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SPECIAL ISSUE ON RECENT RESEARCH CHALLENGES IN BIO-MEDICAL APPLICATIONS

Clinical Support System for Classification of Tumor in Mammogram Images Using Multiple Features and Neural Network Classifier

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An improved Computer Aided Clinical Decision Making System for classifying the tumor has been developed and presented in this paper. The texture and shape features extracted from preprocessed mammograms have been utilized to obtain the optimal multiple feature sets using multiobjective genetic algorithm. The Multilayer Back Propagation Neural Network (MBPN), Self Organising Map(SOM) with major voting method have been used to classify the tumor as benign or malignant. The multiple features with optimal feature selection is found to have the diagnostic accuracy 99.5%. The performance of the proposed clinical decision support system has been estimated and found that this system will provide valuable information to the physicians in clinical pathology.

Key words: Mammogram, Image Denoising and Enhancement, Feature Extraction, Multilayer Back Propagation Network, Self Organising Map.

Breast cancer is a leading cause of deaths among women in the recent past. The existing literatures have revealed that the early detection of the characteristics of tumor cells can reduce the mortality due to cancer. Digital mammography has been found as one of the reliable techniques for early detection of microcalcifications. The developments of Computer Aided Diagnosis systems have been focused by many researchers for providing valuable information to the radiologists. Early detection of breast cancer can play an important role in reducing the associated morbidity and mortality rates[1, 2]. Sheng-chih yang *et al*[3] described the computer classification system having a probabilistic neural network (PNN) coupled with entopic thresholding techniques for mass extraction. Classification of masses in mammograms has been done by single and multilayer perceptron topologies and training set has been developed by Tulio C. S. S. *et al*[4]. The contours on mammograms related to breast masses and tumors were represented by polygonal models for shape analysis. A CAD system for distinguishing malignant from benign masses has been suggested by Rangaraj M. Rangayyan *et al*[5]. The Artificial Neural Network (ANN) based committee machine and computational intelligence have been used to represent the differences between malignant tumors and benign masses. The classification has been done using the area under the Receiver Operating Characteristics Curve and compared with other classifiers.

Later Mohamed A. Alolfe1 *et al*[6] developed a Computer Aided Diagnosis (CAD) system to detect abnormalities in digital mammograms using automatic segmentation, feature extraction and classification techniques. The algorithm has been developed for detecting abnormalities to assist radiologists for effective use of computer-based diagnosis. A CAD system developed by Karen Drukker *et al*[7] demonstrated

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the quantitative techniques to assess the features such as area, homogeneity, microcalcification of breast density from digitized mammograms using image processing and data mining concepts. Guodong Zhang and Hong Zhao[8] created a CAD system for detection and classification of Microcalcification (MCCs) or suspicious areas in digital mammograms that included the digitize module, detection module, feature extraction module, neural network module and classification module. Mohiy Hadhoud *et al*[9] have also developed the computer-based system for the classification of breast tumor using hybrid algorithm of gray-level thresholding and dynamic programming. Giger.M, *et al*[10] investigated the possibility of creating a CAD system for detecting clustered microcalcifications from mammograms. The potential microcalcifications extracted with a series of three different techniques such as a global thresholding based on the grey-level histogram of the full filtered image, an erosion operator for eliminating very small signals and a local adaptive grey-level thresholding. The false-positive signals eliminated by means of a texture analysis technique and a non-linear clustering algorithm was used for grouping the remaining signals.

An automated method for differentiating malignant from benign masses has been suggested by Huo Zhimin *et al*[11]. In this method, the extracted features were related to the margin and density of each mass from the neighborhoods of the computer-identified mass regions. Leonardo de Oliveira Martins *et al*[12] used the computational tools to aid detection and diagnosis of breast masses has gained increasing acceptance in recent years, as a kind of "second readers" of medical images. These tools have been contributing to increase the rate of early detection of breast cancer. Keeping the above facts, the development of computer aided decision support system for classification of breast tumors and presented in this paper.

The main objective of this study is to develop a computer-aided system using multifeature texture analysis and neural network classifiers for the automated classification of breast tumors from mammogram images. The computer-aided classification of breast tumor will contribute toward a more standardized and accurate methodology for the assessment of breast tumor as malignant or benign. The developed system can be able, based on extracted texture feature and shape parameters, to automatically classify tumors into either malignant or benign. The aim is to identify patients at risk of breast cancer. The system is composed from the following modules: 1) image acquisition and preprocessing 2) feature extraction 3) tumor classification. Fig.1 illustrates the flowchart of the system.

The functional block diagram of the proposed medical decision making system for classifying breast tumor as malignant and benign in the mammogram is shown in Fig.1. The mammogram is obtained and processed using various techniques. The features obtained are expected to provide valuable information to analyze the nature of the mammogram for further decision-making in the clinical pathology.

Data Acquisition and Preprocessing

The mammograms can be acquired with dedicated mammographic systems and digitized with a laser film scanner [Lumisys DIS -1000]. The digitized image can be preprocessed prior to feature extraction using shock filter[13]. The filter enhances the discontinuities at the edges and makes the image flat within the region. This filter is capable of providing high performance compared to existing methods. The approach is based on non-linear diffusion, in which the image gradient was used to weight the diffusion process in order to smooth the mammogram images.

Segmentation

The segmentation of the mammographic image is to extract one or more regions of interest (ROIs) from the background after pre-processing. The principle goal of segmentation is to partition an image into homogenous regions (spatially connected groups of pixels called classes, or subsets) with respect to one or more characteristics or features, such that the union of any two neighboring regions yields a heterogeneous. Segmentation techniques can be classified into two main categories: edge-based segmentation techniques and region-based segmentation techniques[14].

In edge-based techniques, segmentation of an object is achieved by locating its boundary using image gradient which has high values at the edges of objects. The edges between regions with different characteristics have been utilized. The edge based technique has the limitation of not enclosing the object completely. The segmentation by region-based techniques is achieved by identifying all pixels that belong to the object based on the intensity of pixels. They are looking for the regions satisfying a given homogeneity criterion. Since mammographic masses mostly have low contrast and ill-defined edges, it is difficult to determine their boundary with edge-based techniques. Region-based techniques are more suitable for mammograms since suspicious regions are brighter than the surrounding tissues. There are many region-based techniques such as Region growing, Watershed algorithm, and Thresholding. In this paper region segmentation based-thresholding method is used for segmentation. Thresholding is based on the image histogram or local statistics such as mean value and standard deviation, or the local gradient[22].

Extraction of multiple features and optimization

A typical mammogram contains a vast amount of heterogeneous information that depicts different tissues, vessels, ducts, chest skin, breast edge, the film, and the X-ray machine characteristics[15]. In order to build a robust diagnostic system for classifying normal and abnormal regions of mammograms, necessary care must be taken to present all the available information that exists in mammograms to the diagnostic system, so that it can easily discriminate between the normal and the abnormal tissue. However, the use of all the heterogeneous information, results to high-dimensional feature vectors that degrade the diagnostic accuracy of the utilized systems significantly as well as increase their computational complexity. Therefore, reliable feature vectors should be considered to reduce the amount of irrelevant information thus producing robust Mammographic descriptors of compact size. Features can be categorized in to three groups such as texture, shape and scalar area features. The multiresolutional texture and shape features are heterogeneous features. Hence an automatic subset selection may be required to select the optimal feature subset from the multiple features set[23].

Texture and Shape Feature Extraction

The third stage of mass detection by CAD (computer aided diagnosis) schemes is the feature extraction and selection. The features can be calculated from the ROI characteristics such as the size, shape, density, and smoothness of borders, etc.[16]. The feature space is very large and complex due to the wide diversity of the normal tissues and the variety of the abnormalities. Only some of them are significant. Using excessive features may degrade the performance of the algorithm and increase the complexity of the classifier. Some redundant features should be removed to improve the performance of the classifier. The feature extraction and selection is a key step in mass detection since the performance of CAD depends more on the optimization of the feature selection. Feature selection is the process of selecting an optimum subset of features from the enormous potential features available in a given problem domain after the image segmentation[17]. The feature space can be divided into two sub-spaces: texture features and shape features.

First Order Statistical Features (FOSF)

FOSF provide different statistical properties of the intensity histogram of an image[16]. In this study, the following features are estimated. Mean(F1), Dispersion(F2), Variance(F3),Average Energy(F4), Skewness(F5), Kurtosis(F6), Median(F7),and Mode(F8) .

Spatial Gray Level Dependent Features(SGLDF)

The SGLDF[16] is based on an estimation of the second-order joint conditional probability density functions(pdfs) that two pixels(k,l) and (m,n) with distance d in direction specified by the angle è,have intensities of gray level i and gray level j.Based on the pdfs the following texture features have been computed.The features include Angular Second Moment (ASM), Contrast (CON), Correlation (COR), Variance (VAR), Inverse Difference Moment (IDM), Sum Average (SV), Sum Entropy (SE), Entropy (ENT), Difference Variance (DV), Difference Entropy (DE), Information of correlation-I (IMC1), Information Correlation-II(IMC2) and Maximum Correlation Coefficient (MCC).

Surrounding Region Dependent Features (SRDF)

Similarly the surrounding dependent features[17] can be obtained from the second order histogram of the surrounding regions.

Horizontal-Weighted Sum (HWS), Vertical –Weighted Sum (VWS), Diagonal-Weighted Sum DWS), Grid-Weighted Sum (GWS).

Gray Level Run Length Feature (GLRLF)

The GLRLF[16] is based on computing the number of gray-level runs of various lengths. The length of the run is the number of pixel points in the run.

Short-run emphasis, Long-run emphasis, Gray-level nonuniformity, Run-length nonuniformity and Run percentage[20]

Gray Level Difference Features (GLDF)

The GLDF[17] is based on the occurrence of two pixels which have a given absolute difference in gray level and which are separated by a specific displacement d.

For any given displacement vector d =(Dx, Dy), let Sd(x,y)=|S(x,y)-S(x +Dx,y+Dy)| and D(i|d) be estimated probability-density function defined by

$$D(i\mid\delta)=\Pr ob[S_{\delta}(x,y)=i] \quad \text{... (17)}$$

Five textural features such as Contrast, Angular second moment, Entropy, Mean and inverse difference moment can be measured from D(i|d).

Shape Features

The shape of the masses is expected to provide the valuable features to distinguish the malignant and benign mass. The shape feature includes the geometric parameters such as area, perimeter, circularity; radial distance mean and standard deviation, area ratio, orientation, eccentricity, moment invariants and Fourier descriptors[18]. Nearly 25 shape features can be calculated from the segmented ROI. In this study only the following shape features are considered. The radial distance is measured by detecting the centroid of the mass[23]. Then the Euclidean distance from the centroid to the edge is measured for the entire boundary. The radial distance is computed as the following:

$$d(i)=\sqrt{(x(i)-X_0)^2+(y(i)-Y_0)^2}\ ,\quad i=1,2\,\ldots.,N \quad \text{...(18)}$$

where (X0,Y0) are the coordinates of the centroid, x(i) and y(i) are the coordinates of the boundary pixel at the ith location, and N is the number of boundary pixels of the extracted region.The shape features can be extracted from the tumor. The tumor circularity C, is defined as

$$C=\frac{P^2}{A} \quad \text{...(19)}$$

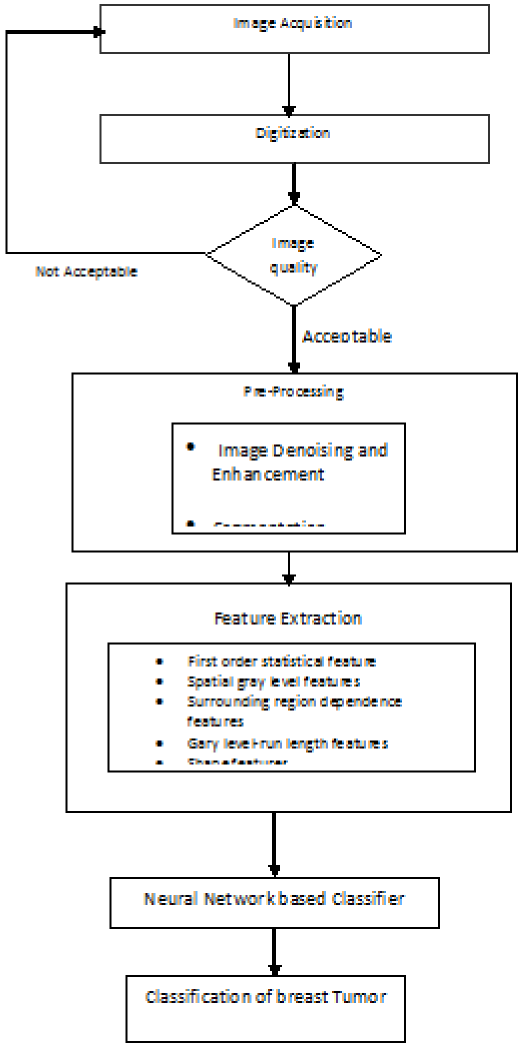

Fig. 1. Flow graph of the Proposed Computer Aided Decision Making System

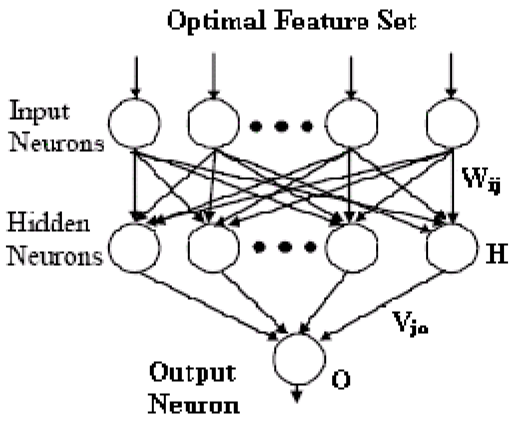

Fig. 2. Back propagation network

where P is the perimeter and A is the area of the tumor. The perimeter can be measured by summing the number of pixels on the border of the mass, and the number of pixels inside the border. The radial distance mean is represented by

$$d_{avg} = \frac{1}{N}\sum_{i=1}^{N} d(i) \qquad ...(20)$$

The standard deviation of the radial distance can be computed from

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d(i)-d_{avg})^2} \qquad ...(21)$$

The entropy of the radial distance histogram is a probabilistic measure represented by

$$E = \sum_{k=1}^{100} p_k \log(p_k) \qquad ...(22)$$

Where p_k is the probability that the radial distance will be between d(i) and d(i)+0.01d(i).The parameter p_k can be computed via a normalized histogram .

The area ratio parameter is defined as

$$A = \frac{1}{d_{avg}N}\sum_{i=1}^{N}(d(i)-d_{avg}) \qquad ...(23)$$

where $A = 0 \quad \forall \quad d(i) \le d_{avg}$

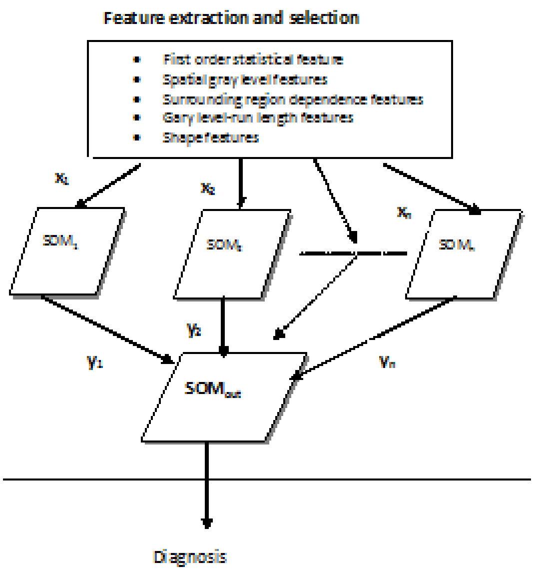

Fig. 3. SOM Classifier

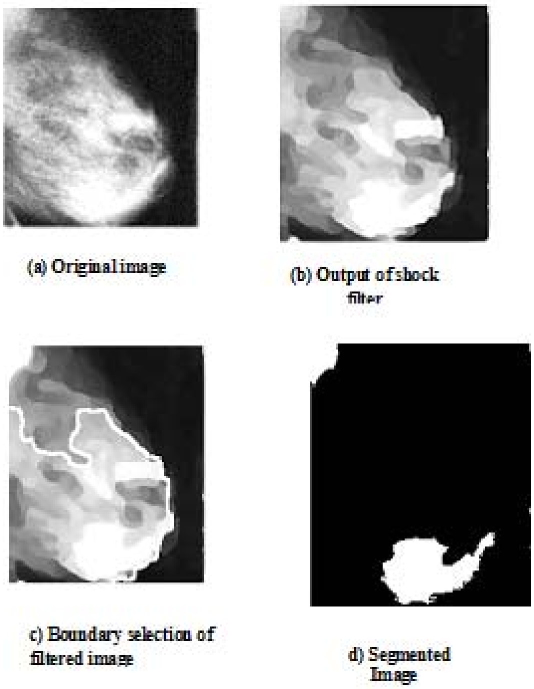

Fig. 4. Preprocessed image

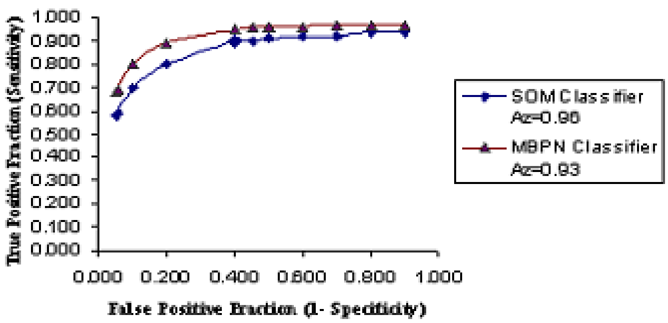

Fig. 5. ROC analysis of SOM and MBPN classifiers with optimal feature set

The Roughness is calculated for each segment using

$$R(j) = \sum_{i=j}^{L+j} | d(i) - d(i+1),$$

where

$$\left[j = 1, \ldots\ldots \frac{N}{L} \right] \quad \ldots(24)$$

and

$$R = \left[\frac{L}{N} \right] \sum_{j=1}^{\frac{N}{L}} R(j) \quad \ldots(25)$$

where R(j) is the roughness index for the jth segment, L is the number of boundary points in the segment and N is the total number of boundary points.

Optimal Feature Selection

The texture and shape features can provide various characteristics of the mammogram. Both texture features and shape features can be extracted from the digitized mammogram after segmentation. As the numbers of features available are high in numbers the optimization of feature set has become necessary. This can be achieved using multi objective genetic algorithm (MOGA) technique[19,20]. The outcome of the optimization is expected to provide the optimal set of features, which can be used as input to the classifier. The main objective of the optimization is to minimize the number of redundant features and minimize the error rate of the classifier.

Classification of tumor

Multilayer Back Propagation Network (MBPN)

The back propagation-learning algorithm is widely used for multi-layer feed forward network[21,23]. The three-layer back propagation neural network as shown in Fig.4 can be considered for optimization to obtain correct responses to the training input data set.

The output of each hidden neurons and output neurons can be calculated using the sigmoid function,

$$H = \frac{1}{(1 + e^{-\lambda x_{jk}})} \quad \ldots(18)$$

Table 1. Performance comparison of Various Texture Features and shape Feature using Diagnostic Accuracy

Feature Set	Feature set vector size	Diagnostic Accuracy % MBPN Classifier	SOM Classifier
FOSF	8	75.37	83.37
SGLDF	13	72.31	82.21
SRDF	4	69.56	78.65
GLRLF	5	79.41	86.19
GLDF	5	61.49	77.93
SHAPE FEATURES	10	59.21	69.21
Combine the feature set with majority voting		76.0	88.20
All 45 features	45	79.91	92.34
12 Optimal features	12	95.19	99.5

Table 2. Performance of the Classifier

Classes	No. of data for training /testing	No. of correctly classifieddata		Percentage of correct classification	
		MBPN Classifier	SOM Classifier	MBPN Classifier	SOM Classifier
Benign	90/85	78	84	91.74	99
Malignant	90/85	77	83	90.05	99
Average	93.55	99			

$$O = \frac{1}{(1+e^{-\lambda x_{OL}})} \quad ...(19)$$

where x_{HL} represents the net input applied to the hidden layer and x_{OL} represents the net input applied to the output layer. The values of the inputs are the normalized features, which lie between 0.1 and 1. The nodes of hidden layer were adjusted in an attempt to achieve optimum classification rates. The output value is set between 0 and 1 and the desired output cab be specified as benign for the threshold value is less than 0.5, and as malignant for the threshold value between 0.5 and 1.The neural networks for classification with different selected inputs can be trained separately by another genetic algorithm. In each generation, evaluation of an individual (a feature subset) involves training neural network.

The SOM Classifier

The SOM classifier is an unsupervised learning algorithm where the input patterns are free distributed over the output node[17]. The weight vectors of the output nodes are adapted without supervision in such a way, so that the density distribution of the input data is preserved and represented on the output nodes.

Subdivide the input feature vectors x so that different feature components of the tumors are learned separately. The features are labeled as x_1, x_2———x_n have been given as input to the SOM_1, SOM_2…………SOM_n.After training these maps,for each input vector xi to map i ,the 2 dimensional coordinates corresponding to the activated node in that map is taken as an”output” y_i of the map.The outputs $y_1, y_2 \ldots\ldots y_n$ of the n maps are next used as a feature vector to be learned by a single SOM in the next layer SOM_{out}.

Finally, labeled samples are presented to the multiplayer maps and output clusters are correspondingly labeled and tested on new data.In the evaluation phase, a new input pattern has been assigned to the winning output node with the weight vector closest to the new input vector. In order to classify new input pattern, the majority labels of the output nodes in a neighborhood window centered at the winning node, has been considered.The number of the input patterns in the neighborhood window for the two classes m={1,2},{1=benign,2= malignant},has been computed as

$$O_m = \sum_{i=1}^{L} W_i O_{mi}$$

where L is the number of the output nodes in the neighborhood window ,and O_{mi} is the number of the training features of the class assigned to the output node i.Wi gives the output nodes near to the winning output node greater weight than the ones farther away. The evaluation input pattern has been classified to the class m of the O_m with the greatest value, as benign or malignant.

Table 3. Performance evaluation of classifier by means of area under receiver operating characteristics (ROC) (Az) corresponding Standard Error (SE) and execution time

Classification Category	A_z	SE	Time (ms)
Classification with MBPN	0.93	0.08	701.23
Classification with SOM	0.96	0.04	8.7

RESULT AND DISCUSSION

The proposed CAD system use two complementary techniques ,image processing and computational intelligence.Image processing techniques are used to extract features to represent the difference between malignant and benign.The extracted features are used as input to the classifier.In this study, the multilayer back propagation neural network and Self organizing map (SOM) with multiple texture and shape features has been proposed for the classification of breast tumor as malignant or benign. The proposed system will help in enhancing the significance of noninvasive tests in the identification of breast tumor at risk of cancer. A total of 45 texture and shape features were extracted from the segmented region of interest (ROI).The SOM has been chosen because it is an unsupervised learning paradigm where the input patterns are freely distributed over the output node matrix, allowing an efficient mapping of the input data with no need to create exact classification boundaries.

The Preprocessed image is shown in Fig.4.Fig 4(a), 4(b) are the original image and the output of the shock filter respectively. From the

Fig 4(b) , it has been noticed that the shock filter is capable of enhancing edges and removes the background noise. Fig 4(c) and 4(d) represents the boundary selection of the filtered image and segmented Region of interest(ROI).

The performance of various characteristics hav been estimated considering the features such as shape and texture as well as multiple features obtained by combining both types of features. The performance is shown in Table 1.It has been seen that in Table 1, the over all accuracy is 99.5% for multiple feature set. The performance of the proposed Self Organizing Map(SOM) and multilayer back propagation neural network and its percentage of classification after training and testing is given in Table 2.

The execution time has been found to decrease while considering optimal feature subset. From Table3,it can be observed that the Self Organizing Map(SOM) has the largest area (0.99) under the curve(A_z) whereas other method gives lesser value. Hence, proposed method provides a higher accuracy than other methods.

Receiver operating characteristics (ROC) analysis is a standard approach to evaluate the sensitivity and specificity of diagnostic procedures. ROC analysis estimates a curve of the true positive rate (sensitivity) versus the false positive rate (1-specificity), which describes the inherent tradeoff between sensitivity and specificity of a diagnostic system. The area below the curve indicates the discrimination capability of the specific system. Fig 5. shows the ROC curves for the MBPN and SOM for the optimal feature set. The area below the curve is slightly higher for the SOM classifier, 0.95,whereas for the MBPN classifier is 0.90.

CONCLUSION

A Neural network based CAD system for classifying the mammogram images of breast tumor has been developed and implemented.Using suitable preprocessing procedure pixels of breast region are retained which facilitate to extract content descriptive features.The study reveals that the Self Organizing Map offers higher classification efficiency than MBPN.It is also believed that the proposed CAD system may assist the physician to predict future possibility of normal subject becoming abnormal based one feature value.The proposed computer system helps the physicians to study extensively to identify the breast tumor as malignant or benign at the early stages.

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