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ORIGINAL PAPER

A Swarm Optimized Neural Network System for Classification of Microcalcification in Mammograms

J. Dheeba · S. Tamil Selvi

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Abstract Early detection of microcalcification clusters in breast tissue will significantly increase the survival rate of the patients. Radiologists use mammography for breast cancer diagnosis at early stage. It is a very challenging and difficult task for radiologists to correctly classify the abnormal regions in the breast tissue, because mammograms are noisy images. To improve the accuracy rate of detection of breast cancer, a novel intelligent computer aided classifier is used, which detects the presence of microcalcification clusters. In this paper, an innovative approach for detection of microcalcification in digital mammograms using Swarm Optimization Neural Network (SONN) is used. Prior to classification Laws texture features are extracted from the image to capture descriptive texture information. These features are used to extract texture energy measures from the Region of Interest (ROI) containing microcalcification (MC). A feedforward neural network is used for detection of abnormal regions in breast tissue is optimally designed using Particle Swarm Optimization algorithm. The proposed intelligent classifier is evaluated based on the MIAS database where 51 malignant, 63 benign and 208 normal images are utilized. The approach has also been tested on 216 real time clinical images having abnormalities which showed that the results are statistically significant. With the proposed methodology, the area under the ROC curve (A_z) reached 0.9761 for MIAS database and 0.9138 for real clinical images. The classification results prove that the proposed swarm optimally tuned neural network highly contribute to computer-aided diagnosis of breast cancer.

Keywords Microcalcification · Mammograms · Computer aided detection · Neural network · Texture energy measures · Swarm optimized neural network

J. Dheeba (✉)
Department of Computer Science and Engineering,
Noorul Islam University,
Kumaracoil, TamilNadu, India
e-mail: deeps_3u4@yahoo.com

S. T. Selvi
Department of Electronics and Communication Engineering,
National Engineering College,
Kovilpatti, TamilNadu, India
e-mail: tamilgopal2004@yahoo.co.in

Introduction

Breast cancer (BC) is the most common cancer among women between the ages of 40–55 years. It is the second leading cause of cancer deaths in women today. However, early detection and effective treatments of breast cancer will decrease the mortality rate among women. Breast cancer refers to the erratic growth and proliferation of cells that originate in the breast tissue. A group of rapidly dividing cells forms a lumps or mass of extra tissue. These masses are called tumors and it can be either malignant or benign. Malignant tumors penetrate and destroy the healthy body tissue. Breast cancer refers to a malignant tumor that has developed from cells in the breast. This shows the importance of breast cancer detection at the early stage. If the breast cancer is diagnosed and treated at the early stage, the survival rate of the BC is 98%. The American Cancer society (ACS) estimates that each year over 178,000 American women and 2,000 American men will be diagnosed with BC (American Cancer Society., 2009) [1].

There are various methods for breast cancer screening like clinical and self breast exams, genetic screening, ultrasound, magnetic resonance imaging and mammography. Mammography is the best and most efficient method for detecting breast cancer at the early stage. Mammography is a specific type of imaging that uses a low dose x-ray system to examine breast. In a phillipine study (Pisani, 2006) [16] a mammogram screening was done to 151,198 women, out of that 3,479 women had this disease and was referred for diagnosis. Mammography can detect a growth as small as 0.5 cm in the depth of the breast that may not be palpable from surface. However mammography combined with breast self examination and clinical examinations is the most optimal method for detection of cancer [11]. Age is one of the risk factor for breast cancer. The ACS has recommended that the women should obtain her first baseline mammogram between the ages of 35 to 40 (American Cancer Society., 2009) [1].

Numerous randomized trials have clearly shown that mammography reduces the risk of dying from BC. Early detection of BC by mammography may lead to a greater range of treatment options, including less aggressive surgery. On the average, mammography will detect about 80–90% of BC in women without symptoms. It is estimated that 48 million mammograms are performed each year in the United States. Mammography can show changes in the breast well before a women or her physician can feel them. However, there is a difficulty in interpreting the mammograms as the images are affected by poor quality, noise and radiologists experience [6].

Microcalcificaitons (MC) are quiet tiny bits of calcium, and may show up in clusters or in patterns and are associated with extra cell activity in breast tissue. Scattered MC can indicate early breast cancer, which are usually a sign of benign breast cancer. MC in the breast show up as white speckles on breast x-rays. The calcifications are small; usually varying from 100 μm to 300 μm, but in reality may be as large as 2 mm.

Researches show that detecting a microcalcification is a challenging problem. The Computer Aided Diagnosis (CAD) system will help the radiologist in detecting suspicious areas on the mammograms [17, 20]. According to ACS, some studies have shown that CAD can help find cancers that radiologist otherwise might have missed. A number of Computer Aided Detection schemes have been adopted for the detection of MC clusters in mammograms. The CAD system will take a small ROI as a subject of recognition. The CAD system will also help the radiologists towards potential abnormalities. It uses algorithms to extract features from the image and these features are given as information to the intelligent classifier to make the final decision. In the past two decades the detection and classification of MC clusters in the mammograms, using the CAD methods has been investigated by several researchers.

Xinbo Gao et al., [6] used a preprocessing technique to improve the mass detection. A morphological component analysis is used to decompose a mammogram into a piecewise smooth component and texture component. Then with the help of intensity thresholds the piecewise smooth parts of the mammograms are separated into different intensity layers. Using the morphological features, the suspicious focal regions are selected. After initial selection the unnecessary regions are removed using single and multiple concentric layers.

Berkman Sahiner et al. [3] used a Convolution Neural Network (CNN) classifier to classify the masses and the normal breast tissue. First, the Region of Interest (ROI) of the image is taken and it was subjected to averaging and subsampling. Second, gray level difference statistics (GLDS) and spatial gray level dependence (SGLD) features were computed from different subregions. The computed features were given as input to the CNN classifier.

Songyang Yu and Ling Guan, [25] has proposed a CAD system automatic detection of clustered microcalcifications in digitized mammograms. Using mixed features the potential microcalcification clusters are segmented, and then the individual microcalcification cluster is segmented using 31 features. The discriminatory power of these features is analyzed using general regression neural networks via sequential forward and sequential backward selection methods. Netsch and Heinz-Otto, [15], uses the Laplacian scale-space representation of the mammogram. First, possible locations of microcalcifications are identified as local maxima in the filtered image on a range of scales. For each finding, the size and local contrast is estimated, based on the Laplacian response denoted as the scale-space signature. A finding is marked as a microcalcification if the estimated contrast is larger than a predefined threshold which depends on the size of the finding.

Cascio et al. [4] developed an automatic CAD scheme for mammographic interpretations. The scheme makes use of the Artificial Neural Network to classify mass lesions using the geometric information and shape parameters as input to the classifier. Brijesh verma and John Zakos, [22] developed a CAD system based on neural network for MC detection. A combination of 14 features was extracted from the mammogram image. A Back Propagation Neural Network was used for classification into benign and malignant cancer. Pelin Gorgel and Ahmet Serlbas et al., [7] designed a wavelet based Support Vector Machine (SVM) for capturing information of the MCs. Decision making is done by extracting features as a first stage by computing wavelet coefficients and classification using the classifier trained on the extracted features. Joaquim, [8] uses a set of shape based features which presents the task of calcification and similarity retrieval of mammographic masses based on shape content. It also uses the statistical based association rule to discriminate the disease from the normal breast tissue. Chen and Chang [5] presents a new texture shape feature coding based classification method for classifying masses on mammograms. A texture shape histogram is used for generating various shape features of masses.

Sung-Nien Yu and Yu-Kun Huang, [26] used a wavelet filter to detect all the suspicious regions using the mean pixel value. In the next stage textural features based on Markov random field and fractal models together with statistical textural features were used and a three layer Neural Network is used for classification. Subash [18] proposed an algorithm by combining Markov random field and Particle Swarm Optimization (PSO) algorithm.

Normal Texture measures includes mean, variance, etc. which will be concatenated to a single feature vector. This will be fed to a classifier to perform classification. In this way, much of the important information contained in the whole distribution of the feature values might be lost. MC clusters usually appear as a few pixels with brighter intensity embedded in a textured background breast tissue [19]. By effectively extracting the texture information within any ROI of the mammogram, the region with MC and the region without MC can be differentiated. Laws texture energy measures (LTEM) has proven to be a successful method to highlight high energy points in the image [13]. Anna et al. [2] suggests that LTEM has a best feature in analyzing texture of tissue for BC diagnosis. By considering the basic feature set like kurtosis, skewness, mean and Standard Deviation the accuracy achieved using LTEM is 90%. In order to find the true microcalcification pixel, a proper classification method must be employed. Moreover, when the number of hidden neurons is increased the classification accuracy will also be increased [21]. Finding the appropriate hidden neurons is a challenging task. Optimal selection of neurons automatically will decrease the burden of selecting neurons manually.

Artificial Neural Network's (ANN) are powerful tool for pattern recognition as they have the ability to learn complex, nonlinear surfaces among different classes. Though ANN performs well when applied for classification, the global classifiers based on static ANN have not performed well in practice. The backpropagation method used for training ANN has certain deficiencies [24]. In particular, the backpropagation is most likely to get trap into local minima, making it entirely dependent on the initial settings. In order to overcome the above deficiencies, in this paper a Swarm Optimized Neural Network (SONN) classifier is proposed, which automatically designs multilayer feedforward neural network in an optimal way using PSO algorithm.

The proposed CAD system consists of three major stages: preprocessing, feature extraction and detection of true microcalcification clusters. Laws features are extracted to focus the high texture energy points in the Region of Interest (ROI). An optimally tuned Feedforward Neural Network is used as a classifier to determine the discriminatory power of the texture features. The proposed scheme optimizes the number of hidden neurons, the learning rate and the momentum factor of the ANN and detects the MC clusters automatically. Optimality is achieved by employing Particle swarm optimizers (PSO), which is a population-based optimization algorithms modeled after the simulation of social behavior of bird flocks [9, 10]. A Receiver Operating Characteristics (ROC) curve is used to evaluate the performance of the proposed system.

The rest of paper is organized as follows. Section "Material and method" describes the materials and methods used for classification of microcalcification. Section "Experimental result" presents the experimental results obtained using the proposed SONN method and the performance analysis. Section "Conclusion" presents the discussion and conclusion.

Material and methods

Mammogram dataset and preprocessing

The UK research group has generated a MIAS database of digital mammograms (Suckling and Parker 1994). The database contains left and right breast images of 161 patients. Its quantity consists of 322 images, which belongs to three types such as Normal, benign and malignant. The database has been reduced to 200 μm pixel edge, so that all images are 1024×1024. There are 208 normal, 63 benign and 51 malignant (abnormal) images. It also includes radiologists 'truth' marking on the locations of any abnormalities that may be present. The database is concluding of four different kinds of abnormalities namely: architectural distortions, stellate lesions, Circumscribed masses and calcifications.

Real Time clinical mammogram dataset consisting of 216 images of 54 patients were taken from mammogram screening centers. The real time dataset includes a wide spectrum of cases that are difficult to classify by radiologists.

Our CAD system consists of a preprocessing stage, feature extraction stage and a detection stage. Preprocessing is done by segmenting the mammogram image into breast region and also the background region. Then, the breast region is chosen as the ROI for the next stage of processing. The proposed scheme is illustrated in Fig. 1.

Feature extraction methodology

In image processing the texture of a region describes the pattern of spatial variation of gray tones in a neighborhood that is small compared to the region. By definition, texture classification is to identify the texture class in a region. The texture energy measures developed by Kenneth Ivan Laws at the University of Southern California have been used for many diverse applications [13]. These texture features are used to extract texture energy measures (TEM) from the ROI containing MC and also in normal breast tissues, these measures are computed by first applying small

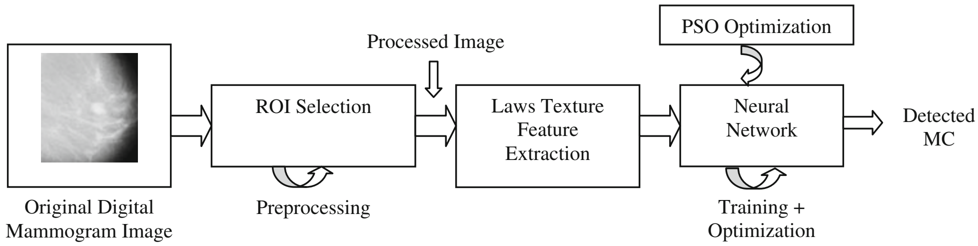

Fig. 1 Block diagram of the proposed mc detection system

convolution kernels to the ROI and then performing a windowing operation.

A set of twenty five 5×5 convolution masks is used to compute texture energy, which is then represented by a vector of 25 numbers for each pixel of the image being analyzed. The 2-D convolution kernels for texture discrimination are generated from the following set of 1-D convolution kernels of length five. The texture descriptions used are level, edge, spot, wave and ripple.

$$\begin{aligned} L5 &= [1 \quad 4 \quad 6 \quad 4 \quad 1] \\ E5 &= [-1 \quad -2 \quad 0 \quad 2 \quad 1] \\ S5 &= [-1 \quad 0 \quad 2 \quad 0 \quad -1] \\ W5 &= [-1 \quad 2 \quad 0 \quad -2 \quad 1] \\ R5 &= [1 \quad -4 \quad 6 \quad -4 \quad 1] \end{aligned}$$

From this above 1-D convolution kernels 25 different two dimensional convolution kernels are generated by convoluting a vertical 1-D kernel with a horizontal 1-D kernel. Example for generating a 2-D mask from a 1-D is given below.

$$E5\begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \\ 1 \end{bmatrix} \times \underset{L5}{\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix}} = \underset{E5L5}{\begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}}$$

Similarly, 25 different two dimensional masks can be formed.

L5L5	E5L5	S5L5	W5L5	R5L5
L5E5	E5E5	S5E5	W5E5	R5E5
L5S5	E5S5	S5S5	W5S5	R5S5
L5W5	E5W5	S5W5	W5W5	R5W5
L5R5	E5R5	S5R5	W5R5	R5R5

The following steps will describe how texture energy measures are identified for each pixel in the ROI of a mammogram image.

Step 1: Apply the two dimensional mask to the preprocessed image i.e. the ROI to get $F(i, j)$, where $F(i, j)$is a set of 25 N×M features.

Step 2: To generate the TEM at the pixel, a non-linear filter is applied to $F(i, j)$. The local neighbourhood of each pixel is taken and the absolute values of the neighbourhood pixels are summed together. A 15×15square matrix is taken for doing this operation to smooth over the gaps between the texture edges and other micro-features. The non linear filter applied is,

$$E(x,y) = \sum_{j=-7}^{7}\sum_{i=-7}^{7}|F(x+i,y+j)|$$

By applying the above equation 25 energy features per pixel are obtained. The TEM images are represented as,

L5L5T	E5L5T	S5L5T	W5L5T	R5L5T
L5E5T	E5E5T	S5E5T	W5E5T	R5E5T
L5S5T	E5S5T	S5S5T	W5S5T	R5S5T
L5W5T	E5W5T	S5W5T	W5W5T	R5W5T
L5R5T	E5R5T	S5R5T	W5R5T	R5R5T

Step 3: The texture features obtained from step 2 is normalized for zero-mean.

Classification of MC using SONN

After extracting the features of suspicious and non suspicious regions in the mammograms, the texture energy measures are collected for training and testing set. The proposed SONN classifier was used for the classification of the MC clusters. SONN encompasses both ANN and PSO.

SONN algorithm

PSO was introduced by Kennedy and Eberhart in 1995 [9] as a population based stochastic search and optimization process. PSO simulates the behavior of bird flocking or fish schooling and used it to solve the optimization problems. In the basic PSO algorithm the system is initialized with a population of random solutions and searches for optima by updating positions and velocity. The potential solutions called particles fly through the problem space by following the current optimum particles. All of the particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. Each particle is updated after every iteration using two values *pbest* and *gbest*. *pbest* is the personal best value, which indicates the best solution achieved so far (i.e. lowest fitness value) and the global best solution achieved so far by any particle in the population. In a *n*-dimensional search space, $\vec{X}_i = (X_{i1}, X_{i2}, \ldots\ldots, X_{in})$ and $\vec{V}_i = (V_{i1}, V_{i2}, \ldots\ldots, V_{in})$are the positions and velocities respectively and they are updated for the d^{th} dimension of the i^{th} particle and is given by,

$$V_{id}(t+1) = V_{id}(t) + c_1.rand_1.(pbest_{id} - X_{id}(t)) + c_2.rand_2.(gbest_d - X_{id}(t)) \tag{1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \tag{2}$$

c_1 and c_2 are the acceleration constants, $rand_1$ and $rand_2$ are the random numbers, $pbest_{id}$ is the individual's personal best i.e. the local best solution found so far. $gbest_d$ is the neighborhood's best solution found in the entire community or in some neighborhood of the current particle. The pseudo code for SONN algorithm is as follows

randomly generate *initial population*
do
for $i = 1$ to $population\_size$
Calculate *fitness value* using equation (5)
if $(F(X_i) < F(pbest_{t-1}))$ **then**
$pbest_t = X_i$
else
$pbest_t = pbest_{t-1}$
$gbest_t = \min(gbest_{neighbors})$
for $d = 1$ to *dimensions*
Velocity update using equation (1)
Position update using equation (2)
end
end
while *maximum iterations (t)* is reached

Back propagation training is a gradient descent algorithm and is susceptible to getting trapped to the nearest local minimum. In order to find optimal network architecture for the problem under study, exhaustive back propagation training is done over every network configuration in the architecture space defined. Performing the training for larger number of times with randomized initial parameters increases the chances of converging to the global minimum of the fitness function. Even if the configuration is made to train large number of times still there is no guarantee of converging to the global optimum with the backpropagation. However a best performance configuration can be achieved in the architecture space defined by the optimality of the network evolved using SONN.

In the proposed method, SONN is applied for evolving fully connected feedforward Neural Network and is optimized with best network architecture by optimizing the number of neurons in the hidden layer, the learning rate and the momentum factor. Finding an optimal learning rate avoids major disruption of the direction of learning when very unusual pair of training patterns is presented. The main advantage of using optimal momentum factor is to accelerate the convergence of error propagation algorithm. The number of neurons in the input layer and output layer is fixed based on the problem defined. Let N_I represents the size of the neurons in the input layer and N_O represents the size of the neurons in the output layer. The number of neurons in the input and output layer are fixed and they are same for the entire configuration in the architecture spaces. The number of hidden layers in this problem is restricted and made as one. The range of the optimization process is defined by two range arrays $R_{\min}=\{Nh_{\min}, Lr_{\min}, Mc_{\min}\}$ and $R_{\max}=\{Nh_{\max}, Lr_{\max}, Mc_{\max}\}$where, Nh is the number of neurons in the hidden layer, Lr is the learning rate and Mc is the momentum factor. Let f be the activation function and is defined as the sum of the weighted inputs plus the bias and is represented as,

$$y_k^p = f(s_k^p) \tag{3}$$

Where $s_k^p = \sum_j w_{j,k} y_j^p + \theta_k$, y_k^p is the output of the k^{th} neuron when a pattern p is fed, $w_{j,k}$ is the weight from the

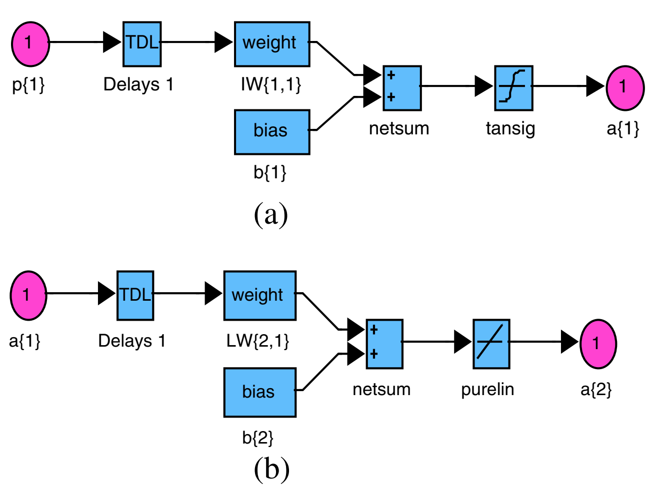

Fig. 2 **a** Simulated structure of hidden layer. **b** Simulated structure of output layer

Table 1 Laws texture energy measures for major regions of the images from MIAS

Regions	E5E5	S5S5	R5R5	E5L5	S5L5	R5L5	S5E5	R5E5	R5S5
Tumor	45	115	85	2282	3453	−1553	−569	−483	265
Non-Tumor	27	−401	5	997	−724	−137	−45	77	23

j^{th} neuron and θ_k is the bias value of the k^{th} neuron in the hidden layer and it is defined by hyperbolic tangent activation function,

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

The fitness function sought for optimal training is the Mean Square Error (MSE) formulated as,

$$MSE = \sum_{p \in T} \sum_{k=1}^{N_O} \left(t_k^p - y_k^{p,o}\right)^2 \tag{5}$$

Where t_k^p is the target (desired) output, $y_k^{p,o}$ is the actual output from the k^{th}neuron in the output layer o, for the pattern p in the training set. With the framed fitness function the SONN algorithm automatically evolve a best solution.

Experimental results

In this section the optimality of the network configuration with respect to the MSE criterion is evolved automatically by SONN algorithm based on the training set of the benchmark database is discussed. The overall results obtained by the proposed method using the MIAS database and the real time clinical images are compared against several state of art techniques in this field.

Optimal ANN design

The algorithm has been designed in a framework of MATLAB 7.10, which aims at developing a CAD system for breast cancer detection. The optimally designed ANN has three-layer architecture: an input layer, hidden layer and an output layer. The number of neurons that structures the input layer is equal to the number of feature vectors extracted (25 TEM). The hidden layer neurons are optimally added to the ANN and are defined by the hyperbolic tangent activation function as in Eq. 4. The output layer contains one neuron which discriminates presence of MC cluster. The neural network architecture space is defined over a multilayer preceptron with the parameters $R_{\min}$={$Nh_{\min}$, $Lr_{\min}$, $Mc_{\min}$} and$R_{\max}$={$Nh_{\max}$, $Lr_{\max}$, $Mc_{\max}$}. The simulated structure of the activation function in the hidden layer and output layer are shown in Fig. 2, in which *p{1}* represent the 25 TEM feature inputs, *a{1}* represents the activation output from the hidden layer, *a{2}* represents the activation output from the output layer, *IW*, *LW* and *b* indicates the inter-connection weights, layer weights and bias of the neural network respectively

Classification performance

To evaluate the performance of the proposed system in detecting the microcalcification clusters [12] Receiver Operating Characteristic (ROC) curve is used. ROC curve is a plot of the True positive Rate (TPR) versus False

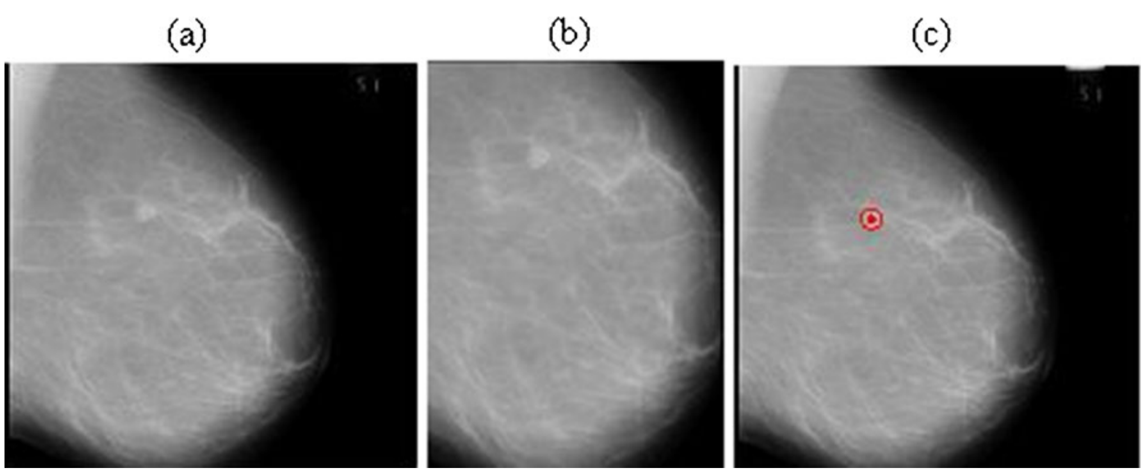

Fig. 3 Detection results for benign case (**a**) Original image (*mdb142*) (**b**) ROI image (**c**) SONN classifier output

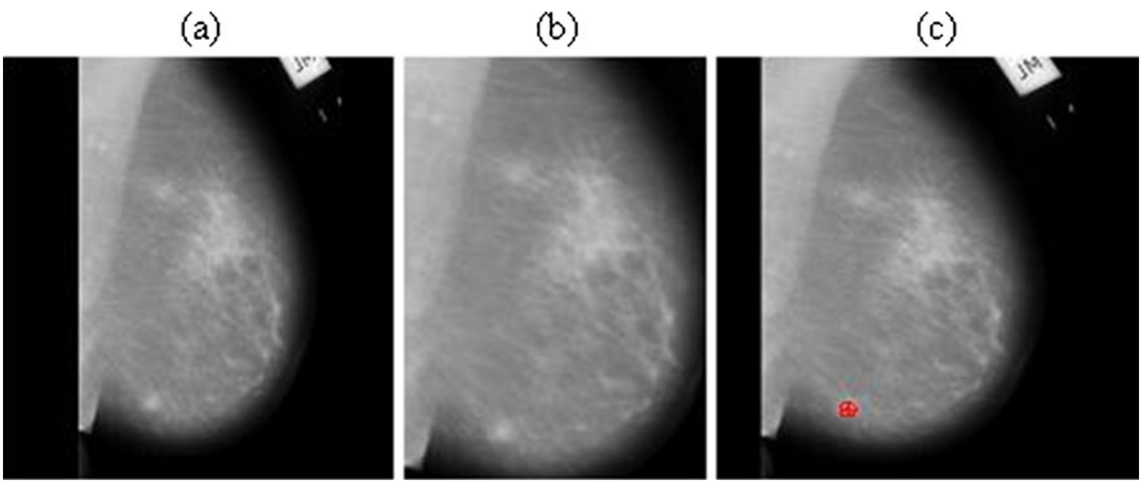

Fig. 4 Detection results for malignant case (**a**) Original image (*mdb206*) (**b**) ROI image (**c**) SONN classifier output

Positive Rate (FPR) [14]. The TPR denote the fraction of patients actually having the tumor and that are diagnosed as positive and the FPR is the fraction of patients actually without the tumor and that are diagnosed as positive. The detection performance is analyzed using the area under the ROC curve (A_Z). In this section experimental results using the MIAS Database and the real-time clinical images were analyzed.

Experimental results using MIAS database

The proposed algorithm is verified using the MIAS database. The first stage is the preprocessing stage, here the breast area is segmented out in order to save processing time and avoid false detections caused by markers and sharp edges near the chest side. Further processing is restricted to the breast area which is chosen as the ROI. During the feature extraction phase, 25 texture energy measures are taken from each pixel. For each preprocessed image, a block of 15×15 pixels is selected as the data to be analyzed. The laws texture energy measures for tumor and non-tumor regions of the images are summarized in Table 1.

For the classification experiments, the training data-set contain a total of 2050 TEM patterns from the MIAS database. These patterns contains TEM pixels including true individual microcalcification clusters, circumscribed masses, ill defined masses and also pixels indicating normal tissues that includes blood vessels and dense breast tissues. The optimization of SONN classifier is performed with the learning rate and the momentum constant varied from 0 to 1 and the hidden neurons varied from 31 to 200. For this training a maximum of 100 PSO iterations is performed with a population size of 50 with 500 training epochs, the acceleration constants c_1=1.8 and c_2=2.4 and $rand_1$ and

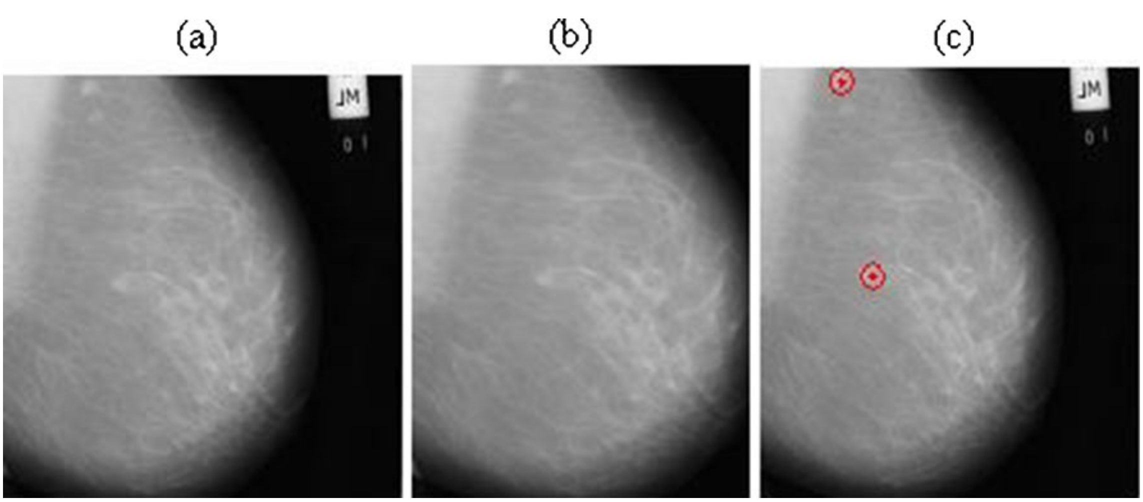

Fig. 5 Detection results for multiple clusters (**a**) Original image (*mdb144*) (**b**) ROI image (**c**) SONN classifier output

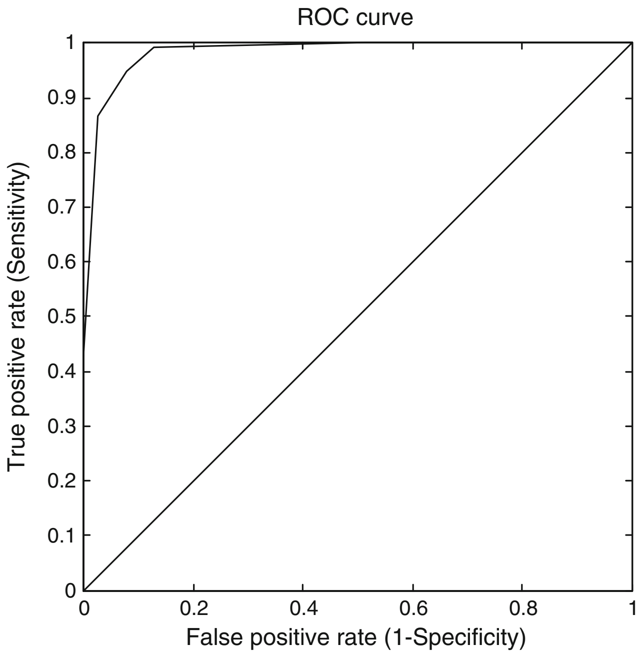

Fig. 6 ROC Curve for SONN classifier obtained using MIAS Database

$rand_2$ returns a uniform random number in the range [0,1] . During each PSO iteration, the best fitness score (minimum MSE) achieved by the particle with the *gbest* at the optimum dimension is stored. Using the proposed SONN algorithm an optimized ANN is achieved with $Nh=137$, $Lr=0.00132$ and $Mc=0.9172$. Thus, the SONN algorithm yields a compact network configuration in the architecture space rather than the complex ones as long as optimality prevails. Testing is done to all images in the database.

Figure 3 shows the detection results for the benign case tumor classification from MIAS. Figure 3 (a) shows the original mammogram image with suspicious benign stage tumor in it. Figure 3 (b) shows the result after the preprocessing procedure, i.e. the ROI area. Figure 3 (c) shows the final output of the SONN classifier where the suspicious regions are marked using red circles.

Figure 4 shows the detection results for the malignant case tumor classification from MIAS. Figure 4 (a) shows the original mammogram image with suspicious malignant stage tumor in it. Figure 4 (b) shows the ROI after preprocessing the original image. Based on the texture features, the final output of the SONN classifier is shown in Fig. 4 (c) where the suspicious regions are marked using red circles.

Figure 5 shows the detection results for multiple suspicious regions in the mammogram. Figure 5 (a) shows the original mammogram image with suspicious benign and malignant stage tumor in it. Figure 5 (b) shows the ROI after preprocessing the original mammogram image. Based on the texture features, the final output of the SONN classifier is shown in Fig. 5 (c) where it shows two clusters having abnormalities. The detection result shows that the classifier is capable of detecting calcifications, ill defined and well defined masses.

Figure 6 presents the ROC curves corresponding to texture feature sets and the SONN classifier. The ROC curve obtained were computed using only the test mammograms and the area under the estimated ROC curve (*Az*), standard error (SE), and the asymmetric 95% confidence interval were analysed. As observed, the proposed scheme has achieved a sensitivity of 95% at a specificity level of 92.3% for MIAS database.

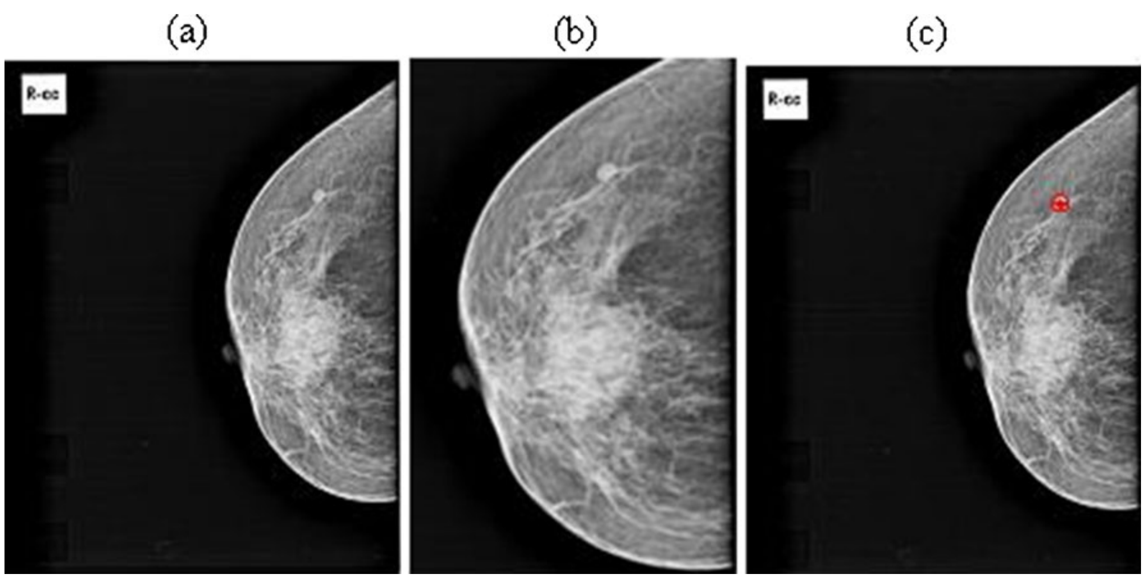

Fig. 7 Detection results for benign case at CC view (**a**) Original image (*case42*) (**b**) ROI image (**c**) SONN classifier output

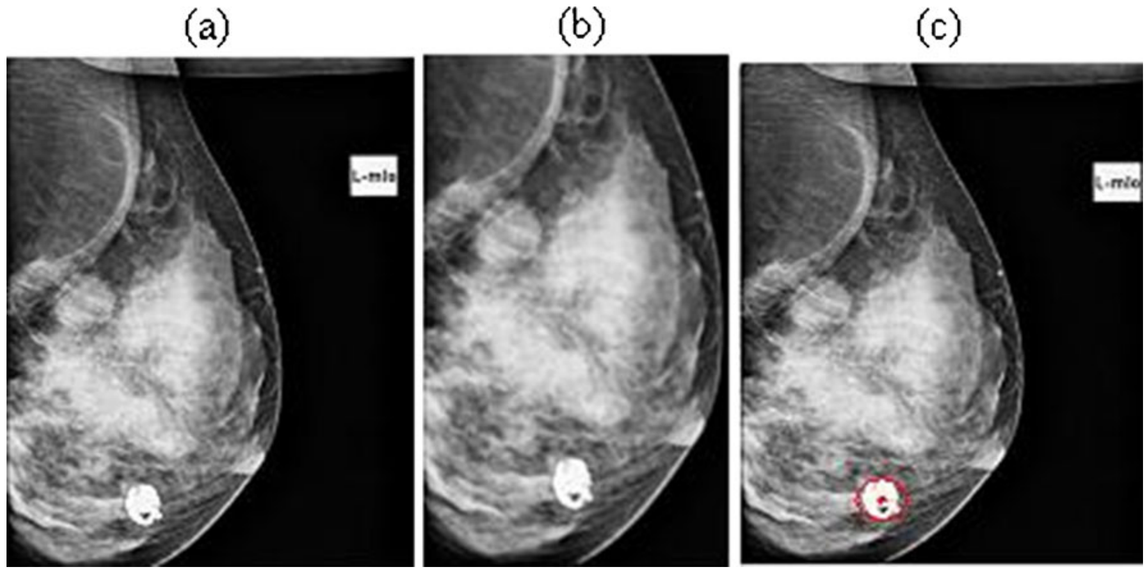

Fig. 8 Detection results for malignant case at MLO view (**a**) Original image (*case23*) (**b**) ROI image (**c**) SONN classifier output

Experimental results using real-time clinical images

This section reports on a study that was taken to analyze screening mammograms of breast cancer patients. The goal of this study is to reduce the number of false positive rates which help to avoid unnecessary biopsies and emotional stress to many women. Women after the age of 40 are advised to take mammograms every year and hence the total number mammograms evaluated worldwide in 1 year may be in the order of millions. Hence, when it comes to practical applications appropriate models and optimum parameter values are generally very difficult to obtain. It is also difficult to interpret a mammography as its accuracy is seriously affected by image quality and radiologists experience. By using the proposed automated CAD system, suspicious regions are pointed out in the digital mammograms for further evaluation.

All clinical mammograms that were collected from screening clinics were positive for presence of microcalcifications. Mammograms were collected from 54 patients and all these patients have agreed to have their mammograms to be used in research studies. For each patient 4 mammograms were taken in two different views, one is the Craniocaudal (CC) and the other is the Mediolateral Oblique (MLO) view. The two projections of each breast (right and left) were taken for every case. The suspicious regions were identified by the automated system based on SONN algorithm and was reviewed by experienced radiologists.

For this study a total of 216 mammograms were taken, all the mammograms were digitized to a resolution of 290× 290 Dots per Inch (DPI) which produces 24 bits/pixel. Each digitized mammograms was incorporated into a 2020× 2708 pixel image (5.47 Mpixels).

After preprocessing the clinical mammograms, 25 TEM features are extracted from each pixel of the ROI image. The data is taken from 15×15 pixels from the ROI and is subjected to further analysis. The training dataset contains a total of 1,064 patterns taken from 216 mammograms. These patterns contain normal, benign and malignant tissues. The SONN algorithm was trained with the same parameters used for analyzing the MIAS database. An optimized ANN is achieved with Nh=116,

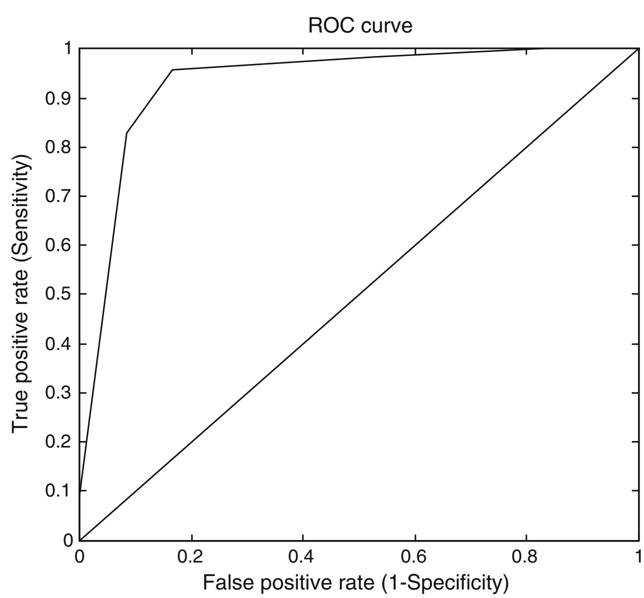

Fig. 9 ROC Curve for SONN classifier obtained using Real Time Clinical Mammograms

Table 2 Classification results for different classifiers

	MIAS database			Real time clinical database		
	SVM	FFNN	SONN	SVM	FFNN	SONN
Az	0.8755	0.8541	0.9761	0.8343	0.8021	0.9138
S.D	0.0201	0.0259	0.0106	0.0211	0.0199	0.0221
95% CI	0.8380	0.8103	0.9553	0.8012	0.7988	0.8704

Lr=0.00114 and Mc=0.9238. Testing is done for all the 216 real time clinical images.

Figure 7 shows the detection results for the benign case tumor classification from real time clinical mammograms. Figure 7 (a) shows the original mammogram image with suspicious benign stage tumor in it. Figure 7 (b) shows the ROI image after preprocessing. Figure 7 (c) shows classifier output where the suspicious regions are marked using red circles.

Figure 8 shows the detection results for the malignant case tumor classification from real time clinical mammograms. Figure 8 (a) shows the original mammogram image and Fig. 8 (b) shows the ROI after preprocessing the original image. Based on the texture features, the final output of the SONN classifier is shown in Fig. 8 (c) where the suspicious regions are marked using red circles.

Figure 9 shows the ROC curves obtained using only the test mammograms from the clinical images. As observed, the proposed scheme has achieved a sensitivity of 91% at specificity level 86.1% when applied to clinical images.

Performance analysis

The detection results obtained using various classifiers were analyzed and the area under the ROC curve for each method using both MIAS and Real Time database are shown in Table 2. and it shows the area under the ROC curve, Standard Deviation and 95% Confidence Interval (CI) for each classifier. Results shows that high performance was obtained by the proposed scheme when compared to other classifier models dealt in Liyang Wei et al., [23]. TEMs also have demonstrated a superior performance signifying that image energy provided to texture is of high discriminating power when compared to other feature set discussed in literature. Table 2 illustrates the classification results obtained using Support Vector Machine (SVM), Feedforward Neural Network (FFNN), and the Proposed scheme (SONN).

A comparative analysis of different classifiers based on the Area under the ROC is shown in Fig. 10, tabulated in Table 2. shows that the proposed SONN classifier has proved to have good performance when comparing the *Az* values with other classifiers since it takes the optimized values for hidden neurons, learning rate and momentum factor.

Conclusion

In this paper, we have investigated the use of SONN classifier for detecting tumors in digital mammograms. These classifier models were first trained using TEMs for discriminating between normal and abnormal tissues. The classifier was tested using two databases: the standard MIAS database containing 322 mammograms and also 216 real time clinical images obtained from various mammogram screening centers. The results obtained from the SONN classifier was compared with other well known classifiers. The results demonstrate that the optimized feedforward Neural Network has yielded best performance when compared with SVM and FFNN. The optimized neural network accelerates the convergence of the error back propagation algorithm and also it avoids major disruptions in the direction of learning. The proposed method also has proved that the Laws texture energy measure has best discriminating power even when considering multiple-view mammograms.

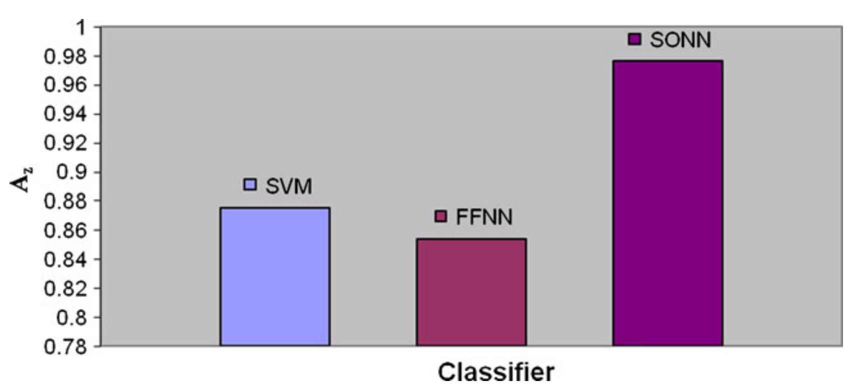

Fig. 10 Comparative analysis for different classifier used for microcalcification detection

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