Echocardiography heart diagnosis using Artificial Neural Networks

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Summary
Over the past decades a considerable amount of time and effort has been expended researching and developing to recognize heart valves diseases. The purpose of this paper is to set out an investigation into Echocardiography for the development of a heart valves diagnosis system. Artificial neural networks are finding many uses in the medical diagnosis application .The goal of this paper is to evaluate artificial neural network in heart disease diagnosis from Echocardiography video file. The cases are studied on valves dieses. Classification is an important tool in medical diagnosis decision support. Feed-forward back propagation neural net work is used as a classifier to detect type of valve diseases.The results of applying the artificial neural net works methodology and find which get high performance corresponding to symptoms of the person. In this study, the data were obtained from Echocardiography video file to diagnosed diseases. The data is separated into inputs and targets the diagnosis of heart diseases; the percent correctly classified in the simulation sample by the feed-forward back propagation network is 95percent.

Keywords:
Artificial Neural Networks, Medical Diagnosis, Feed-forward back propagation network, Artificial intelligence, and Decision Support Systems, ECO Echocardiography

1. Introduction

Echocardiography (ECO) provides a substantial amount of structural and functional information about the heart. Still frames provide anatomical detail. Dynamic images tell us about physiological function the quality of an ECO is highly operator dependent and proportional to experience and skill, therefore the value of information derived depends heavily upon who has performed it.

Artificial neural networks provide a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications. The experiments and also the advantages of using a fuzzy approach were discussed as well. The various techniques of Artificial Neural Network applied for the diagnosis of heart diseases [1] successfully are: A simple Multi Layer Percepton is used for prediction of Heart Attack [2] and to design a Decision Support System for Heart Disease Diagnosis [3], A Back Propagation Neural Network model is applied to diagnose Heart Value Diseases [4] and to design a Decision Support System for Heart Disease Diagnosis [5], A Multichannel Adaptive Resonance Theory is used for Heart Disease Diagnosis successfully. As these models gave more accurate results in the diagnosis of heart diseases, in the present study also Back Propagation Neural Network model has been implemented for the classification of Congenital Heart Disease Diagnosis based on Signs, Symptoms and Physical Examination of a patient.

Back propagation Neural Network is a multilayer Feed Forward Neural Network Model [6] which contains one input layer, one output layer and one or more hidden layers. As the name implies the input layer receives signals from the external nodes and transmits these signals to other layers without performing any computations at that layer. The output layer receives the signals from an input layer through a weighted connection links, performs computations at that layer and produces output of the network. The hidden layer of a network receives signals from an input layer through a weighted connection links The architecture of a Back propagation Neural Network Model [7].In order to improve the diagnosis accuracy and to reduce the diagnosis time, it has become a demanding issue to develop an efficient and reliable medical Decision Support System to support yet and still increasingly complicated diagnosis decision process. Hence soft computing methods such as neural networks have shown great potential to be applied in the development of medical Decision Support System for Heart Diseases [8].

Representing video material in a digital form requires a large number of bits. The volume of data generated by digitizing a video signal is too large for most storage and transmission systems. This means that compression is essential for most digital video applications. Statistical analysis of video signals indicates that there is a strong correlation both between successive picture frames and within the picture elements themselves. However, better compression performance may be achieved by exploiting the temporal redundancy in a video sequence or the similarities between successive video frames. This may be achieved by introducing two functions: 1.Prediction: create

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a prediction of the current frame based on one or more previously transmitted frames. 2. Compensation: subtract the prediction from the current frame to produce a residual frame. Then the residual frame is compressed by an image CODEC. In order to decode the frame the technology, decoder adds the prediction to the decoded residual frame. This is described as inter-frame coding for frames are coded based on some relationship with other video frames. Video compression is necessary in a wide range of applications to reduce the total data required for the transmission or storage of video data. Video compression algorithm aims at exploiting the temporal and spatial redundancies by using some form of motion compensation followed by transform coding. The key step in removing temporal redundancy is the motion estimation where a motion vector is predicted between the current frame and a reference frame. Following the motion estimation, a motion compensation stage is used to obtain the original frame with the help of reference frame and motion vector [9].

Over the past decades a considerable amount of time and effort has been expended researching and developing biomedical diagnosis systems capable of recognizing heart diseases.

In this paper is to set out an investigation into the use of heart biomedical data for the development of a cardio diagnosis system. In Section 1 describes proposed algorithm, In Section 2 explains ECO compression by Simulink, In Section 3 introduces clearing preprocess step, In Section 4 focuses on performing feature extractions from a standard medical database like Gabor, In Section 5 developing a neural network classifier based on back-propagation architectures with different training methods and test its performance by changing parameter for it. Finally we make conclusion and evaluate performance.

2. Proposed algorithm

The system focuses on performing feature extractions from a standard compressed Echocardiograph video file database then developing a neural network classifier based on back-propagation architectures with different training methods. Gabor features are used to extract features at feature extracting phase. In matching phase, the neural network is applied or a correlation matching [11], here we applied only neural network. As seen on fig 1.

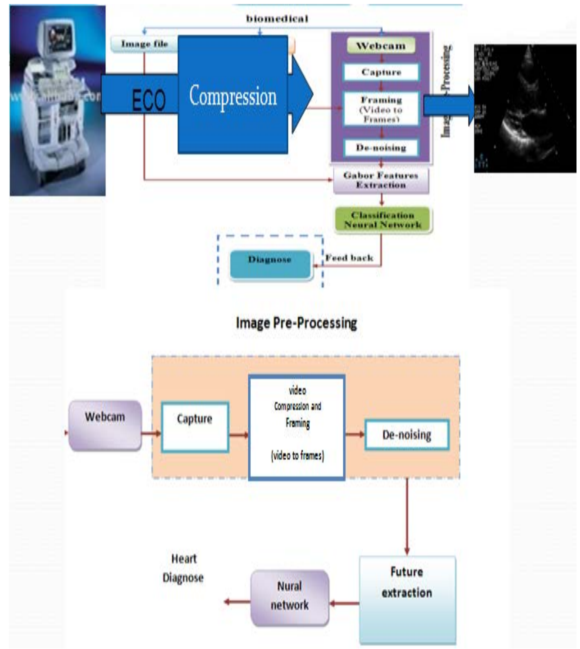

Fig 1.probosed algorithm

3. Capturing and Framing

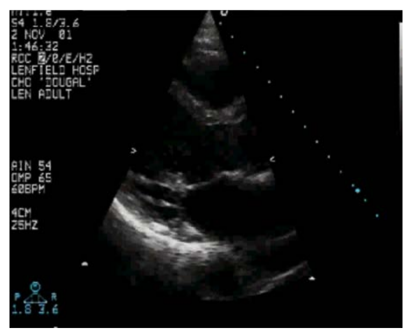

Fig .2 Original image of the 2nd frame of sequence "Echocardiography"

Our Experiments were done on the compressed Echocardiography of 80 frames (10 videos, 8 frames each) under special conditions and possible consideration of scaling, Translation, Rotation, Color and Illumination variance. Figure (2) shown the original image of the 2nd frame of sequence "Echocardiography"

4. Video Compression

This model in fig 2 illustrates video compression using motion compensation and discrete cosine transform (DCT) techniques with the Video and Image Processing Blockset™. It calculates motion vectors between successive frames and uses them to reduce redundant information. Then it divides each frame into submatrices and applies the discrete cosine transform to each submatrix.

Finally, model applies a quantization technique to achieve further compression. The Decoder subsystem performs the inverse process to recover the original video. Block sends 16-by-16 submatrices of each video frame to the Block Processing block's subsystem for processing. Within this subsystem, the model applies a motion compensation technique and the DCT to the video stream. By discarding many high-frequency coefficie1

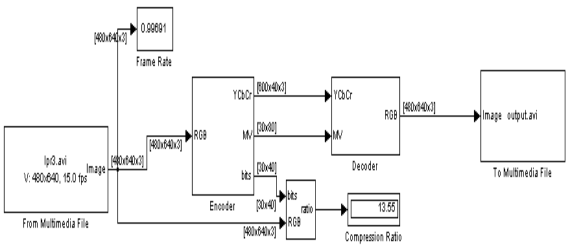

Fig.3 Video Compression Model

4.1 Video compression result

The decoder window shows the compressed video stream. Figure 4 show compressed video frame. This frame is not clear as the original video, but it still contain many of its features.

Fig. 4Compressed frame

5. Preprocessing step

Pre-processing is mainly used to enhance the contrast of the image, removal of noise and isolating objects of interest in the image. Pre-processing is any form of signal processing for which the output is an image or video, the output can be either an image or a set of characteristics or parameters related to image or videos to improve or change some quality of the input. Pre-processing helps to improve the video or image such that it increases the chance for success of other processes

5.1Binarization

For a given gray scale image, we examine the intensity value of each pixel. If it is above a threshold, we mark it as white; otherwise we mark it as black. The threshold chosen for the candidate selection process is 102 (given intensity values ranging from 0 to 255). This threshold is chosen based on examining and experimenting Having only black and white pixels makes the image much easier to work with, as one can clearly see, a binarized image is much less confusing to the edge detector. Thus binarizing the image is desirable in candidate selection. Although the binarization threshold is chosen based on extensive experimentation, there is always the chance that the threshold we chose will not work well for some images, in spite of the histogram equalization .Instead of using an arbitrary threshold, perhaps an adaptive threshold is possible which appear in fig5.

Fig 5.using adaptive threshold

5.2 Segmentation

A segmentation and mode decision method has been proposed to allocate bits perceptually. The steps of this method are listed as follows.

Step1) Calculate the Sobel operator:

$$G_x = I_{x-1,y+1} + 2I_{x,y+1} + I_{x+1,y+1} - I_{x-1,y-1} - 2I_{x,y-1} - I_{x+1,y-1}$$

$$G_y = I_{x+1,y-1} + 2I_{x+1,y} + I_{x+1,y+1} - I_{x-1,y-1} - 2I_{x-1,y} - I_{x-1,y+1} \quad (1)$$

Step 2) Calculate the average squared gradients

$$G_{xx} = \sum_W G_x^2 \; G_{yy} = \sum_W G_y^2, G_{xy} = \sum_W G_x G_y \quad (2)$$

Step 3) Calculate the coherence of the squared gradient

$$COH = \sqrt{\frac{(G_{XX}-G_{YY})^2+4G_{xy}^2}{G_{xx}+G_{yy}}} \quad (3)$$

Step 4) Determine the block patterns according to edge threshold and texture threshold

$$Pattern = \begin{cases} Edge & if\ COH > T_{Edge} \\ Texture & if\ T_{Texture} < COH \le T_{Edge} \\ Background, & \text{others} \end{cases} \quad (4)$$

The result of the above segmentation process can be shown in Fig6 the original image of the 2nd frame of sequence "Echocardiography."Figure 2show segmentation image. In Fig.1 the black area is the back-ground which is not important and can be greatly compressed. The white area is the ROI which has the most important cardiac information and should be compressed perceptually. It can be seen that most of the important edges and textures can be recognized in the segmentation image.

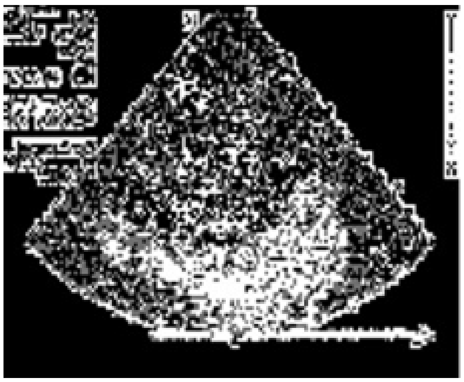

Fig.6 segmentation frame

5.3 Reducing noise

This next section now begins to take this frame and investigate the capabilities of image filters. Particularly, the effects of a Gaussian filter. The known outcome was that the Gaussian filter is capable of reducing noise in an image. In effect, it blurs the image [10]

Image's noise reduction based on the Laplacian of Gaussian (Log) is used with threshold = 5.As shown in fig7.

Fig7: Laplacian of Gaussian Applied to 2nd frame

5.4 Image Enhancement

The major disadvantage in echocardiograph image is the presence of noise, which perturbs features locations and creates artifacts, thus, we need method to suppress this heavy noise without presenting additional artifacts or losing image features.

In our method, the first step is applying median filter to each frame of echocardiograph video, where median filter is non-linear technique widely used as smoother. Simply it is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value, if the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.

The smallest size of neighborhood is 3 pixels, in the medical images often they use 5 pixel because they have the problem of noise and poor quality of image and when increase the size of neighborhood they gain better result because anything smaller than the radius of the neighborhood cannot contribute the median value will eliminated. So in our method we propose a simple and effective enhancement, by increasing the size of neighborhood which used to define the size of details to 9pixels. This step is needed because we care about the boundaries of the heart and the movement of valves, and we assume that all small details that are defined as noise can be ignored. After testing different sizes of neighborhood we conclude that the size proposed give better smoothing performance while sustaining the edge preserving characteristic of the conventional median filter as sown on figure8.

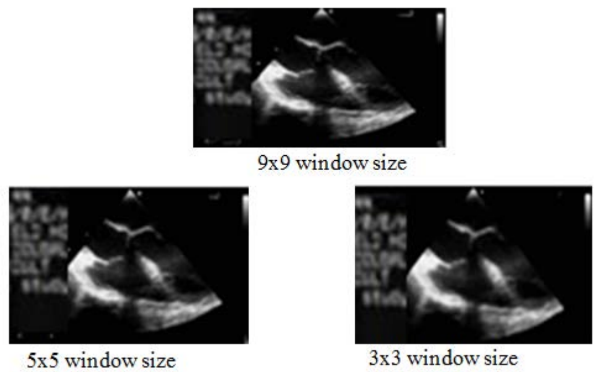

Fig. 8 Different window size of median filter

5.5 Prewitt edge detection

One method of detecting edges in a picture is to calculate the gradient of a pixel in its neighborhood. A simplified method is to use the Prewitt estimate as an approximation of the gradient. The Prewitt estimation can be used to detect the edges in the picture as shown on fig 9.

Fig 9Prewitt Derivative Applied to ECO frame

Once edge has been detected by using Prewitt operator, the pixel values of two images will be combined to highlight selected pixels in the input image, where each pixel of the

output image is a linear combination of the pixels in each input image.
This overlay help in presenting better illustrative view for the anatomy of the heart, where it clarifies the boundaries of the heart and the movement of valves in interactive visualization as shown on fig10.

Fig. 10 Contour detection after applying our method

6. Features Extraction

Feature extraction is the transformation of the original data (using all variables) to a data Set with a reduced number of variables. In the problem of feature selection, the aim is to select those variables that contain the most discriminatory information. Alternatively, we may wish to limit the number of measurements we make, perhaps on grounds of cost, or we may want to remove redundant or irrelevant information to obtain a less complex classifier.
In feature extraction, all variables are used and the data are transformed (using a linear or nonlinear transformation) to a reduced dimension space. Thus, the aim is to replace the original variables by a smaller set of underlying variables. There are several reasons for performing feature extraction: (i) to reduce the bandwidth of the input data (with the resulting improvements in speed and reductions in data requirements) ;(ii) to provide a relevant set of features for a classifier, resulting in improved performance, particularly from simple classifiers; (iii) to reduce redundancy;(v) to recover new meaningful underlying variables or features that the data may easily be viewed and relationships and structure in the data identified .There are two kinds of methods for extracting feature, which are holistic methods and partial methods. Holistic methods usually extract features for the whole image; these methods can extract plenty of feature information, but need large computation, and cannot meet the demand of the real-time environment like ECO. At the same time, there is redundant information in the feature information. The partial methods usually extract feature only for the feature components, these methods extract few feature information compare with the holistic methods, and usually ignore the sensitive feature.

6.1 Gabor filter:

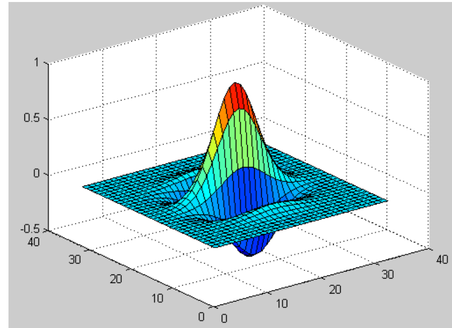

Fig.11 Gabor filter

A Gabor filter as show in Fig (11) is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. The main objective of the Gabor filter step is to enhance the ridges and soften the valleys.
Gabor filters were proposed to detect the slowly varying sinusoidal-shaped waveforms. Gabor filters are widely used in signal detection, as it possesses the unique feature of having optimal joint spatial-frequency localization creating orientation-rotated and center frequency-shifted copies of a base filter can construct a Gabor filter bank.

$$f(i,j,\emptyset,\omega) = exp\left(-\frac{1}{2}\left(\frac{i_{\emptyset}^2}{\sigma_i^2} + \frac{j_{\emptyset}^2}{\sigma_j^2}\right)\right)\cos\left(\omega_{j\emptyset}\right) \qquad (5)$$

The orientation of the Gabor depends on how many filter orientations are wanted due to symmetry a rotated Gabor filter. [11]
The filter orientations are computed by using the following equation:

$$\theta_n = \pi\frac{n}{k-1}, n = [0\ldots(k-1)] \qquad (6)$$

Where n is the orientation and k is the number of filter directions. [11]
Figure 12 show the directions for a Gabor filter in 8 directions (left) and 16 directions (right).

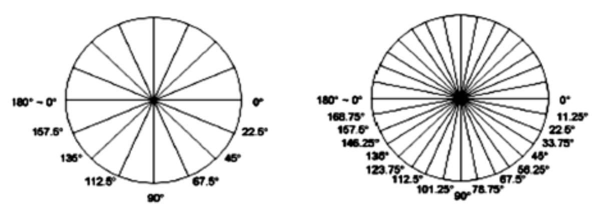

Fig.12 Directions for a Gabor filter in 8 directions (left) and 16 directions (right).

This filter is specified by four parameters: ω,σ_i, andσ_j, the angle φ represents the orientation of the Gabor filter and ω represents the sinusoidal frequency of the filter. The variances $\sigma_i$and $\sigma_j$represent the reciprocals of the vertical

and horizontal decaying rates of the Gaussian window. Larger values of σ_i and σ_j allow more robust noise removal, but poorer ridge and valley localization [11].
Smaller values allow better core localization, but less robust noise removal. The value of φ is chosen to closely match the local orientation of the image pixel to which the filter is applied. The value of ω is chosen to closely match the estimated local “sinusoidal” frequency. The estimation of the local “sinusoidal” frequency is discussed in the section on ridge flow and ridge width. This method need less computation and can meet the demand of real-time environment. At the same time, it can extract sensitive features, and obtain higher recognition rate.
Figure 13 show the operation of future extraction using Gabor transform.

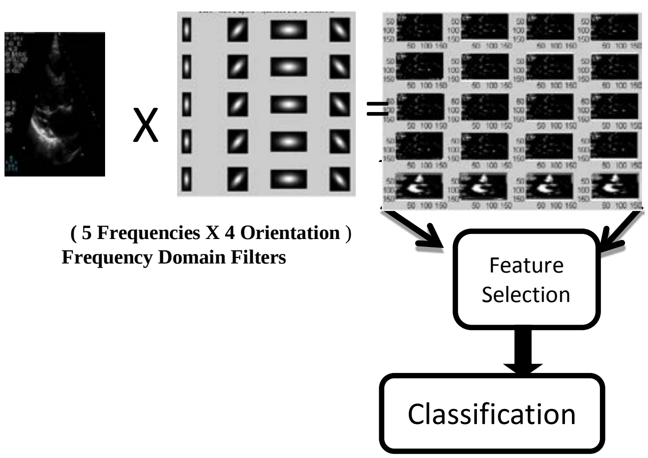

Fig. 13 operation of feature extraction

7. Feature Classification using Artificial Neural Networks

As mentioned before, different Gabor channel-features have different contributions to different heart diseases recognition. In order to perform the heart disease recognition task, we have developed an expression recognition system based on Multiple Gabor Features, which represents the contributions of the different channel features to different heart diseases, is obtained in the training stage.
The neural network has a general back propagation structure with three layers. Input layer 45 neural, followed by a hidden layer of 20 neurons. The output layer has 7 nodes which give the recognition result.
The structure and the training performance of the neural network are illustrated in Fig14.

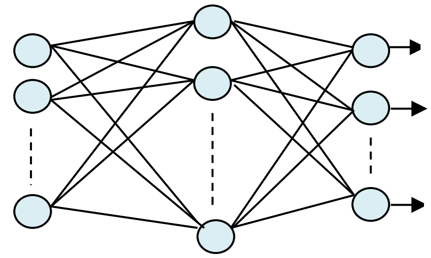

Fig.14A typical neural network

The best-known examples of this technique occur in the back propagation algorithm, the delta rule, and the percptron rule. In unsupervised learning (or self-organization), a (output) unit is trained to respond to clusters of pattern within the input. In this paradigm, the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather, the system must develop its own representation of the input stimuli. Reinforcement learning is learning what to do so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them. These two characteristics, trial-and- error search and delayed reward are the two most important distinguishing features of reinforcement learning.
A typical feed-forward back propagation neural network is proposed to detection heart disease .It consists of three layers: the input layer, a hidden layer, and the output layer. A one hidden layer with 20 neurons is created and trained. The input and target samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely in dependent measure of network accuracy. The information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network. The proposed neural networks are showninFig.14.

The output of the hidden layer can be represented by

$$Y_{NxI} = f(W_{NxM}X_{MxI} + b_{NxI}) \qquad (7)$$

Where Y is a vector containing the output from each of the N neurons in a given layer, W is a matrix containing the weights for each of the M inputs for all N neurons, X is a vector containing the inputs, b is a vector containing the biases and f(·) is the activation function [12] as shown in fig 15.

8. Performance Evaluation

Neural network toolbox from Matlab 7.9 is used to evaluate the performance of the proposed networks: multi-layer feed-forward back-propagation

Number of input neurons: 43.Number of hidden neuron in hidden layer: 20 by guess work. Number of output neurons: depends on number of classes (diseases) which are 7.Such net can fit multi-dimensional mapping problems. Arbitrarily well, given consistent data and enough neurons in its hidden layer as shown in Fig.15.

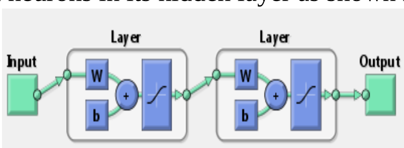

Fig. 15 The proposed heart disease diagnosis neural network

However, we tried many topologies before reaching to this topology. If we use Training method is log-sigmoid, 'logsig' in matlab ,Activation function is momentum gradient decent, 'traingdx' in Matlab With Error rate measure is sum of squared error, 'sse' in Matlab and Stopping criteria when error reaches 0.001; or maximum training epochs reaches 5000Giving performance of 0.0783 and MSE is 0.224 e-10.When using Activation function , momentum gradient decent, 'traingdx' Error rate measure , sum of squared error, 'sse' performance is 0.0783 and error 0.224eUsing Activation function , scaled conjugate, 'trainscg' and use Error rate measure : mean of squared error with regularization, 'msereg' performance is 0.000982 .If we use Activation function : scaled conjugate, 'trainscg' And error rate measure : mean of squared error, 'mse'Stopping criterion: performance goal met

9. Conclusions

This study aimed to evaluate artificial neural network in disease diagnosis. The feed –forward back propagation neural network with supervised learning is proposed to diagnose the disease. Artificial neural net works showed significant results in dealing with data represented in ECO and images .Results showed that the proposed diagnosis neural network could be useful for identifying the valve diseases.

Levenberg-Marquardt back propagation algorithm was used with train the network. The results of applying the artificial neural networks methodology to distinguish between valves diseases. Feature patterns extracted from compressed ECO frame showed very good abilities of the network to learn the patterns. The network was simulated in the testing set. The results were very good; the network was able to classify 95% of the cases in the testing set.

Fig(16) shows the training state values. Best validation performance is 0.088329 at epoch 3 .Best training performance is 4.86802 e-3 and best testing performance is 7.4761e-2,as shown in Fig (17).

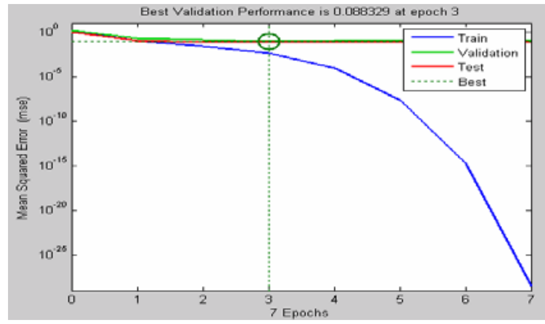

Fig.16

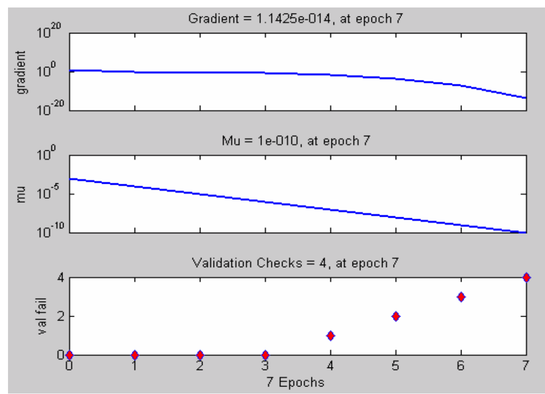

Fig. 17

Table1: The Mean Square Error (MSE) and Regression values for the training, validation and testing.

	MSE	R
Training	4.86802e-3	9.92593e-1
Validation	8.83292e-2	8.50794e-1
Testing	7.47611e-2	8.72846e-1

The percent correctly classified in the simulation sample by the feed-forward back propagation network is 95 percent. The MSE is equal to 2.78711e-2 and the regression is equal to 9.50148e-1.

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