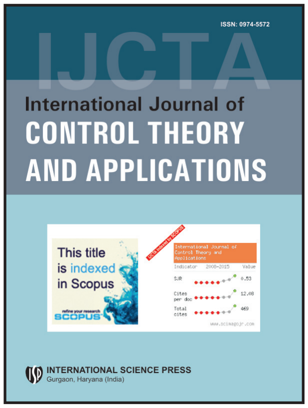

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Detection and Classifications of Abnormal Mammogram by Morphological Enhancement and Artificial Neural Network

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Abstract: One of the major challenges of analyzing digital mammogram is extracting efficient features for accurate cancer classifications. A combination of edge based segmentation method with Back Propagation Neural Network in identifying the micro calcification in Mammogram is proposed. Preprocessing of the image is done by Morphological filters. The training of the Artificial Neural Network algorithm is done by using the features extracted. The proposed system is used to classify the mammogram image as Normal or abnormal. The Mammography Image Analysis society (MIAS) database is used for evaluation.

Keyword: Edge based segmentation, Backpropagation Neural Network, Morphological filter, Microcalcification.

1. INTRODUCTION

Cancer has become one of the leading cause of death. Mammography is a specific low dose X-ray to examine breast. Mammogram is an X-ray examination of breasts used to detect and diagnose breast diseases. Digital Mammography is considered as the standard procedure to detect cancer. The detection of tumors and classification of the mammogram image is the standard clinical practice for diagnosis of breast cancer. Instead of doing, unnecessary biopsy which is time consuming and inconvenient, researchers is focusing on the CAD system to identify the clusters. The abnormalities in mammogram image is detected by CAD system. There are four signs of breast cancer that can be seen on a mammogram image, they are focal masses, microcalcification, architectural distortions and asymmetric breast tissue. This paper focuses on identifying the microcalcifications. Microcalcifications are in different shapes like round, linear, coarse, granular, monomorphic, pleomorphic. Boulehmi et. al., [1] has proposed a new CAD system using Generalized Gaussian Density (GGD) estimation for segmenting and Bayesian back propagation neural network for breast microcalcification diagnosis. Different techniques of feature extraction are available for detection of microcalcification[2]. The identified calcification can be either Benign or malignant, Singh et. al., extracted ROI using edge detection and morphological operation and SVM classifier was used to classify MC clusters[3].To improve the diagnostic accuracy of microcalcifications a semi automated Segmentation method was used to characterize all microcalcifications[4]. The extraction of objects from the background is called segmentation. After the enhancement of the mammogram image the abnormal area where the cluster appears can be extracted for further examination. Top-Hat operation in morphology as well as log filtering is used to enhance the microclacification features in mammographic features[5]. Possiblistic clustering algorithms, , hard and fuzzy clustering algoritnm, Fuzzy c-Means and possiblistic fuzzy c-means is compared to help in improving the detection of microcalcification clusters in digitized mammograms[6].

2. METHODOLOGY

The proposed CAD system has main three steps, Image enhancement using morphological filter, Feature extraction by edge based segmentation, classification by back propagation neural network algorithm. The enhanced mammogram image is segmented by edge based segmentation method. The segmented image is classified and its performance is evaluated with back propagation network algorithm. The CAD system detects the microcalcification of size between 0.1-0.3 mm. The detection of microcalcifications in mammogram is given in block diagram Figure 1. The MIAS database is used. The processing of mammogram image by morphological filters includes opening closing operation with structure elements. Better PSNR value than any other filter is obtained without any loss of information. The mammogram image is segmented using edge based segmentation and the classification is done by back propagation network, the proposed method detects the calcifications.

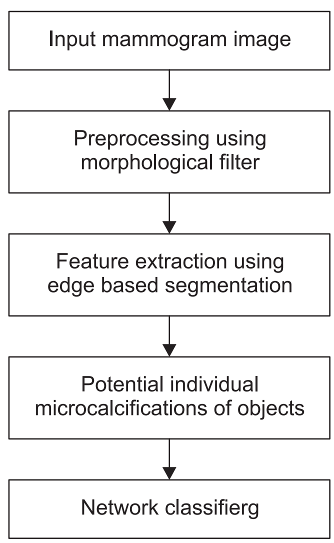


Figure 1: Block diagram for detection of microcalcifications

3. MORPHOLOGICAL FILTERS FOR GRAY LEVEL IMAGES

Extending morphological operators from binary to gray level images can be done by using set representations of signals and transforming these input sets via morphological set operations. Consider an image signal F(x) defined on continuous or discrete plane E = R^2 and assuming values inR = RU$\{-\infty, +\infty\}$. Thresholding f at all amplitude levels v produces an ensemble of binary images represented by the threshold sets.

$$\mathrm{X}v(f) \triangleq \{\mathrm{X} \in \mathrm{E} : f(x) \geq ®v\}, -\infty < v < +\infty$$

The image can be reconstructed

$$f(x) = \sup\{v \in \mathbb{R} : x \in x_v(f)\}$$

where, sup denotes supremum. Transforming each level set of the input signal f by a set operation Ψ and viewing the transformed sets as level sets of a new image creates a flat image operator ϕ whose output signal is

$$\phi(f)(x) = \sup\{v \in \mathbb{R} : x \in \Psi[X_v(f)]\}$$

The most general translation invariant morphological dilation and erosion of a gray level image signal $f(x)$ by another signal g are

$$(f \oplus g)(x) \triangleq \vee_{y \in E} f(x - y) + g(y)$$

$$(f \ominus g)(x) \triangleq \wedge_{y \in E} f(x + y) - g(y)$$

4. BACK-PROPAGATION NEURAL NETWORK ALGORITHM

The computing elements of Artificial Neural Network is based on structure and function of biological neurons. The neural network consists of interconnected processing units. The processing units consists of summing part and output part. The summing part calculates the weighted sum by using the input values and weight values. The weighted sum is called the activation value. The sign of the weight determines whether the input is excitatory or inhibitory. The input weights can be analog or digital. The processing units are interconnected according to the topology selected. The external source or the output of other processing unit is given as input to the processing unit. The learning of the network can be supervised or unsupervised. In supervised learning both the inputs and outputs are presented, but in unsupervised learning only the input is presented to the network. Artificial neural network is mostly used in pattern recognition analysis. A pattern is a set of inputs and outputs. Either supervised or unsupervised training method can be used to train the network based on the topology.

Training in Back-Propagation Algorithm: Supervised training is given to the feed forward back propagation network, with patterns consisting of input and target output pattern. The neurons from the input layer is passes the pattern activations to the next layer neurons in the hidden layer. By using bias and threshold function the output of the hidden layer is calculated. This output is given as inputs to the output neurons. The activations of the output unit deternines the final output. The input pattern and the computed pattern are compared and the weight is adjusted between the output layer and hidden layer. The connection weights between the input and hidden layers is adjusted according to the error in output. After the BPA network obtains the correct classification for a set of inputs in a training set, it can be tested on untrained pattern for a second set of inputs.

Step 1: The weights of the ANN are initialized.

Step 2: The inputs and outputs of a training pattern are presented to the network. The output of each node in the successive layers is calculated using equation

$$o(\text{output of a node}) = 1/(1 + \exp(-\Sigma wij\ xi))$$

Step 3: The error of a pattern is calculated using equation

$$E(p) = (1/2)\ \Sigma(d(p) - o(p))2$$

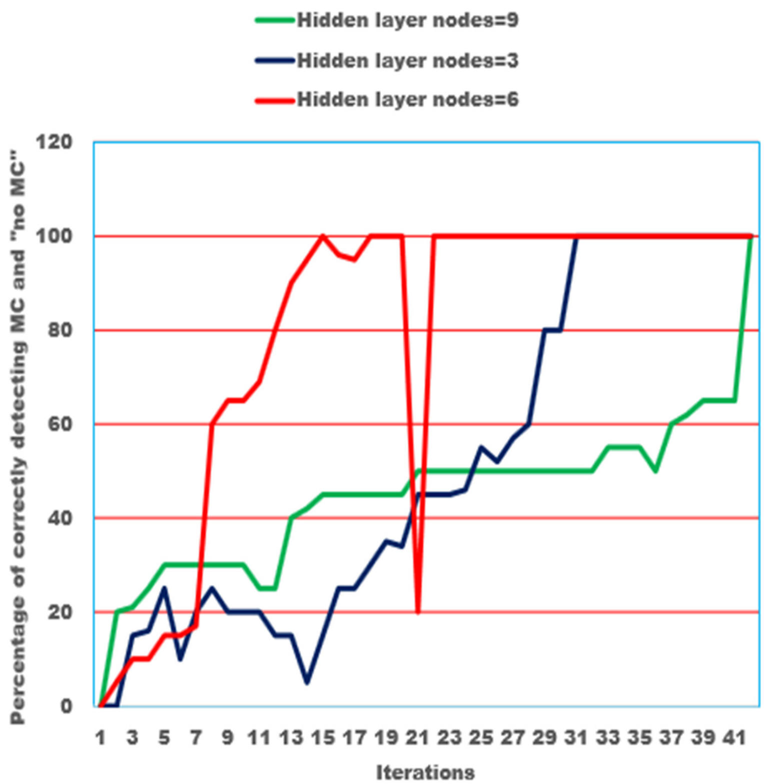
Reverse Propagation (Weight updation)

Step 4: The error for the nodes in the output layer is calculated using equation

$$\delta(\text{output layer}) = o(1 - o)(d - o)$$

Step 5: The weights between output layer and hidden layer are updated using equation

$$W(n + 1) = W(n) + \eta\delta(\text{output layer})\ o(\text{hidden layer})$$



$$\text{Percentage} = \frac{\text{(MC correctly detected + "no MC" correctly identified)}}{\text{Total number of test patterns}}$$

Assigning values for TP, TN, FP, FN based on the output of BPA

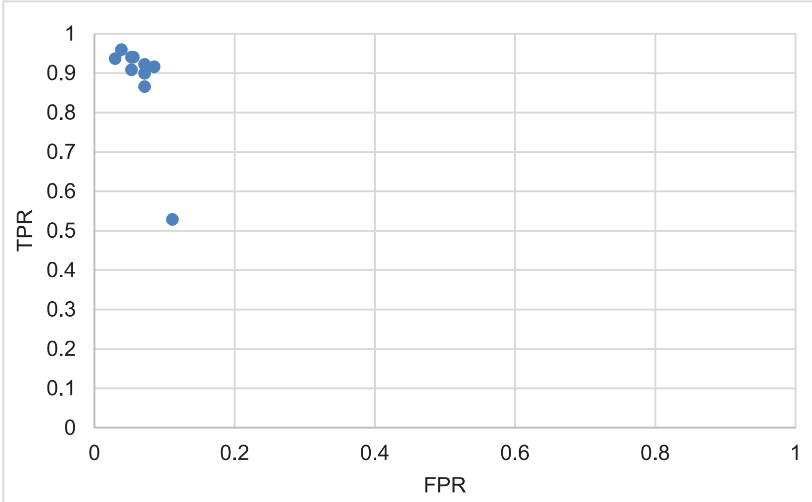
	Output of BPA	*TP*	*TN*	*FP*	*FN*
Pixel consists MC	<0.5	1	0	0	0
Pixel consists MC	>=0.5	0	0	0	1
Pixel has “no MC”	<0.5	0	0	1	0
Pixel has “no MC”	>=0.5	0	1	0	0

5. RESULTS AND DISCUSSIONS

Matlab 13 software was used to implement the approach. The digitized mammogram were taken from MIAS database. The false positive and false negative has beeb decreased by employing high resolution mammograms. Back propagation neural network is used for detection. Region of characteristic (ROC) is the plot between false positive rate and true positive rate. The points plotted here represent the performance of an algorithm in meeting the expected criteria, it is 80% or above. The BPA algorithm has more accuracy in detecting microcalcification in mammogram.

6. CONCLUSIONS

In this work Morphological filters is used for image enhancement. Features are extracted using edge based segmentation and back propagation algorithm have been used for classification of calcification on mammographic image analysis (MIAS) mammogram database. The MC identification accuracy of BPA is better. BPA. Performance can be tested using other mammogram database.



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