. Each file contains two leads; with modified- lead II available in 45 files, V1 in 40files and II, V2, V4 and V5 distributed among 11 files. The database is annotated both in timing information and beat classification. [19].

b) Euro Database

This database consists of 90 annotated excerpts of ambulatory ECG signals from 79 patients. Each record is two hours in duration and sampled at 250 samples per second [20]. Each of the signal files is 5,400,000 long. Wavelet transform algorithm is used for extracting features from the ECG signals. Artificial neural network is used for the analysis of the data. An artificial neural network is a computer network consisting of artificial neurons that are used to solve problems without creating a model of the real system. This is used by a computer program MATLAB to get the desired results. The input data is given to this neural network for training and after which validation and testing of the data was done.

c) Malignant Ventricular Arrhythmia Database

This database includes 22 half –hour recordings of subjects who experienced episodes of ventricular tachycardia, ventricular fibrillation, ventricular flutter [21].

d) Supra ventricular Database

This database includes the 78 half-hour recordings of the ECG signals [22].

e) ST Change Database

ST change (ST) database includes beat annotation but currently no ST annotations. The recordings are primarily from exercise stress test and exhibits transient ST changes.

f) Long- Term ST Database

It consists of 86 ECG recordings of 80 human subjects, which is chosen to exhibit a variety of events of ST segment changes.

2) Methods

a) Feature extraction

i. Wavelet Transform Algorithm

Wavelet transform algorithm [5] is the decomposition of the signal, which is the combination of a set of basis function obtained by Dilation and Translation.

$$\omega_a x(b) = \frac{1}{a^{0.5}} \int_{-\infty}^{\infty} x(t)\varphi((t-b)/a)dt, a > 0 \quad (1)$$

The ECG wave has to be detected for extracting the features.

The WT algorithm is applied to the digitized ECG signal, without pre-filtering. Then the ECG signal is pre processed in order to remove noise. The following steps describe the significant peak detection of ECG waves.

ii. ECG Segmentation

- *QRS Complex Detection*

From the digitized ECG signal, the noise is removed. Then the Stationary wavelet transform (SWT which is a translation invariant) is applied to the noise removed ECG signal. Then the maximum amplitude signal in the ECG wave have to be selected, therefore R wave is selected, which is having the maximum amplitude. From the detected R peak the onset and offset points are detected by setting the search window before and after the R peak, this is to avoid the effect of Baseline drift.

- *QRS delineation*

In the delineation process the WT algorithm starts from the detectors position, $n_{qrs.}$ The morphology depends on the number of significant maxima; the delineation looks before n_{pre} and after n_{post} within the QRS complex, to do this the samples of first and last peaks in the QRS complexes are identified.

- *T Wave Detection*

The T wave is detected by fixing the search window $(W_{2^4}X[n])$ after the offset of QRS complex. The threshold is fixed and the maximum value exceeding the threshold is the T wave peak.

- *T Wave Delineation*

T wave is found at the scale 2^4. The maximum of the search window greater than the given threshold are the significant slope of T wave.

- *P Wave Detection*

Fixing the search window before the offset of the QRS complex the T peak is detected and finding the maxima of $(W_{2^4}X[n])$in that window and the value which exceeds the threshold value are considered to be the P peak.

- *P Wave Delineation*

P wave delineation is done similar to that of P wave delineation.

In this paper, Wavelet algorithm is used for feature extraction, 11 sets of input features such as QRS time, QRS delineation time, R wave time, R wave delineation time, P wave time, P wave delineation time, R amplitude, S amplitude, threshold for QRS complex Pre-processing and post processing were extracted from 60 samples are taken from MIT-BIH, Arrhythmia, EURO, Malignant Ventricular Arrhythmia and Supra ventricular Database. Pattern recognition tool box in MATLAB is used for the detection, analysis and for the classification of the ECG signals.

b) Feature Reduction

i. Principal Component Analysis

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. In large data sets with many features, it may be more efficient to find a smaller and more compact feature representation using a feature transformation. One method is to use PCA, which applies a projection to the features to find a reduced representation. The principal component vectors are constructed so that they are orthogonal to one another and hence have maximum variance (principal components). Generally, the training data is first normalized to zero mean and unit variance before application of the PCA algorithm. PCA has been used in many ECG applications, some of which include filtering of ECG beats, analysis of features extracted from the QRS complex, computer simulations of the cardiovascular system, individual beat recognition, and diagnosis of CVD from ECG. In the feature extraction module 120 samples of 11 features is used which has been reduced to 11 samples of 11 features after feature reduction which reduces the training period and increases the accuracy.

ii. Singular value Decomposition

The Singular Value Decomposition (SVD) is one of the most important matrix decompositions used in computer vision. SVD has the added benefit that in the process of dimensionality reduction, the representation of items that share substructure become more similar to each other, and items that were dissimilar to begin with may become more dissimilar as well. In the SVD test like PCA 120 samples were reduced to 11 samples with 11 features which reduce the dimensionality of the matrix and also the training period, which increases the accuracy.

c) Classifier Module

i. ECG Classification Flow

This stage consists of the Segmentation, Extraction and classification process. The heart beat begins from the P wave and finishes at the next P wave of the following heart beat. After this process feature extraction was done for extracting the significant features of ECG (11 features) mentioned above was extracted [23], after which the classification was done using the ANN classifier. The classification algorithm checks for any abnormalities in the heart beat.

- *Classification of Arrhythmias using artificial Feed Forward neural network*

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems. To constrain the outputs of a network (such as between 0 and 1), the output layer should use a sigmoid transfer function (such as log sig). This is the case when the network is used for pattern recognition problems (in which a decision is being made by the network).

A network can have several layers. Each layer has a weight matrix **W**, a bias vector **b**, and an output vector **a**.

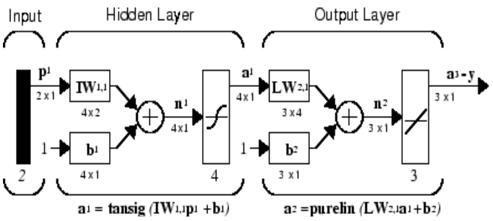

Fig .1. Feed Forward Neural Network with Back Propagation Algorithm.

It consists of three layers the first layer is the input layer which takes the input and middle layer is the hidden layer, which has no connection with the other layers. Each neuron is connected to every other neuron and hence the input information is fed to all the other neurons and the last later is the output layer which produces the output.

In Back propagation algorithm the inputs and outputs are fed into the network for many cycles, by which the network clearly learns the relationship between the input and the output, in this when every time the input vector is given for training the output is compared with the target called the error, which is calculated by

$$\text{Error}= (\text{Target}-\text{Output})^2$$

The goal is to minimize the error with minimum iteration. In the Back propagation algorithm the weights between the processing units are iteratively adjusted, So that the overall error is minimized.

In Feed forward neural network, linear transfer function is used. Neurons of this type are used in the final layer of multilayer networks that are used as function approximators.

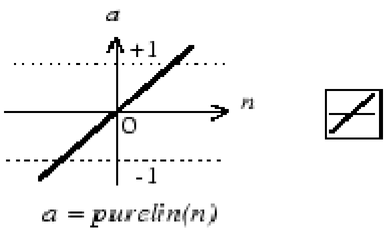

Fig. 2. Linear transfer function.

For the Classification, Back Propagation Algorithm with momentum is used to train the Feed Forward Neural Network Classifier [24]. To minimize the least square error the weights and biases of the artificial neural network are adjusted. The weights and biases are calculated using the generalized delta rule. The gradient technique was used for solving the mean square error. When using the momentum the network is not proceeding in the direction of gradient, but in the direction of the combination of the current gradient and the previous direction of the weight correction.

The classification of arrhythmias is based on the Back propagation neural network whose inputs are the features from the wavelet transform algorithm. The outputs are 1 and 0 in which 1 corresponds to particular arrhythmia and 0 does not belongs to that arrhythmia. The network consists of three layers: Input layer, Hidden Layer and an Output layer. The Input layer has 11 features and an Output layer has 6 nodes representing the six different types of arrhythmias. The hidden layer consists of 9 nodes of effective size of the network and efficiency. The Arrhythmias are

1. Myocardial Infarction

2. Premature Ventricular Contraction

3. Ventricular Tachycardia

4. Supra Ventricular Tachycardia

5. ST depression

6. Ischemic disease

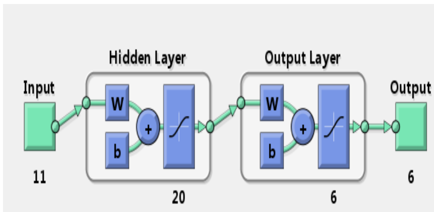

Fig 3. Setup for the beat analysis of ECG signals using Feed forward artificial neural networks.

III. RESULTS AND DISCUSSIONS

Twenty signals are chosen for each classification with a total of 120 samples for training and 120 samples for testing. Nearly 1000 iterations are performed. The datasets are trained for different percentage of samples for training, validation and testing [(70, 15, 15), (80, 10, 10), (60, 20, 20)] respectively. For every percentage of samples the number of hidden neurons is also updated and the datasets are trained for different weights. The overall classification error is 11.1%. In Medical statistics Sensitivity (S), Positive predictivity (+p) has to be evaluated.

$$\text{Se} = \frac{TP}{TP+FN} \tag{2}$$

$$+\text{p}= \frac{TP}{TP+FP} \tag{3}$$

Where TP is True Positive, FP is False Positive, FN is false negative. BP performs the gradient search for reducing the mean square error, which is obtained from training the network

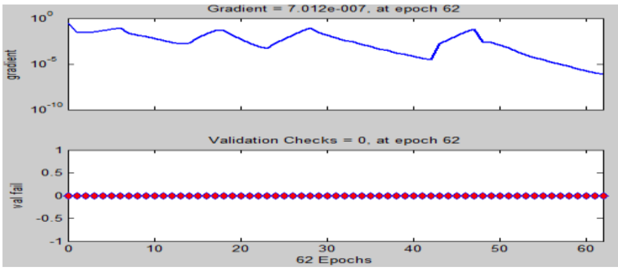

Fig. 4. Training State (Gradient and Validation Checks) for Feed Forward neural networks.

TABLE 1. COMPARISON OF MSE FOR MINIMUM ITERATIONS BEFORE AND AFTER FEATURE REDUCTION.

The minimum gradient is $7.012e^{-007}$ at epoch 62.

Table 1 shows the minimum Mean Square Error for

Samples	Iterations	MSE			Training Period (ms)
		Training	Validation	Testing	
Before Feature Reduction	31	$9.7e^{-7}$	$1.2e^{-7}$	$1.3e^{-7}$	0.01
	33	$3.7e^{-7}$	$3.1e^{-7}$	$3.3e^{-7}$	0.01
	34	$2.6e^{-7}$	$3.1e^{-7}$	$3.1e^{-7}$	0.01
	39	$2.6e^{-7}$	$2.7e^{-7}$	$2.7e^{-7}$	0.01
	43	$3.9e^{-7}$	$4.1e^{-7}$	$4.1e^{-7}$	0.01
	62	$7.0e^{-7}$	$7.0e^{-7}$	$7.0e^{-7}$	0.01
After Feature Reduction Using PCA	6	$3.4e^{-1}$	$6.1e^{-1}$	$5.3e^{-1}$	0.00
	7	$9.1e^{-2}$	$3.3e^{-1}$	$3.3e^{-1}$	0.00
	14	$1.1e^{-3}$	$3.2e^{-1}$	$4.2e^{-2}$	0.00
Using SVD	6	$3.3e^{-1}$	$3.1e^{-1}$	$3.6e^{-1}$	0.00
	7	$1.9e^{-1}$	$1.0e^{-1}$	$1.8e^{-1}$	0.00
	7	$1.9e^{-1}$	$3.6e^{-1}$	$4.0e^{-1}$	0.00

minimum iterations before and after feature reduction using SVD and PCA. In feature reduction the minimum mean square is achieved in minimum iterations itself.

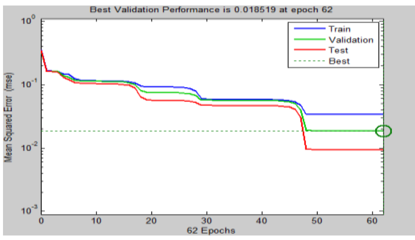

Fig. 5. Validation Performance for feed forward neural network.

The validation is 0.018519 at epoch 62, the data is trained up to 11 epochs, which is plotted against the mean square error. The overall classification result is plotted by using confusion matrix.

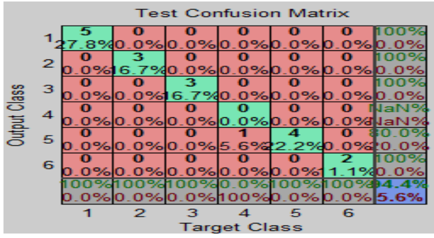

Fig. 6. Overall Performance plot for arrhythmia classification using artificial neural networks before feature reduction for test data set.

Fig 6 shows the Classification of arrhythmias using Confusion matrix. The Confusion matrix is between the output class and the target class. In the test matrix the overall classification error is 5.6%. 5 samples are correctly classified as MI, 3 samples are correctly classified as PVC. 3 samples as VT,

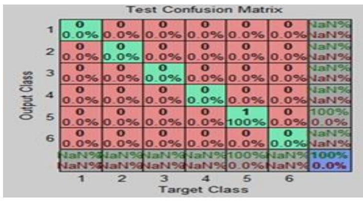

Fig . 7. Overall Performance plot for arrhythmia classification using artificial neural networks after feature reduction using PCA for test data set.

1 only one sample is for SVT and it is misclassified as ST depression, 4 samples are correctly classified as ST depression and 2 samples as Ischemic disease.

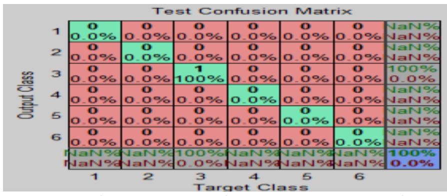

Fig . 8. Overall Performance plot for arrhythmia classification using artificial neural networks after feature reduction using PCA for test data set.

TABLE 2. COMPARISON BETWEEN ACTUAL AND DETECTED ARRHYTHMIA.

Actual arrhythmia	**Detected arrhythmia**						**Total**
	MI	**PVC**	**VT**	**SVT**	**ST**	**LT**	
MI	20	0	0	0	0	0	60
PVC	0	20	0	0	0	0	60
V T	0	0	20	0	0	0	60
SVT	0	0	20	0	0	0	60
ST	0	0	0	0	0	0	60

TABLE 3. DETERMINATION OF SENSITIVITY AND PREDICTIVITY FOR TRAINING, TESTING AND VALIDATION DATA SET.

Arrhythmia	**TP**	**FP**	**FN**	**+p (%)**	**Se (%)**	
MI	20	0	100	100	100	PVC
20	0	0	100	100	VT	20
0	0	100	100	SVT	0	20
0	50	0				
LT	20	0	0	100	100	
ST	20	0	0	100	100	

Table 3 shows the classification results of the data using Feed Forward neural network classifier with Back Propagation algorithm and also arrhythmias are misclassified in some cases. All the SVT's are misclassified as VT The sensitivity is 100% for MI, PVC, LT, ST and VT. The Positive predictivity is 100% for MI, PVC, VT, LT and ST. The overall sensitivity is 83% and Positive predictivity is 92%. Similarly, another one set of samples are taken with the total of 120 samples, 20 samples for each class and the accuracy is calculated before and after feature reduction for every weights and neurons.

TABLE 4. COMPARISON OF SENSITIVITY, POSITIVE PREDICTIVITY AND ACCURACY BEFORE AND AFTER FEATURE REDUCTION

Performance evolution	**Without feature reduction**	**With feature reduction**	
		SVD	**PCA**
Sensitivity	84%	85%	85%
Positive Predictivity	91%	91.6%	91%
Testing Accuracy	94.4%	100%	100%
overall Accuracy	83.3%	83.3%	83.3%

Table 4 shows the comparison of sensitivity, positive predictivity and accuracy before and after feature reduction, which shows that after feature reduction the percentage of sensitivity, positive predictivity and testing accuracy is increased.

Table 5 shows the comparison of improved accuracy before and after feature reduction for different weights and neurons.

TABLE 5. COMPARISON OF IMPROVED ACCURACY

Samples(20 per class)	Weights						Neurons			Samples			Accuracy (%)		
													Before Feature Reduction	After Feature Reduction	
	1	2	3	4	5	6	5	10	15	80 20 20	70 15 15	60 20 20		PCA	SVD
set1 samples					√		√			√			33	100	50
					√			√		√			16.7	33.3	50
						√		√		√			50	83.3	66.7
						√		√			√		66.7	100	66.7
		√					√					√	16.7	50	50
	√						√					√	33.3	50	66.7
			√					√				√	33.3	50	50
				√			√					√	16.7	50	50
Set 2 Samples					√		√			√			33	66.7	50
		√						√		√			16.7	33.3	33.3
						√			√		√		16.7	83.3	66.7
		√							√		√		16.7	66.7	50
						√			√			√	16.7	60.7	33.7

IV. CONCLUSIONS

The Feed Forward neural network with back propagation algorithm performs better than other networks in terms of sensitivity Positive Predictivity and accuracy.. In this study the cardiac arrhythmias such as MI, PVC, VT, ST, LT and SVT has been detected and classified using six different types of databases. Similarly, large number of arrhythmias can be classified using other databases. After feature extraction, feature reduction is done which reduces the training period and increases the accuracy.

V. FUTURE SCOPE

As ANN's gets better at analysis, they could be used in pacemakers. There is much potential in this line of research and analysis for predicting arrhythmias. In the future, more arrhythmias could be analyzed. Depending on the arrhythmias being analyzed, the FFT of the signals could be taken and used to help validate the ECG. An idea is to continue analyzing the whole signal as well as the FFT. This could have the potential to correct some of the inaccuracies of just analyzing the FFT or just the signal. Also, more patients could be analyzed to better train the network. There is variation in every heart and signals that were not accounted for by only selecting a few patients. More databases could also be used to acquire more patient data.

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