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Performance Analysis of Different Architectures of ANN for Digital Mammogram Analysis Using Image Registration Techniques

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ABSTRACT

Breast cancer is the second most common reason of women's deaths happening due to cancer. Early diagnosis of this disease permits treatment which enhances survival rate or avoids further clinical evaluation or breast biopsy diminishing the unnecessary expenditure. Mammography is right now the best technique for identification of breast cancer. Survival rate can be enhanced by detecting the breast cancer in early stages by using Mammogram Images. This paper presents the use of Image Registration Techniques for the enhancement of the effectiveness of interpreting digital mammograms by Artificial Neural Networks. Different Network architectures are employed for breast cancer diagnosis and their accuracy is investigated and compared.

Keywords: Image Registration, Mammogram, Artificial Neural Network

1. INTRODUCTION

The most frequently diagnosed cancer in women is breast cancer excluding the cancer of skin [1] and is the second main reason of women cancer death [2]. Ultrasound imaging, MRI imaging and digital Mammography are available for imaging of the breast cancer [3]. Mammography is considered to be most commonly employed for diagnosis of breast cancer [4]. It is really very hard for the Radiologists to read the mammogram correctly because of low contrast [5] leading to misinterpretation of the results. Double reading of mammogram is taken to reduce the proportion of missed cancers, although it is time consuming and costly. By Adopting the CAD system the experts' workload could be reduced and detection rate can be increased [6-7].

2. RELATED WORKSE

Image registration techniques are very helpful for breast cancer diagnosis [8]. Different methods such as wavelets [5] and statistical methods [9] used Feature Extraction to detect breast cancer. Several Researchers used feature selection extraction methods for ANN based breast cancer diagnosis. Ritthipravat et al. explained the ulitization of Artificial Neural Networks for Recurrence Prediction of cancer [10]. Kala et al. proposed breast cancer diagnosis by evolutionary neural network architecture [11]. Salim et al. used Artificial Neural Network and Hybrid Magnetoacoustic method (HMM) for diagnosing breast cancer [12]. Ahmad et al. have discussed the mammogram interpretation by using Probabilistic Neural Network.

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[13]. Guzman-Cabrera et al. analyzed the digital mammograms using texture segmentation [14]. Senapati et al. proposed K-particle swarm optimization (KPSO) which provides more accurate result and better classiûcation [15].

3. METHODOLOGY

The known Mammogram images are first processed through various image preprocessing steps such as selection of image acquisition, Region of Interest, Image Enhancement by Histogram Equalization followed by the process of feature extraction. Features extracted may be reduced using some feature section algorithm. Images of digital mammography for breast cancer detection are collected from a Consultant Radiologist. The number of images i.e. malignant and benign is classified into training and testing set of images. The details of all the phases used for conducting the research are described as under:

3.1. Selection of Region of Interest

Initially mammogram images may be cropped to remove undesired areas as a part of preprocessing so as to keep area of interest only for further processing. The details of the four phases used for conducting the research have been described in the current research.

3.2. Image Enhancement by Histogram Equalization

Histogram Morphological Equalization or Enhancement may be used for Image Enhancement of Mammogram images. The contrast of the image is adjusted by Histogram equalization by increasing dynamic range of grey level.

3.3. GLCM Feature Extraction

The next step i.e. feature extraction is extracting the most important features from the images using image-processing techniques. Initially Intensity Histogram features were used for feature selection which includes mean, energy, skewness, entropy and kurtosis etc. In GLCM (Gray Level Co-occurrence Matrix), the relationship between pixels of different gray levels is considered spatially. Texture features of second-order such as Contrast, Autocorrelation, Inertia, Entropy, Correlation and Dissimilarity Energy may be computed using GLCM which gives the complete details of the image.

3.4. Diagnosis/Classification

After extracting and selecting, the GLCM features are provided as inputs for training, testing and validating an ANN based breast cancer diagnosis System.

4. RESULTS AND DISCUSSIONS

Different Artificial Neural Network architectures to diagnose breast cancer are employed for breast cancer diagnosis. Accuracy of all the configurations is investigated and best possible network is chosen based on Mean Square Error (MSE). The best possible design of ANN will be decided through trial and error. Various Artificial Neural Network architectures Network architectures had been trained and evaluated. Fig. 1 to Fig. 6 shows the training state and Performance of training process for different architectures. The validation check, Mutation and gradient graphs are shown in training state of the Systems. The MSE is shown for training, testing and validation process in the performance graph of the Systems.

The classification or detection accuracy of different configurations of the Artificial Neural Networks is compared and shown in Fig. 7.

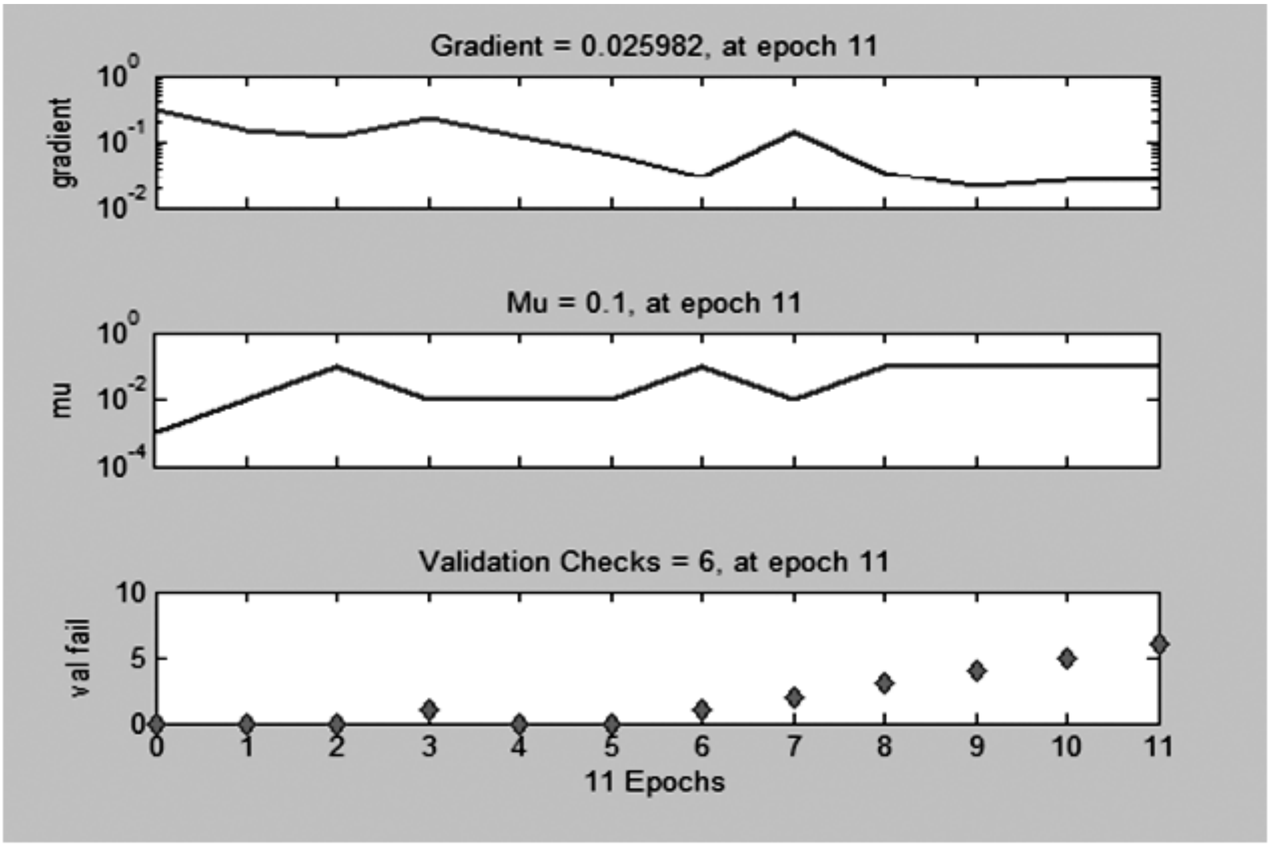

Figure 1(a): Training State

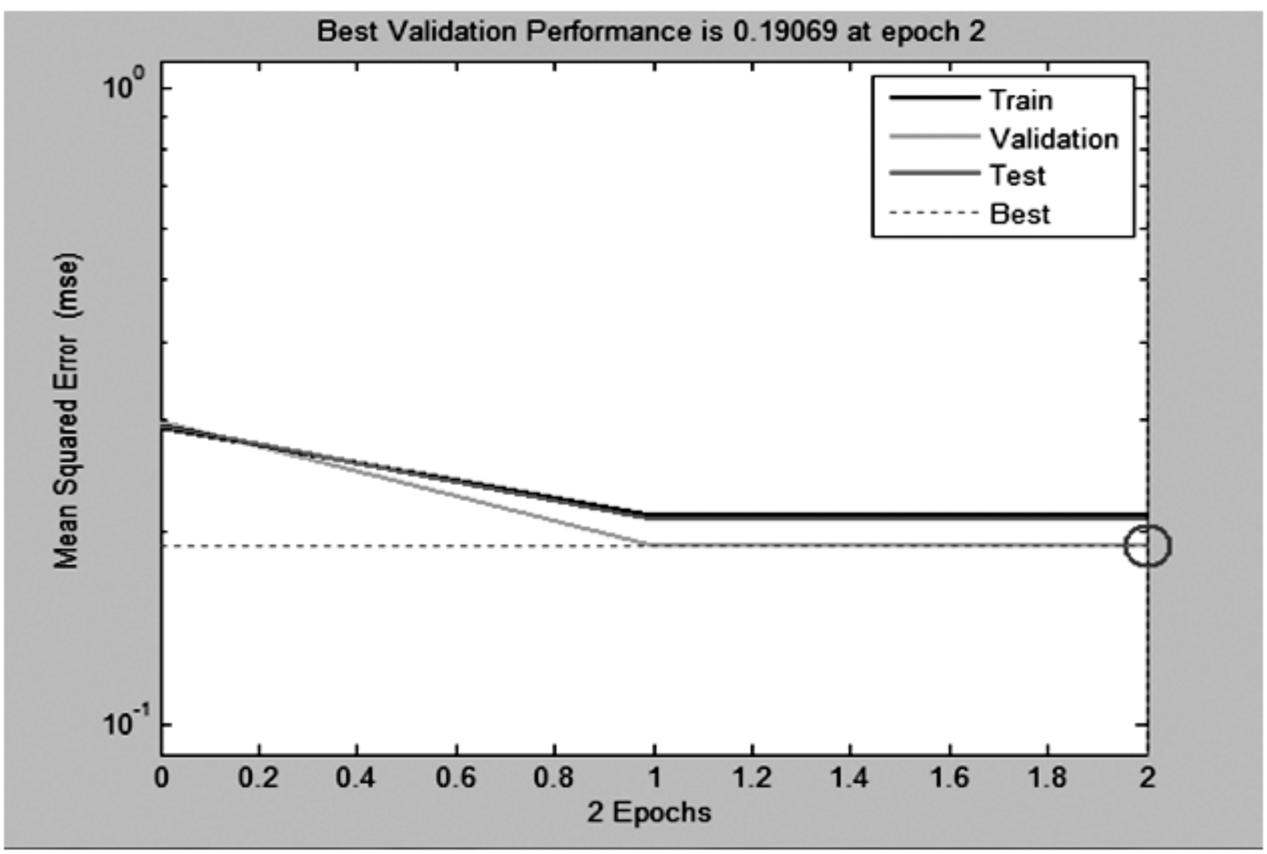

Figure 1(b) Performance of the training process for Feed-forward Time-delay Network

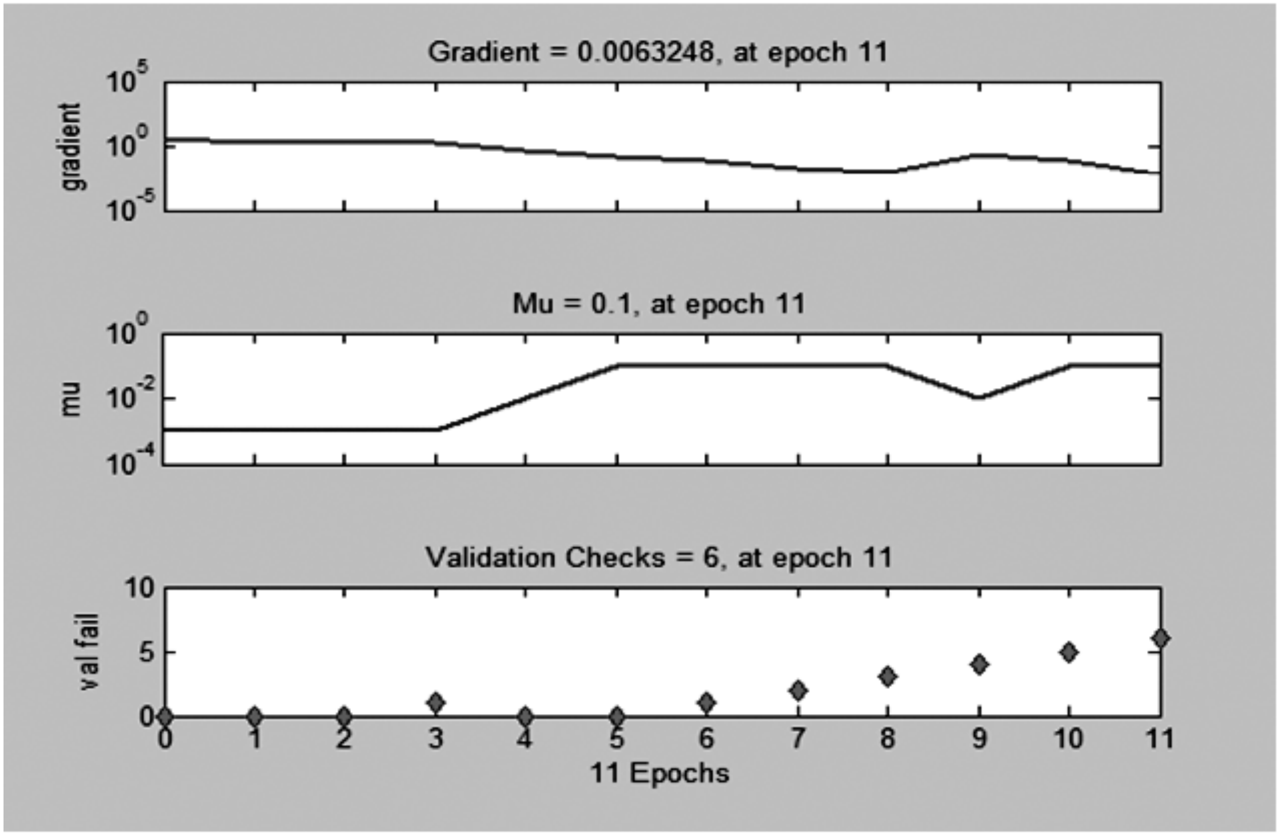

Figure 2(a): Training State

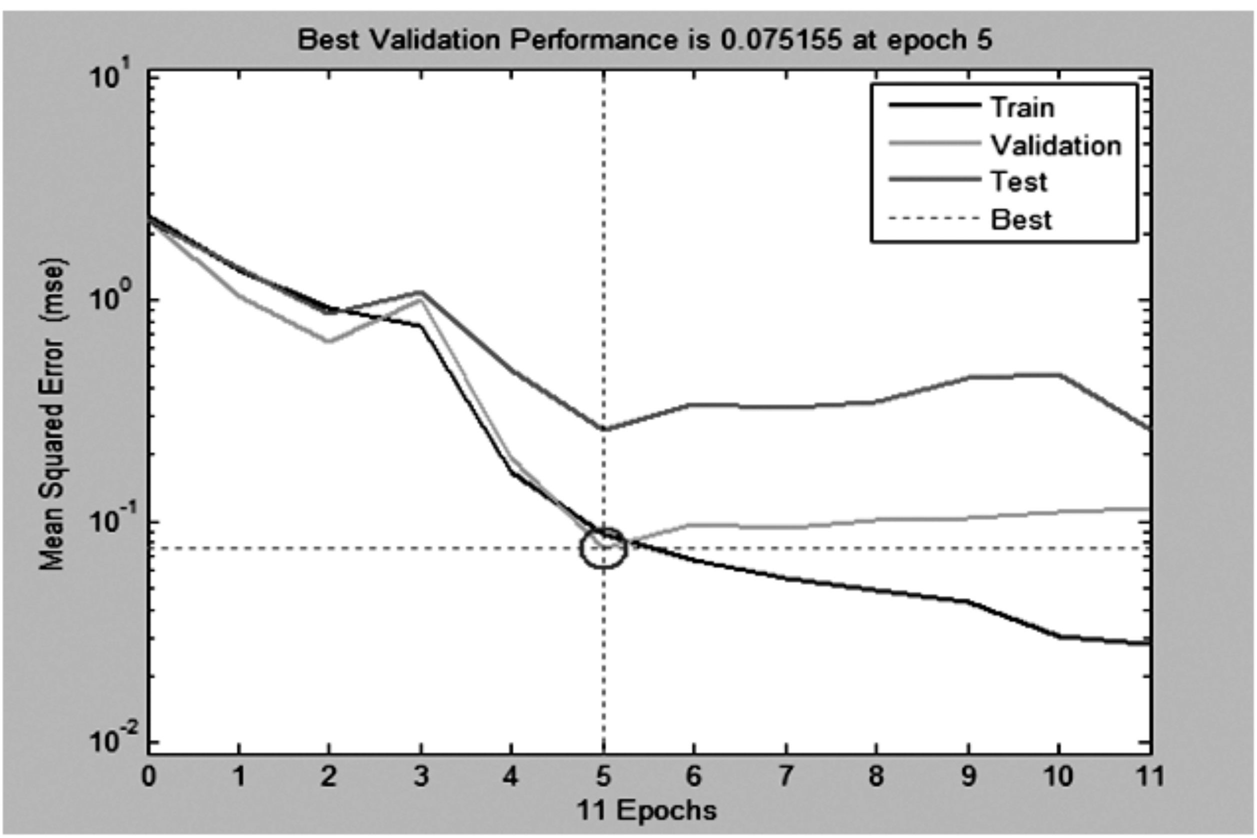

Figure 2(b): Performance of the training process for Feed-forward Time-delay Network

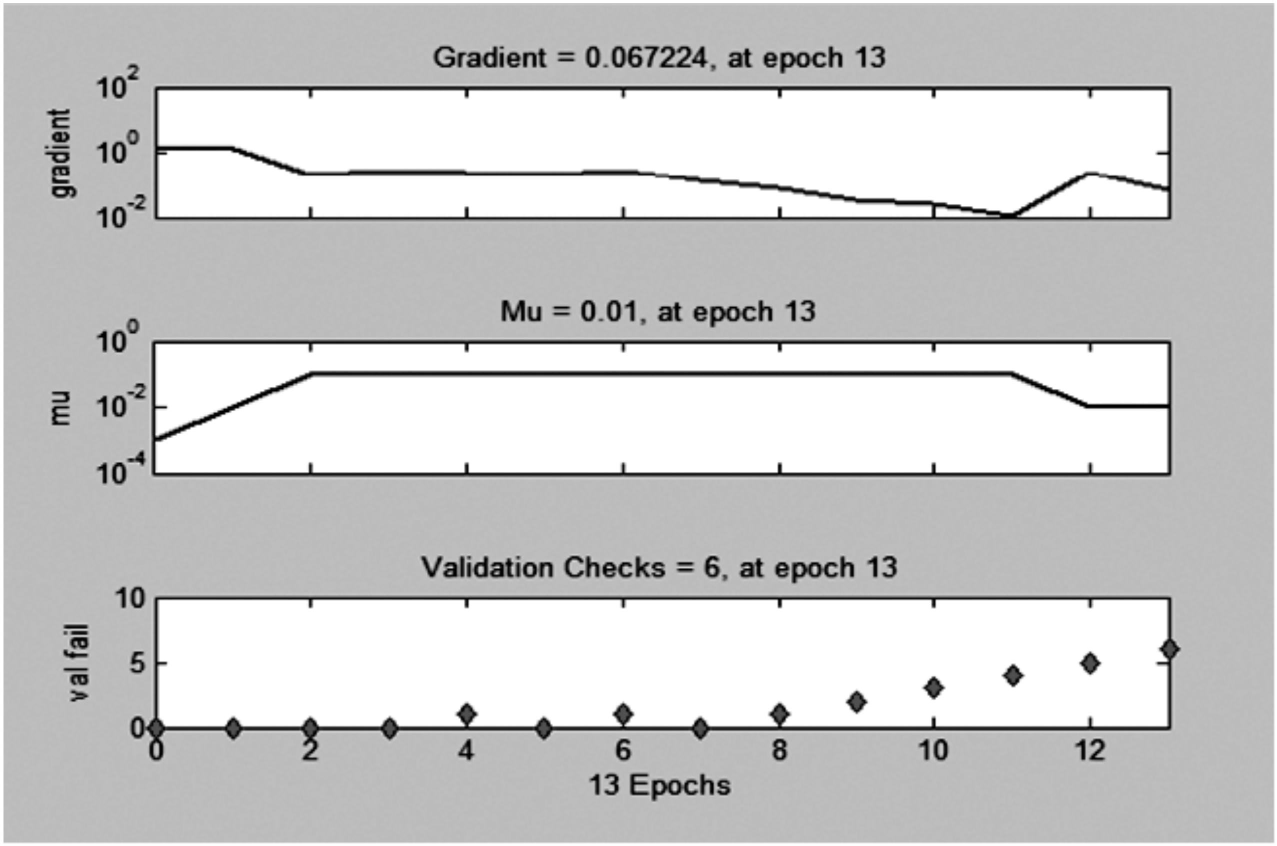

Figure 3(a): Training State

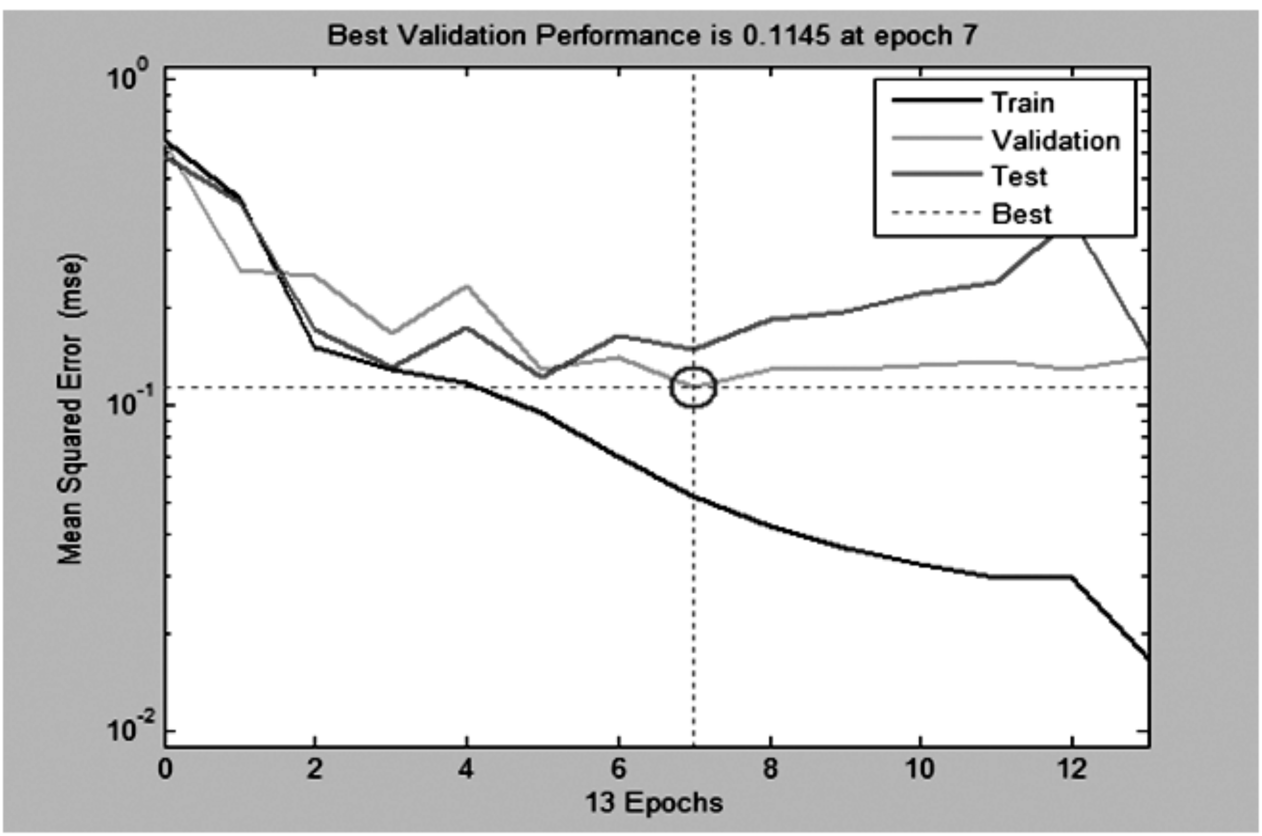

Figure 3(b) Performance of the training process for Feed-forward Backpropagation Network

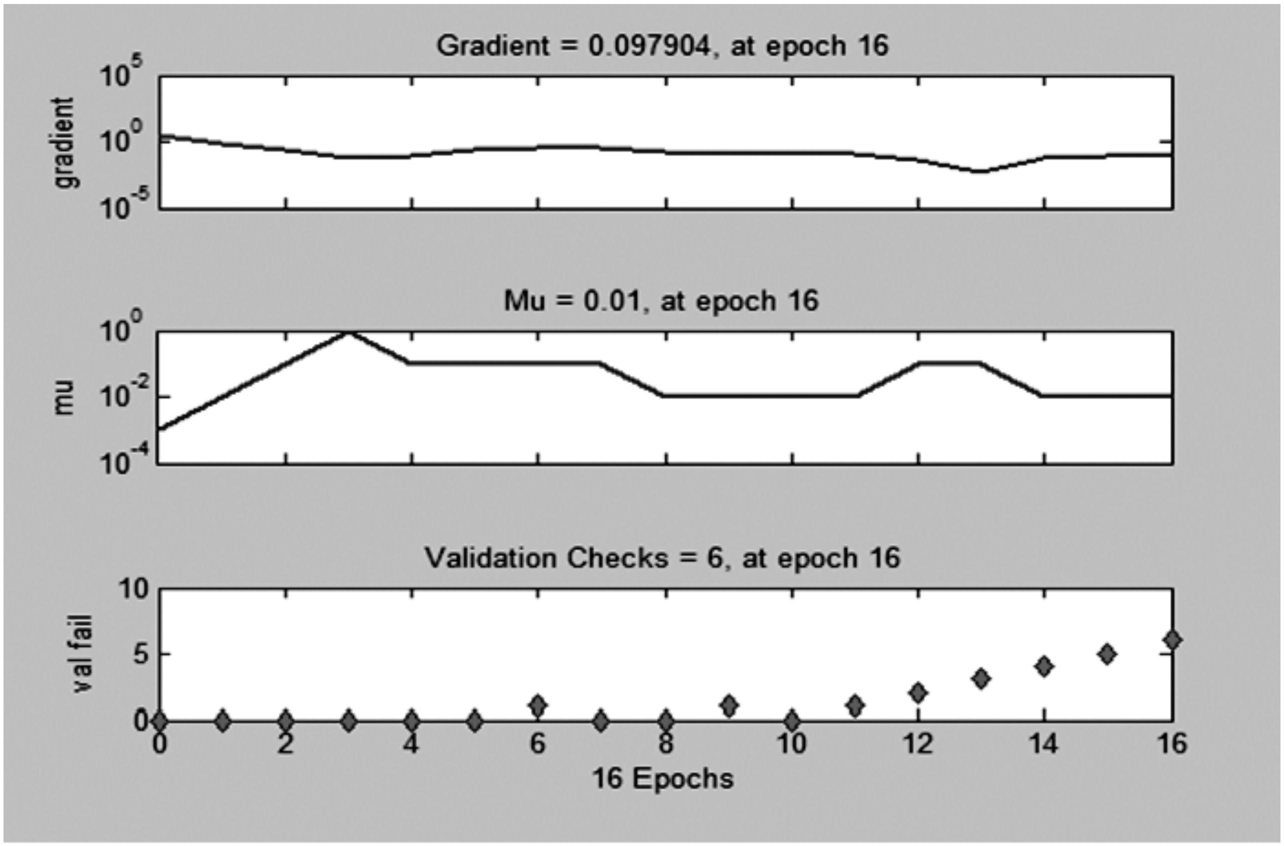

Figure 4(a): Training State

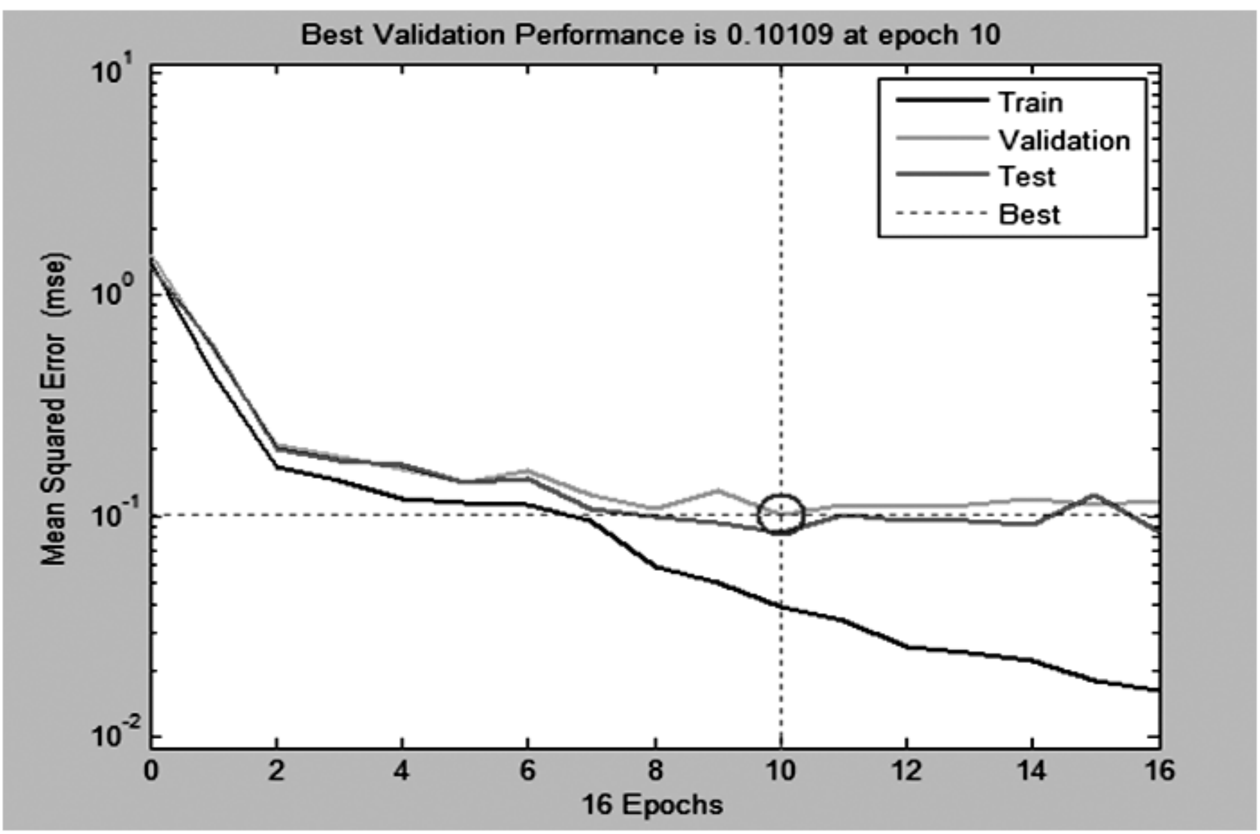

Figure 4(b): Performance of the training process for Cascade-forward Backpropagation Network

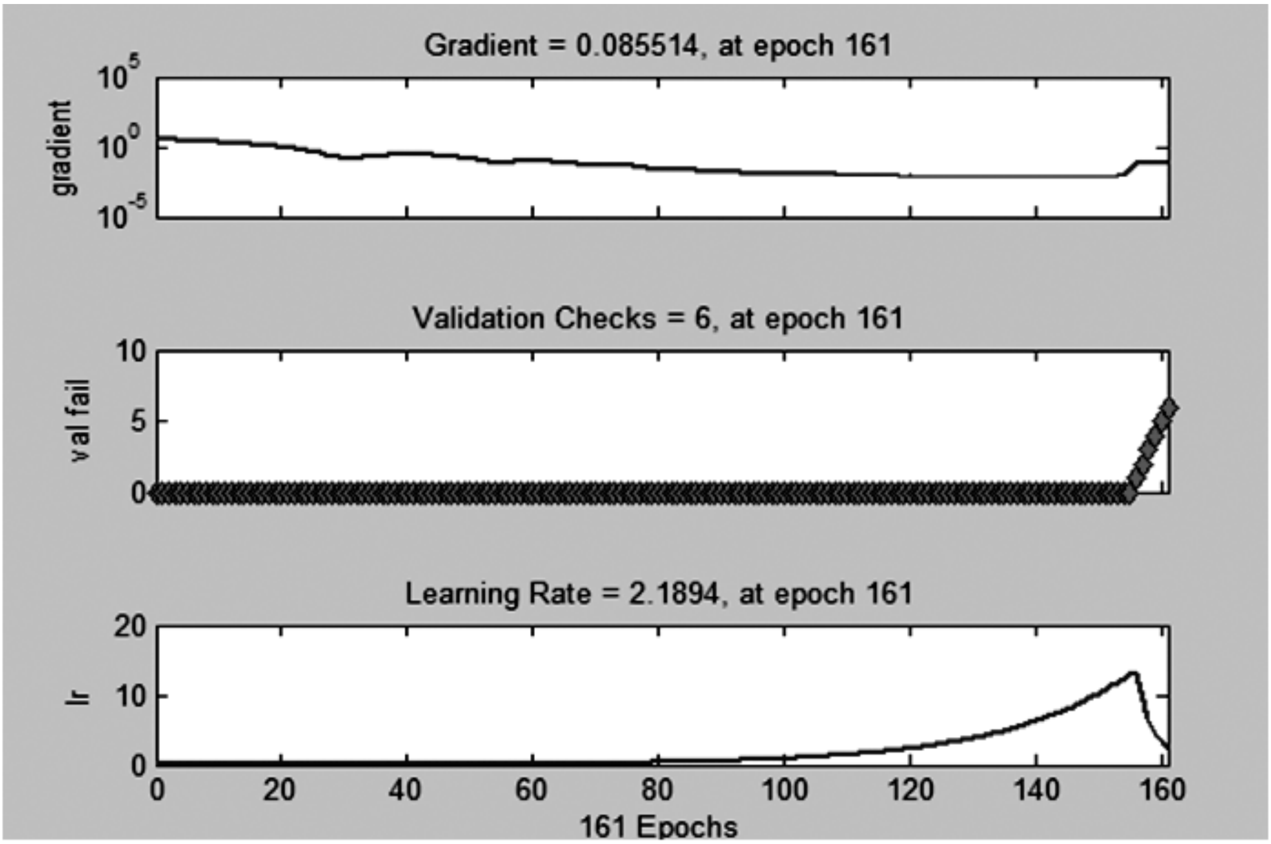

Figure 5(a): Training State

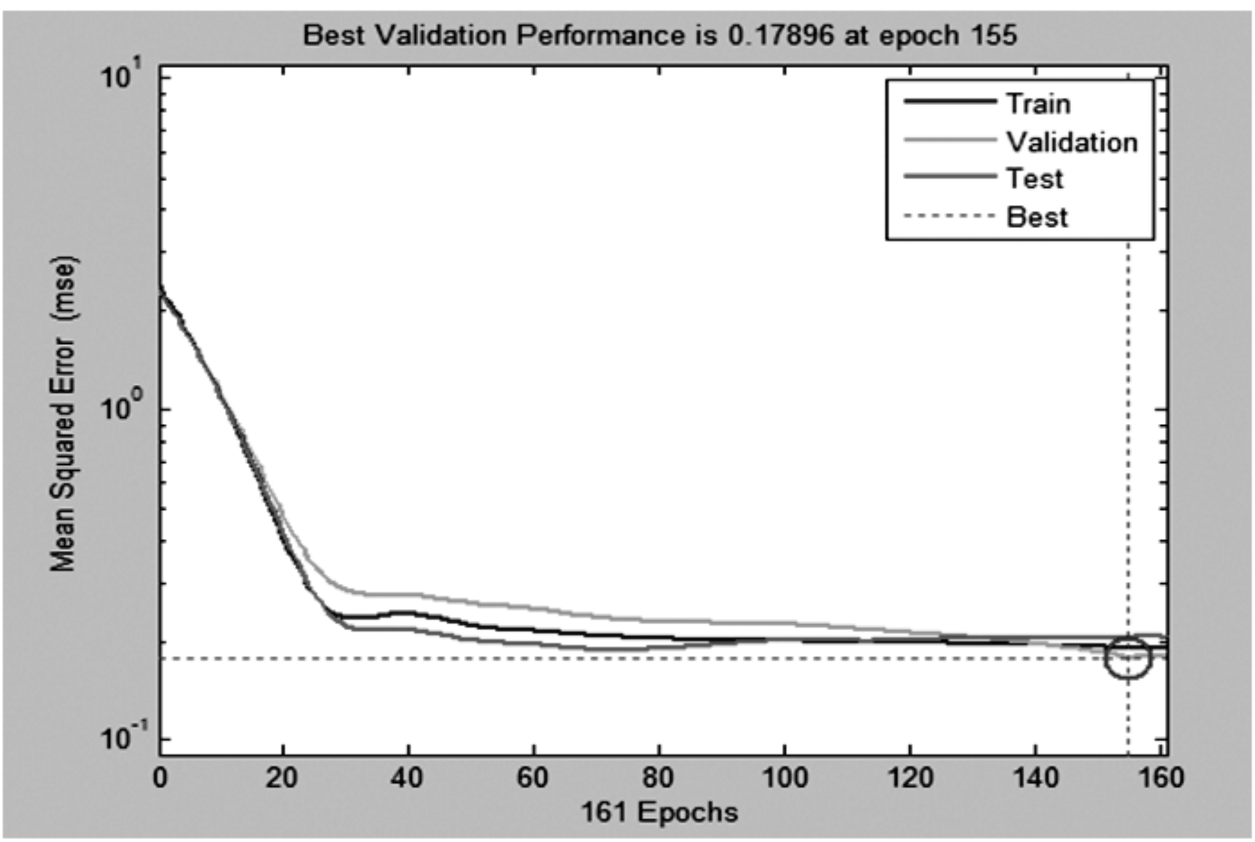

Figure 5(b): Performance of the training process for Elman Backpropagation Network

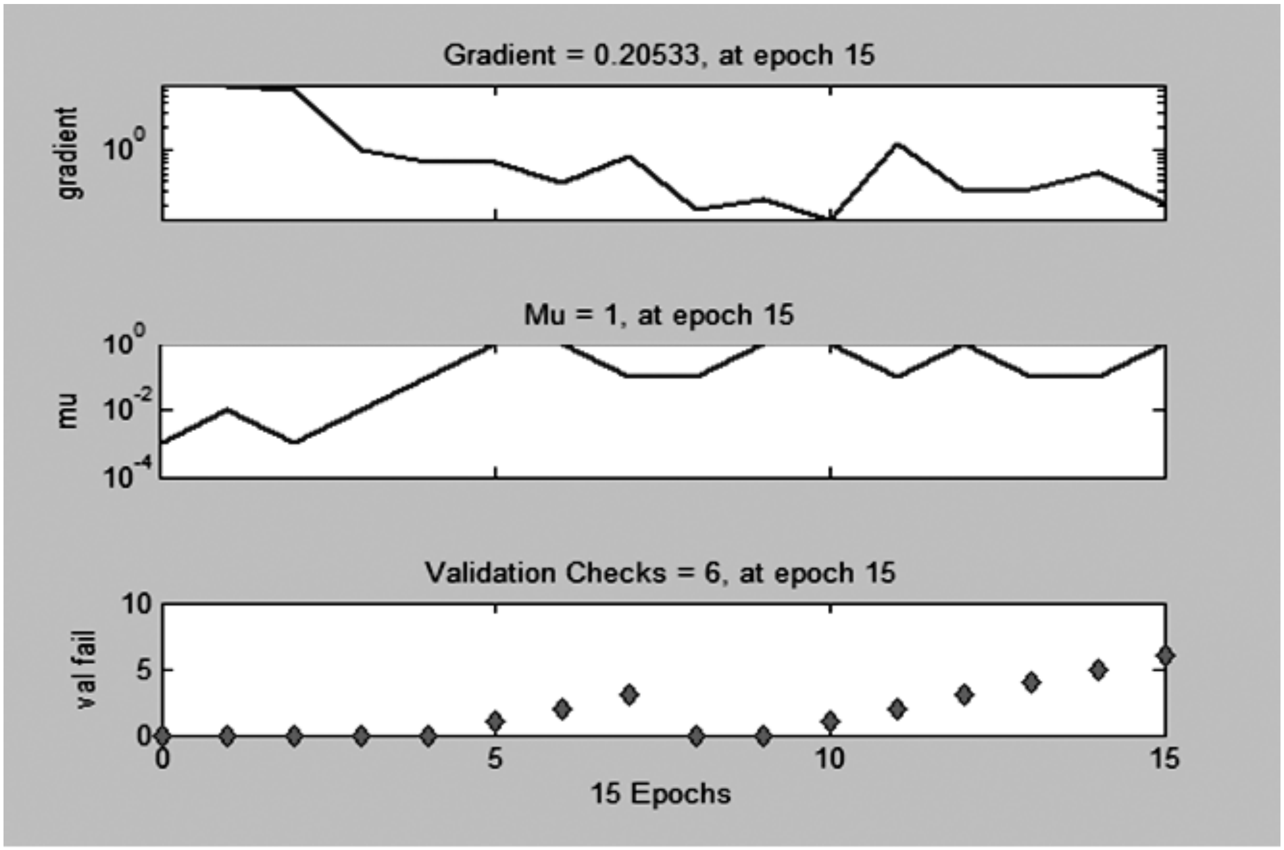

Figure 6(a): Training State

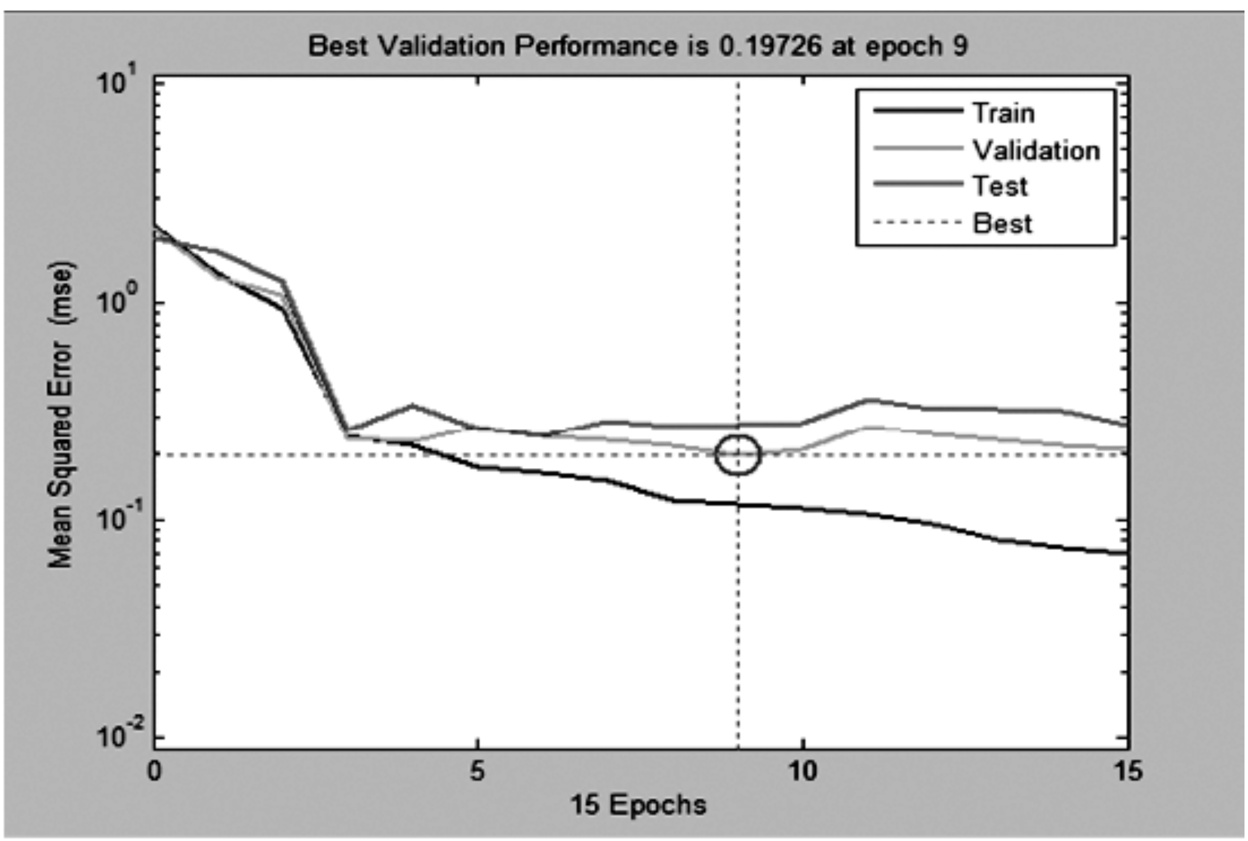

Figure 6(b): Performance of the training process for Distributed Time-delay Network

The accuracy of different Artificial Neural Networks investigated is tabulated in Table I.

Table 1
Accuracy for Different Architectures of ANN

Architecture Name	*Percentage Accuracy*
Feed-forward Time-delay Network	70
Layered-recurrent Network	55
Feed-forward Backpropagation Network	92.8
Cascade-forward Backpropagation Network	90
Elman Backpropagation Network	70
Distributed Time Delay Neural Network	70

Feed-forward backpropagation Network gives optimum performance and with an accuracy of 92.8% followed by Cascade-forward backpropagation Network with accuracy of 90%. Layered-recurrent Network gives worst performance with achieved accuracy of 55%. So for the given problem of breast cancer detection the Feed-forward backpropagation Network is chosen as the best method for the given set of images.

It can be seen that the feedforward backpropagation Network gives optimum performance and the achieved accuracy of the system is 92.8 % Layered-recurrent Network gives worst performance with achieved accuracy of 55%. So for the given problem of breast cancer detection the Cascade-forward backpropagation

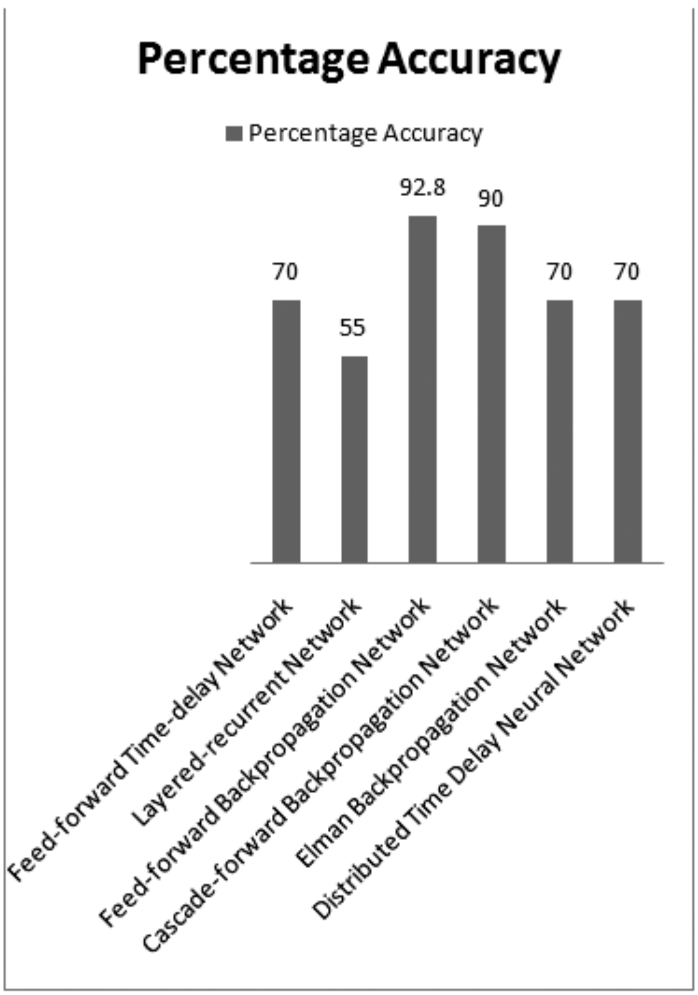

Figure 7: Plot of Accuracy vs different Architectures of ANN

Network is chosen as the best method for the given set of images among the six methods. Further, the feed-forward back propagation Network ANN model for breast cancer detection can be tested to determine the predictive accuracy of detection for different number of neurons and layers and optimum number of neurons and layers is chosen.

5. CONCLUSION

Different ANN based breast cancer diagnosis systems using Image Registration Techniques using Artificial Neural Network have drawn much recognition from both radiologists and researchers. Image registration techniques were employed in digital Mammography for diagnosing breast cancer by different architectures of ANN. For breast cancer detection by Image Registration Techniques and given set of images, Feed-forward backpropagation Network gives optimum accuracy of 92.8% followed by Cascade-forward backpropagation Network with accuracy of 90%. Layered-recurrent Network gives worst performance with achieved accuracy of 55%. After some modifications the system to diagnose other types of cancers can also be designed and accuracy may be enhanced by including more images and texture features. Different classifiers may be employed to the proposed system as the classifier plays an important role in classification

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