

Classification of Clustered Microcalcifications using Resilient Backpropagation Training Algorithm

Baljit Singh Khehra

Baba Banda Singh Bahadur
Engineering College,
Fatehgarh Sahib, Punjab

Amar Partap Singh

Sant Longowal Institute of
Engineering and Technology,
Longowal, Punjab

ABSTRACT

Breast cancer continues to be the leading cause of death among women nowadays all over the world. Most frequent type of breast cancer is ductal carcinoma in situ (DCIS) and most frequent symptoms of DCIS recognized by mammography are clusters of Microcalcifications. In this paper, Resilient Backpropagation training algorithm is investigated for automated classification of clustered Microcalcifications (MCCs) as benign or malignant. The classifier is a part of computer aided disease diagnosis (CAD) system that is widely used to aid radiologists in the interpretation of mammograms. The performance of Resilient Backpropagation training algorithm is compared with a well known Batch Gradient Descent training algorithm. Such methods are explored not only for accuracy point of view but also for computational efficiency for MCCs characterization in mammograms. As input, these methods used mammogram features extracted from MCCs. Such methods are tested using images of mini-MIAS database (Mammogram Image Analysis Society database (UK)). Receiver operating characteristic (ROC) analysis is used to evaluate and compare classification performance of these methods. Experimental results demonstrate that Resilient Backpropagation training algorithm could greatly reduce the computational complexity of Multi layer Feed Forward Backpropagation Artificial Neural Network (MLFFBP-ANN) while maintaining its best classification accuracy. It can produce lower false positives and false negatives than Batch Gradient Descent training algorithm.

Keywords

Batch Gradient Descent, Breast Cancer, Mammography, Microcalcification, Resilient Backpropagation

1. INTRODUCTION

Cancer is one of the most leading causes of deaths among men and women in the world. Among the cancer diseases, breast cancer is especially a concern in women. According to the statistics, breast cancer is a major occurrence of cancer in women over the age group of 15-54 years old nowadays all over the world [1]. However, the causes of breast cancer are unknown and no single dominant cause has emerged. Still, there is no known way of preventing breast cancer but early detection is the key to improving breast cancer prognosis.

Mammography is one of the most effective tools in early detection of breast cancer [2]. It is reliable, low cost and highly sensitive method. Mammography offers high- quality images at low radiation doses. Mammography uses low-energy x-rays that pass through a compressed breast and are absorbed by film during an examination. Mammography is the only widely

accepted imaging method for routine breast cancer screening. It is recommended that women at the ages of 40 or above should have a mammogram every one to two years [3]. Although mammography is widely used around the world for breast cancer detection, it is difficult for expert radiologists to provide both accurate and uniform evaluation for the enormous number of mammogram generated in widespread screening. There are some limitations of human observers such as some anomalies may be missed due to human error as a result of fatigue. These limitations are the main cause of false positive and false negative readings of mammogram. A false- positive detection causes unnecessary biopsy. It has been estimated that only 15-30% of breast biopsy cases are proved to be cancerous [4]. On the other hand, in a false- negative detection an actual tumor remains undetected. Retrospective studies [5] have shown that 10-30% of the visible cancers are undetected. So, false-positive and false-negative have caused a high proportion of women without cancers to undergo breast biopsies or miss the best treatment time. Thus, there is a significant necessity to improve the correct diagnosis rate of cancer. Several solutions were proposed in the past to increase accuracy and sensitivity of mammography and reduce unnecessary biopsies. Independent double reading of mammograms by two radiologists is one of the solutions and has proved to significantly increase the sensitivity of mammographic screening [6]. The basic idea for independent double reading is to read the mammograms by two radiologists independently. However, this solution is both highly costly and time consuming. Instead of double reading, radiologists have an opportunity to improve their diagnosis with the aid of computer aided disease diagnosis (CAD) system. It might provide a useful second opinion to radiologists during mammographic interpretation.

The most frequent type of breast cancer, detected before the invasion stage, is ductal carcinoma in situ (DCIS). The most frequent symptoms of ductal carcinoma recognized by mammography are clusters of Microcalcifications (MCCs) [7]. Microcalcifications (MCs) are tiny granular deposits of calcium that appear on the mammogram as small bright spots [8]. A MCC is typically defined as a group of at least three or five MCs within a 1 cm² region of the mammogram [9, 10]. Although CAD system has been studied over two decades, automated classification of MCCs as benign or malignant is a challenging task and a difficult problem for researchers [11].

A number of classifiers have been proposed for CAD system to classify clustered MCs as benign or malignant. D. Kramer et al. [12] used K-nearest neighbor (KNN) classifier to classify MCs in digitized mammograms using multi scale statistical texture analysis. Hakayama R et al. [13] used linear discriminant

analysis (LDA) to analyze malignant and benign MCs on digitized mammograms. Bottema MJ et al. [14] used decision trees for detection and classification of lobular and DCIS (small cell) Microcalcifications in digital mammograms.

In 2004, Hamid Soltanian-Zadeh [15] used genetic algorithm to select most discriminating features for k-nearest neighbor classifier. In 2007, Nicandro Cruz-Ramirez et al. [16] used Bayesian network classifiers for the diagnosis of breast cancer. Aboulella Hassanien [17] used fuzzy rough sets hybrid scheme for breast cancer detection. Artificial neural networks (ANNs) have also been widely used for classification of MCs as benign or malignant [18, 19, 20]. Main advantages of ANNs are that ANNs have capability to operate based on a multivariate intrinsically noisy or error prone reduced training data set. ANNs have also potentiality of conveniently modeling non-linear characteristics.

Multilayer feed-forward Backpropagation (MLFFBP) is the most important ANN that has been applied successfully to solve many problems [6, 21, 22]. Mainly Backpropagation training algorithm, Batch Gradient Descent, is commonly used. Main disadvantage of such algorithm is that it is too slow for classification of MCCs as benign or malignant.

In this paper, Resilient Backpropagation training algorithm is investigated for such purpose and compared the performance of this algorithm with Batch Gradient Descent training algorithm. Such algorithms are explored not only for accuracy point of view but also for computational efficiency for MCs characterization in mammograms. As input, these algorithms used mammogram features extracted from clustered MCs. Such algorithms are tested using images of mini-MIAS database (Mammogram Image Analysis Society database (UK)). Receiver operating characteristic (ROC) analysis is used to evaluate and compare classification performance of these algorithms.

The remaining part of this paper is organized as follows: Section II describes methodology; Experimental results are given and discussed in Section III; the paper is concluded in Section IV.

2. DESCRIPTION OF METHODOLOGY

The operation of CAD system is presented as a series of consecutive processing stages. The basic steps in the system for the characterization of MCCs as benign or malignant are shown in figure 1.

In this study, mammogram images are taken from mini-MIAS database (Mammogram Image Analysis Society database (UK)). In this database, expert radiologists marked areas where MCCs are present. Such areas are called Regions of Interest (ROIs).

2.1 Feature Extraction

Feature extraction is the most important process in CAD system for the overall system performance. We compute a set of features for each benign and malignant cluster using a 7×7 block. Such blocks are taken from ROI of each mammogram. The gray level values within a 7×7 block is denoted as

$$\begin{bmatrix} g_{1,1} & g_{1,2} & g_{1,3} & g_{1,4} & g_{1,5} & g_{1,6} & g_{1,7} \\ g_{2,1} & g_{2,2} & g_{2,3} & g_{2,4} & g_{2,5} & g_{2,6} & g_{2,7} \\ g_{3,1} & g_{3,2} & g_{3,3} & g_{3,4} & g_{3,5} & g_{3,6} & g_{3,7} \\ g_{4,1} & g_{4,2} & g_{4,3} & g_{4,4} & g_{4,5} & g_{4,6} & g_{4,7} \\ g_{5,1} & g_{5,2} & g_{5,3} & g_{5,4} & g_{5,5} & g_{5,6} & g_{5,7} \\ g_{6,1} & g_{6,2} & g_{6,3} & g_{6,4} & g_{6,5} & g_{6,6} & g_{6,7} \\ g_{7,1} & g_{7,2} & g_{7,3} & g_{7,4} & g_{7,5} & g_{7,6} & g_{7,7} \end{bmatrix}$$

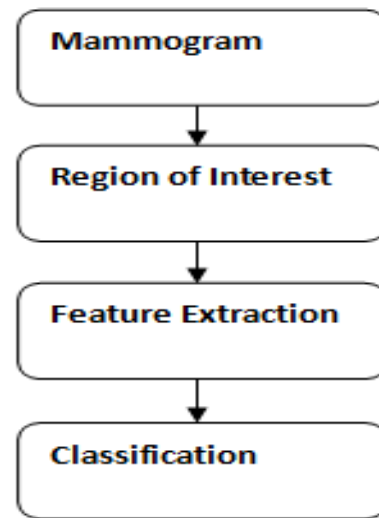


Fig. 1 Microcalcification cluster characterization system

The following features [23] are extracted from each MCC whose centre gray level value is $g_{4,4}$:

2.1.1 Average (μ)

$$\mu = \frac{1}{49} \sum_{i=1}^7 \sum_{j=1}^7 g_{i,j}$$

2.1.2 Standard Deviation (σ)

$$\sigma = \sqrt{\text{Variance}}$$

$$\text{Where } \text{Variance} = \frac{1}{49} \sum_{i=1}^7 \sum_{j=1}^7 [g_{i,j} - \mu]^2$$

2.1.3 Relative Smoothness (R)

$$R = 1 - \frac{1}{1 + \sigma^2}$$

2.1.4 Skewness (μ_3)

$$\mu_3 = \frac{1}{48\sigma^3} \sum_{i=1}^7 \sum_{j=1}^7 [g_{i,j} - \mu]^3$$

2.1.5 Kurtosis (μ_4)

$$\mu_4 = \frac{1}{48\sigma^4} \sum_{i=1}^7 \sum_{j=1}^7 [g_{i,j} - \mu]^4$$

2.1.6 Busyness (B)

$$B = \frac{1}{84} \left[\sum_{i=1}^7 \sum_{j=1}^6 |g_{i,j} - g_{i,j+1}| + \sum_{i=1}^6 \sum_{j=1}^7 |g_{i,j} - g_{i+1,j}| \right]$$

2.1.7 Potential of a Point (PP)

$$PP = \sum_{i=1}^7 \sum_{j=1}^7 e^{-\alpha \left[\sqrt{(g_{i,j} - g_{4,4})^2} \right]}$$

2.1.8 Mean Energy (μ_E)

$$\mu_E = \frac{1}{49} \sum_{i=1}^7 \sum_{j=1}^7 (g_{i,j})^2$$

2.1.9 Point Mask (PM)

$$PM = \left| \sum_{i=1}^7 \sum_{j=1}^7 f_{i,j} g_{i,j} \right|$$

2.1.10 Energy Variance (σ_E)

$$\sigma_E = \frac{1}{49} \sum_{i=1}^7 \sum_{j=1}^7 [(g_{i,j})^2 - \mu_E]^2$$

$$\text{where } f_{i,j} = \begin{cases} 48 & \text{if } i = j = 4 \\ -1 & \text{otherwise} \end{cases}$$

2.1.11 Entropy (E)

$$E = p(1-p)$$

$$\text{where } p = \frac{g_{4,4}}{\sum_{i=1}^7 \sum_{j=1}^7 g_{i,j}}$$

2.2 Classification

An artificial neural network is a computational model that is commonly used in situations where the expert knowledge is

not explicitly defined and a complex nonlinear relation needs to be learned. So, ANNs are most suitable for classification of MCCs as benign or malignant. ANNs are used to classify MCCs as benign or malignant based on features extracted from mammograms. Classification of clustered MCs is a two-class pattern classification problem. One is benign and other is malignant. Let $X_j \in [x_1, x_2, x_3, \dots, x_i, \dots, x_n]$ be a set of normalized features extracted from mammograms that acts

as input vector for ANN and $Y_j \in [0,1]$ be output vector of ANN. '0' represents benign clustered of MCs and '1' represents malignant clustered of MCs. Let M^k be one training set of L samples, i.e. $M^k = [(X_j, Y_j)], j = 1, 2, 3, \dots, k, \dots, L$

Multilayer feed-forward Backpropagation (MLFFBP) (a supervised learning algorithm) is known to be a powerful ANN for prediction and classification problems. It is arguably the most commonly used and well-studied ANN architecture. A typical MLFFBP-ANN paradigm is structured in layers of neurons (nodes) to characterize MCCs as shown in figure 2. Input Layer Hidden Layer Output Layer.

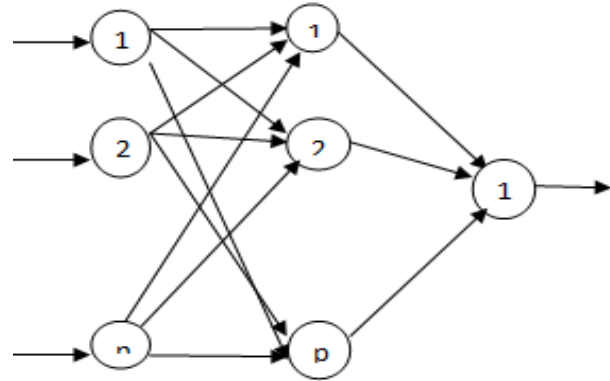


Fig: 2 MLFFBP-ANN based model for characterization of MCCs

As shown in figure 2, MLFFBP-ANN has three layers: input layer, hidden layer and output layer. Number of neurons in input layer depends upon input vector and number of hidden neurons is chosen experimentally. Classification of MCCs is a two-class pattern classification problem. So, output layer has only one node to represent binary output. For each interconnection between two nodes, a weight is also assigned to represent the link-strength between the neurons. Normalized features are used as inputs of the neurons of input layer. The output from the neurons of input layer is transmitted to the hidden layer with sigmoid activation function (f_j). The sigmoid activation function (f_j) is defined by the following expression:

$$f_1(x) = \frac{1}{1 + e^{-x}}$$

The graphical representation of sigmoid activation function is shown in figure 3. The output from the neurons of hidden layer is transmitted to the output layer with a single neuron with pure linear activation function (f_2). The pure linear activation function (f_2) is defined by the following expression:

$$f_2(x) = x$$

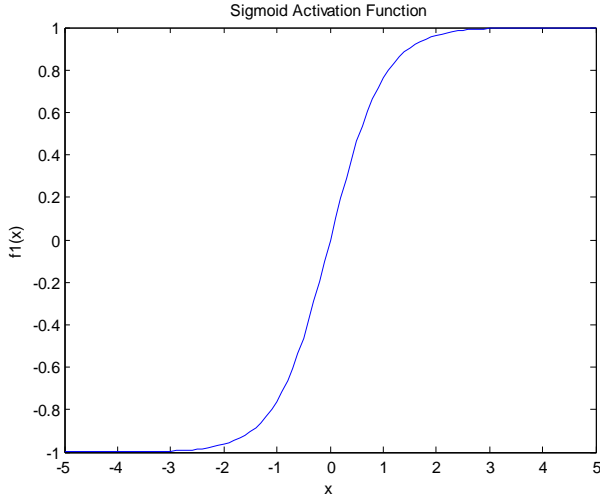


Fig: 3 The graphical representation of sigmoid activation function

The graphical representation of pure linear activation function is shown in figure 4.

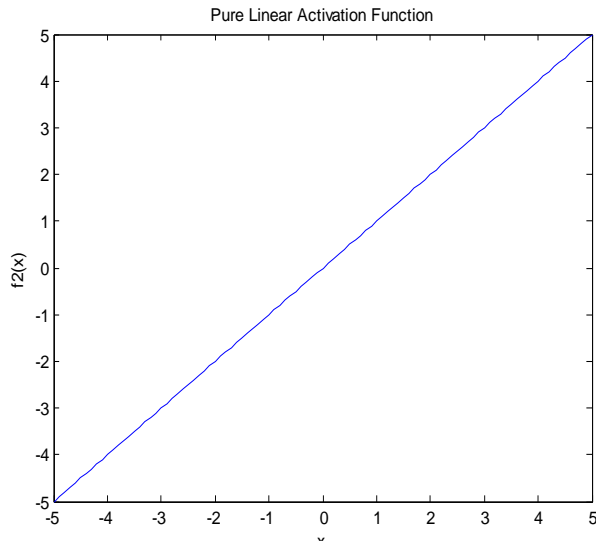


Fig: 4 The graphical representation of pure linear activation function

MLFFBP-ANN model is based on supervised learning. So, Resilient Backpropagation algorithm can be used to train

MLFFBP-ANN for characterization of MCCs as benign or malignant.

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, we discuss the experimental results obtained using Resilient Backpropagation training algorithm to classify Microcalcifications as benign or malignant. Such algorithm is explored not only for accuracy point of view but also for computational efficiency for MCs characterization in mammograms. Experiments are conducted on images of mini-MIAS database (Mammogram Image Analysis Society database (UK)). To obtain simulation results, MATLAB 7.7 is used.

3.1 Data Set

As mentioned above, experiments are conducted on images of mini-MIAS database (Mammogram Image Analysis Society database (UK)). Total 378 suspicious MCCs are collected, which contain 197 benign and 181 malignant samples, from mammogram images of mini-MIAS database. In order to validate results, MCCs are collected from a number of different kinds of mammogram images (fatty, fatty-glandular and dense-glandular) of mini-MIAS database. The collected MCCs are then randomly divided into two subsets for training and testing. Examples of benign and malignant cases are shown in figure 5.

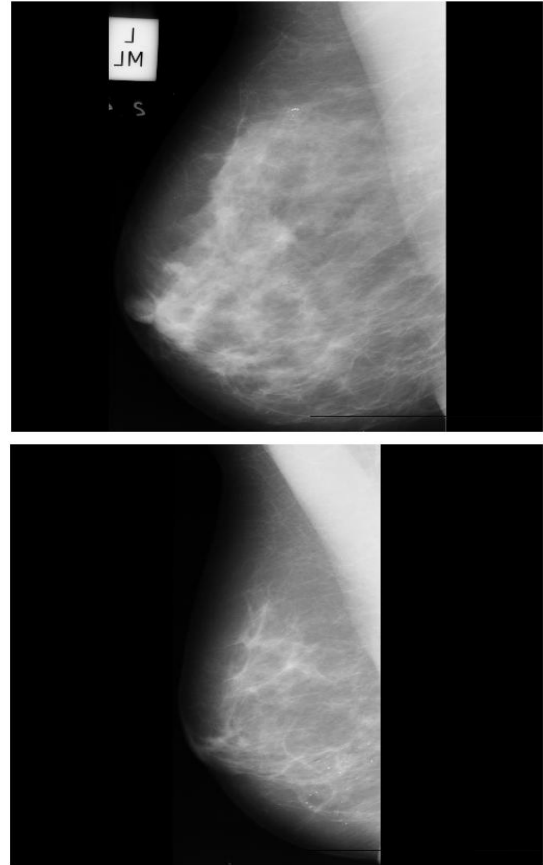


Fig: 5 Examples of mammogram images of mini-MIAS database (a) benign mdb219, (b) malignant mdb245

3.2 Training Phase

For classification of MCCs as benign or malignant, MLFFBP-ANN is used. Such architecture has three layers: input layer, hidden layer and output layer. Number of nodes in input layer depends upon number of features extracted from each MCC. In this study, 11 features as mentioned in section II are extracted from each MCC. So, 11 input nodes are used. We have experimented with different number of hidden nodes and decided to use 15 hidden nodes for the better results achieved. Classification of MCCs is a two-class pattern classification problem. One is benign and other is malignant. '0' represents benign MCCs and '1' represents malignant MCCs. Thus, output layer has only one node to represent binary output.

In this study, Batch Gradient Descent and Resilient Backpropagation training algorithms as mentioned in section II are used to train MLFFBP-ANN for classification of MCCs as benign or malignant. 105 benign and 101 malignant samples are used for training and results obtained in terms of performance parameters such as number of epochs taken by each algorithm for training and Mean Square Error (MSE) for each algorithm are shown in table 1. MSE is the sum of the squared differences between the target output and the actual output of the output node averaged over all training pairs. Thus, MSE is defined as

$$MSE = \frac{1}{L} \sum_{j=1}^L [t_j - Y_j]^2$$

Where t_j , Y_j and L are target output, actual output and number of training pairs respectively.

Learning characteristics of Resilient Backpropagation and Batch Gradient Descent training algorithms to train MLFFBP-ANN for classification of MCCs as benign or malignant are shown in figures 5-6. From table 1 and figures 5-6, it is observed that Resilient Backpropagation training algorithm needed only 569 epochs to reduce MSE level to a low value 1.00e-8. So, from computational load point of view, Resilient Backpropagation training algorithm is fast training algorithm to train MLFFBP-ANN for classification of MCCs as benign or malignant as compared to Batch Gradient training algorithm.

3.3 Performance Evaluation

For compare and evaluate performance of Resilient Backpropagation training algorithm and Batch Gradient training algorithms to classify MCCs as benign and malignant, receiver operating characteristic (ROC) analysis is used. ROC analysis is based on statistical decision theory that has been widely used in medical decision making. In ROC analysis, ROC curve is a popular tool to measure classifier performance in CAD system. ROC curve is a plot of classifier's sensitivity versus its 1 minus specificity at all possible threshold values. To draw ROC curve, x-axis is 1 minus specificity and y-axis is sensitivity. The terms "sensitivity", "specificity" and "1- specificity" are synonymous with true positive rate, true negative rate and false positive rate respectively. Sensitivity, specificity and 1 minus specificity are defined as

$$Sensitivity = \frac{TPs}{TPs + FNs}$$

$$Specificity = \frac{TNs}{TNs + FPs}$$

$$1 - Specificity = \frac{FPs}{TNs + FPs}$$

Where, TPs , TNs , FNs and FPs are number of true positive decisions, number of true negative decisions, number of false negative decisions and number of false positive decisions taken by a CAD system respectively.

TP , TN , FN and FP decisions taken by a CAD system are defined as:

- TP (true positive) decision is a correct judgment of a malignant MCC
- TN (true negative) decision is a correct judgment of a benign MCC
- FN (false negative) decision is a wrong judgment of a malignant MCC
- FP (false positive) decision is a wrong judgment of a benign MCC

Table1. Performance of Resilient Backpropagation and Batch Gradient Descent training algorithms used to classify MCCs as benign or malignant

Training Algorithm	Number of Epochs	MSE	Area under ROC Curve (Az)
Batch Gradient Descent	10000	0.000193	0.6762
Resilient Backpropagation	569	1.00e-08	0.8563

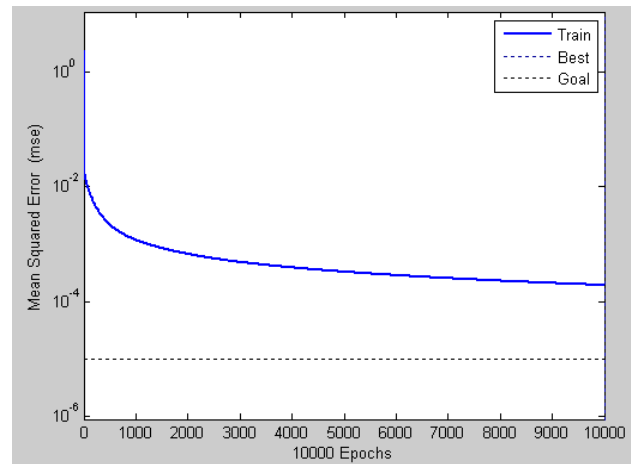


Fig: 6 Learning characteristics of Batch Gradient Descent algorithm for MLFFBP-ANN

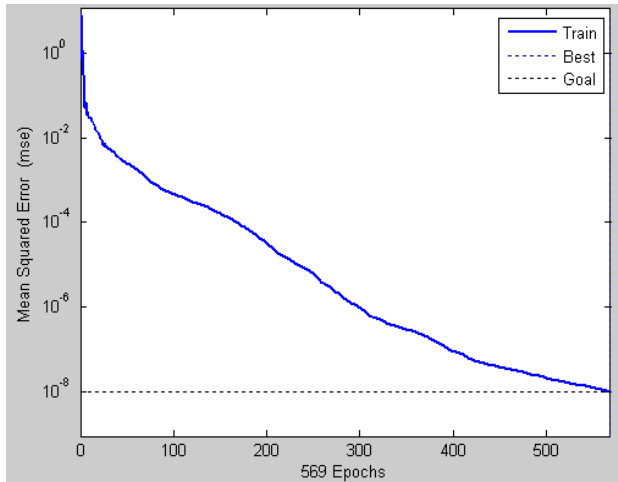


Fig: 7 Learning characteristics of Resilient Backpropagation

The area under the ROC curve (A_z) is an important criterion for evaluating diagnostic performance [24]. The ROC curve is in the range between 0.0 and 1.0. So, A_z lies between 0.0 and 1.0. The value of A_z is equal to 1.0 when CAD system has perfect performance i.e. TP rate is 100% and FP rate is 0%. The value of A_z is computed by Simpson's 3/8 rule.

Trained MLFFBP-ANNs are tested for classification of MCCs as benign or malignant using 92 benign and 80 malignant test samples. ROC curves of such classifiers are shown in figures 7 and the values of A_z for trained MLFFBP-ANNs to classify MCCs as benign or malignant are shown in table1. It is observed that area under ROC (A_z) of Resilient Backpropagation training algorithm based MFFBP-ANN is higher than Batch Gradient Descent training algorithm. Thus, Resilient Backpropagation training algorithm based MFFBP-ANN can act as a good classifier to classify MCCs as benign or malignant.

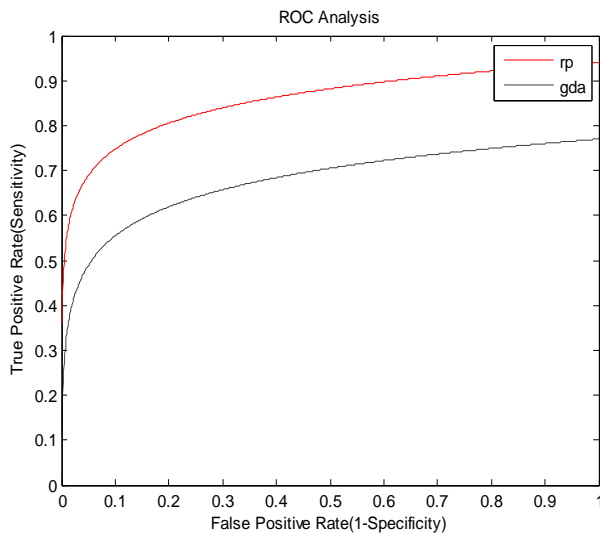


Fig: 8 ROC Curves for Resilient Backpropagation and Batch Gradient Training algorithms

4. CONCLUSION

In this paper, an attempt is made to analyze Resilient Backpropagation training algorithm to train MLFFBP-ANN for automated classification of MCCs as benign or malignant and compared the results of this algorithm with a well known Batch Gradient Descent training algorithm. The performance of such algorithms is checked not only for accuracy point of view but also for computational efficiency point for MCCs characterization in mammograms. The experiments are conducted on 378 samples extracted from the well-known mini-MIAS database and the main findings can be summarized as follows.

Firstly, it is found that Resilient Backpropagation training algorithm needed only 569 epochs to reduce MSE level to a low value $1.00e-8$. Thus, Resilient Backpropagation training algorithm is fast training algorithm to train MLFFBP- ANN for classification of MCCs as benign or malignant as compared to Batch Gradient Descent training algorithm. Secondly, to show effectiveness of Resilient Backpropagation training algorithm to train MLFFBP-ANN for automated classification of MCCs as benign or malignant, ROC analysis has been used. By comparison of ROC curves of Resilient Backpropagation and Batch Gradient Descent training algorithms, we can see that area under ROC curve (A_z) obtained with Resilient Backpropagation training algorithm is bigger than that of the curve obtained with Batch Gradient Descent training algorithm. Finally, it is observed that Resilient Backpropagation training algorithm is best training algorithm as comparison of Batch Gradient Descent training algorithm in terms of the speed of computation and accuracy achieved. The results of this study are quite promising.

In the future work, additional features of MCCs will be included in the used features and applying feature selection approaches to select optimal subset of features for improving efficiency as well as reducing false positive and false negative cases for more robustness.

5. ACKNOWLEDGMENT

Authors are greatly indebted to the Department of Electronics and Communication Engineering, SLIET, Longowal-148106 (District: Sangrur) Punjab, India for providing excellent lab facilities that make this work feasible.

6. REFERENCES

- [1] C. C. Boring, T. S. Squires, T. Tong and M. Montgomery, "Cancer Statistics 1994", CA-Cancer J. Clinicians, 44, pp.7-26, 1994.
- [2] H. D. Cheng and Muiy Cu, "Mass Lesion Detection with a Fuzzy Neural Network", J. Pattern Recognition, 37, pp.1189-1200, 2004.
- [3] Jun Xu and Jinshan Tang, "Detection of Clustered Microcalcifications using an Improved Texture based Approach for Computer Aided Breast Cancer Diagnosis System", J. CSI Communications, vol. 31, no. 10, pp. 17-20, 2008.
- [4] Sickles E, "Breast Calcifications: Mammographic Evaluation", J. Radiology, 160, pp.289-293, 1986.

- [5] Wallis M, Walsh M and Lee J, "A Review of False Negative Mammography in a Symptomatic Population", *J. Clin. Radiology*, 144, pp.13-15, 1991.
- [6] Celia Varela, Pablo G. Tahoces, Arturo J. Mendez, Miguel Souto and Juan J. Vidal, "Computerized Detection of Breast Masses in Digitized Mammograms", *J. Computers in Biology and Medicine*, 37, pp.214-226, 2007.
- [7] J. C. Fu, S. K. Lee, S. T. C. Wong, J. Y. Yeh, A. H. Wang and H. K. Wu, "Image Segmentation Features Selection and Pattern Classification for Mammographic Microcalcifications", *J. Computer Methods and Programs in Biomedicine*, 29, pp.419-429, 2005.
- [8] Thor. Ole Gulsrud and J. H. Husoy, "Optimal Filter-based Detection of Microcalcifications", *IEEE trans. on Biomedical Engineering*, vol.48, no.11, pp.1272-1280, Nov 2001.
- [9] M. G. Linguraru, K. Marias, R. English and M. Brady, "A Biologically Inspired Algorithm for Microcalcification Cluster Detection", *J. Medical Image Analysis*, 10, pp.850-862, 2006.
- [10] Huai Li, K. J. Ray Liu and Shih-Chung B. Lo, "Fractal Modeling and Segmentation for the Enhancement of Microcalcifications in Digital Mammograms", *IEEE trans. on Medical Imaging*, vol.16, no.6, pp. 785-798, Dec1997.
- [11] Brijesh Verma and Ping Zhang, "A Novel Neural-Genetic Algorithm to find the Most Significant Combination of Features in Digital Mammograms", *J. Applied Soft Computing*, 7, pp.612-625, 2007.
- [12] D. Kramer and F. Aghdasi, "Classifications of Microcalcifications in Digitized Mammograms using Multi-scale Statistical Texture Analysis", *Proc. of the South African Symposium on Communications and Signal Processing*, Sept. 7-8,1998, pp.121-126.
- [13] Nakayama R, Uchiyama Y, Hatsukade I, Yamamoto K, Watanabe R, Namba L et al., "Discrimination of Malignant and Benign Microcalcification Clusters on Mammograms", *J. Computer Aided Diagnosis of Medical Images* ,3, pp.1-7,1999.
- [14] Bottema MJ and Slavotinek JP, "Detection and Classification of Lobular and DCIS (small cell) Microcalcifications in Digital Mammograms", *J. Pattern Recognition Letters*, 21, pp.1209-1214, 2000.
- [15] Hamid Soltanian-Zadeh, Farshid Rafiee-Rad and Siamak Pourabdollah-Nejad D, "Comparison of Multi wavelet, Wavelet, Haralick and Shape Features for Microcalcification Classification in Mammograms", *J. Pattern Recognition*, 37, pp.1973-1986, 2004.
- [16] Nicandro Cruz-Ramirez, Hector Gabriel Acosta-Mesa, Humberto Carrillo-Calvet, Luis Alonso Nava-Fernandez et al., "Diagnosis of Breast Cancer using Bayesian Networks : A Case Study", *J. Computers in Biology and Medicine*, 37, pp.1553-1564, 2007.
- [17] AboulElla Hassanien, "Fuzzy Rough Sets Hybrid Scheme for Breast Cancer Detection", *J. Image and Vision Computing*, 25, pp.172-183, 2007.
- [18] I. Christoyianni, A. Koutras, E. Dermatas and G. Kokkinakis, "Computer Aided Diagnosis of Breast Cancer in Digitized Mammograms", *J. Computerized Medical Imaging and Graphics*, 26, pp.309-319, 2002.
- [19] Stelios Halkiotis, Taxiarchis Botsis and Maria Rangoussi, "Automatic Detection of Clustered Microcalcifications in Digital Mammograms using Mathematical Morphology and Neural Networks", *J. Signal Processing*, 87, pp.1559-1568, 2007.
- [20] Maciej A. Mazurowski, Piotr A. Habas, Jacek M. Zurada, Joseph Y. Lo, Jay A. Baker and Georgia D. Tourassi, "Training Neural Network Classifiers for Medical Decision Making: The Effects of Imbalanced Datasets on Classification Performance", *J. Neural Networks*, 21, pp.427-436, 2008.
- [21] Dursun Delen, Glenn Walker and Amit Kadam, "Predicting Breast Cancer Survivability: A Comparison of Three Data Mining Methods", *J. Artificial Intelligence in Medicine*, 34, pp.113-127, 2005.
- [22] Amar Partap Singh, Tara Singh Kamal and Shakti Kumar, "Virtual Curve Tracer for Estimation of Static Response Characteristics of Transducers", *J. Measurement*, 38, pp. 166-175, 2005.
- [23] Nikhil R. Pal, Brojeshwar Bhowmick, S. K. Patel, S. Pal and J. Das, "A Multi-stage Neural Network Aided System for Detection of Microcalcifications in Digitized Mammograms", *J. Neurocomputing*, 71, pp.2625-2634, 2008.