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Analysis and Diagnostic of Women Breast Cancer Using Mammographic Image

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Abstract: The mammographic image analysis to predict the breast cancer is research of interest now. The death rates of women are increased every year due to the lack of knowledge about the breast cancer in many parts of the world. The diagnosis is simple and survivals of the patient are high if the breast cancer is predicted at the early stage accurately. This study presents a new mammographic image analysis model to detect the cancer affected area in the breast. The proposed system consists of three processes, namely, transformation, segmentation and classification. The Non Subsampled Shearlet Transform (NSST), Robust Support Vector Machine (RSVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm are utilized for various processes. The proposed system is evaluated under two scenarios namely, visual evaluation and quantitative analysis. The quantitative evaluation reveals that the proposed system achieves a sensitivity, specificity and accuracy rate of 98.73, 96.15 and 98.36%, respectively.

Key words: Mammography, NSST, RSVM, ANFIS, image

INTRODUCTION

In women, breast cancer is commonly found one among various types of cancer which leads to mortality every year. From WHO (World Health Organization) concludes that >5 lakhs feminine genders are dying due to breast cancer. The survival chance of the cancer affected patients is high, if the disease is detected in the initial stage itself. In many countries, screening programs have been established to detect the disease at the early stages. The mammography is simple and easy to handle the initial screening process of the breast cancer disease. The efficiency (Lee *et al*., 2010) of the detection in the initial screening process is high by utilizing the mammography. As the screening program is familiar among the people, analyzing the mammogram is large.

The abnormalities which cause cancer has been ignored due to many factors such as radiologist fatigue and complex breast structure. The Computer Aided Detection (CAD) (Destounis *et al*. (2004) is entertained, since there is a 10-25% error (i.e., ignored) by the physicians. The various abnormalities found in mammogram images are, mass lesion, breast asymmetric nature, microcalcification and distorted breast and dense tissue as shown in Fig. 1.

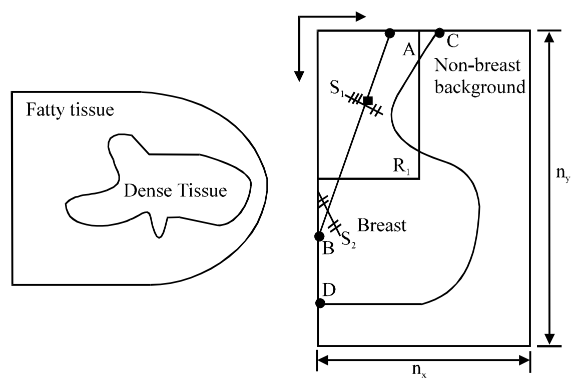

Fig. 1: Tissue classification

Benign and malign breast disease: The classifications of breast disease are studied by examining the various biopsies by a pathologist in different hospitals. The reports from various pathologists (Fitzgibbons *et al*., 1998; Dupont and Poge, 1985) suggest that the benign and malign breast disease is classified into three categories based on the nature of risk. They are Proliferative disease with atypia non proliferative disease and Proliferative disease without atypia. The non proliferative diseases are cysts, microcalcification, fibro adenoma and fibrosis. The proliferative disease with atypia is phyllodes, malign tumor in the breast and

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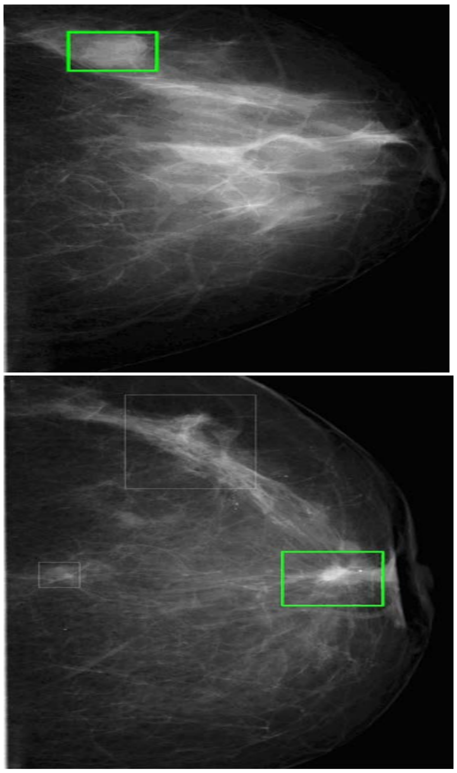

Fig. 2: Benign and malign classification

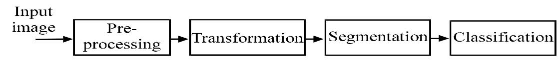

Fig. 3: Mammographic flow

atypias; finally, proliferative disease without atypia is a benign tumor in the breast and lobular hyperplasia. The pathologist concluded that if more than one risk is diagnosed then it is highest graded biopsy. From Fig. 1, describe that misunderstanding will arrive between dense tissue and benign disease, in similar, fatty tissue and malign disease. The breast image with malign and benign marking is shown in Fig. 2. Finally, two medical terms have been used to identify the location of cancer cells; they are, contralateral and ipsilateral. The benign breast disease and cancer cells are found in different breast, then it is contralateral, else if it is found in same breast then it is ipsilateral.

Mammographic flow: The four critical processes in mammography are:

- Pre-processing
- Transformation
- Segmentation and
- Classification as shown in Fig. 3

The initial input images are filtered to remove the noise at the preprocessing stage. In Zhen and Chan (2001), Discrete Wavelet Transform (DWT) is used to develop an artificial intelligent algorithm for tumor detection. Hough transforms and Gabor filter is used to differentiate the variation between pectoral muscles from breast tissues (Ferrari *et al*., 2004). Eulidean denoising algorithm is to detect and removes the impulse noise from the medical images and prove to provide better suppresses noise and enhances the objective areas (Thirurmurugan and Veerakumar, 2016). A mammography image of 85 samples is taken and analysis using Discrete Wavelet Transform (DWT), here, the wavelet coefficients features are compared to the Region of Interest (RoI) for malign breast disease (Karahaliou *et al*., 2008). For proposer diagnosis, the radiographies are enhanced to a greater extent. The un-sharp masking technique is replaced by multiscale decomposition for better performance improvement. The multilevel decomposition is achieved by Fast Wavelet Transform (FWT) and Laplacian Pyramid (LP) (Dippel *et al*., 2002). In Mencattini *et al*. (2008), the dyadic wavelet transform is used for multilevel decomposition as a result the mammographic image is transformed to noise free enhanced images. This technique found to be promising, since it shows better performance in the initial stages of the breast cancer compared to the conventional approaches. To make the analysis of the breast cancer at various frequency levels, the idea of Discrete Wavelet Transform (DWT) is replaced by Wavelet Packet (WP) in (Mello-Thoms *et al*. (2003). The mammographic density structure and breast tissue pattern is identified by phase and magnitude of the Gabor filter (Casti *et al*., 2015). As a result, the achieved specificity, sensitivity and accuracy are 0.88, 1 and 0.94, respectively. In (Wong, 2009), the resolution of the mammography image is increased by utilizing the complex wavelet transform. The visual evaluation of this method shows that it is very effective when compared with the existing enhancement methods. The diagnosis of breast cancer is easy to predict, if the mammography image contains more and efficient information in it. The multiresolution representation of the mammography image is obtained by two dimensional wavelet transform to have greater information for better diagnosis (Liu *et al*., 2001). The texture analysis of the mammogram plays an important role, curvelet transform (Eltoukhy *et al*., 2010) are used to classify the fatty tissue from dense tissue. Here, the abnormalities are detected and classified into malignant or benign tumor.

Eltoukhy *et al*. (2014), the normal and abnormal tissue that causes breast cancer is classified by utilizing the curvelet coefficients. The features of the mammography image are formed from a set of curvelet coefficient and combine with feature ranking method for better improvement in classification. The acquired results found to be promising when compared to Support Vector Machine (SVM) method. The smoothness of th image is well studied Eltoukhy *et al*. (2009) and the application of the curvelet transform is well established to classify the classes of cancer in mammography images.

The segmentation of the mammography image is established by obtaining the neighborhood operator in the image itself Chandrasekhar and Attikiouzel (2000). The Euclidean difference between the maximum and minimum pixel will estimate the octagonal neighborhood. Hong and Sohn (2010), the segmentation algorithm is applied only to the Region of Interest (RoI) area. Hence, the breast boundary can be identified with minimum complexity from the pectoral muscles. The mass detection in mammography image is easy by adopting this method. An adaptive algorithm (Kwok *et al*., 2004) is presented to define automatically the pectoral muscle from the mammography images. This method will reduce the misinterpretation by the physician and this method achieves an accuracy of 83.9%. Wirth *et al*. (2004), the edge sharpness and size of the deviation of the neighborhood pixel are given as input to a fuzzy algorithm for segmentation. This fuzzy algorithm achieves a correctness and completeness of 0.98 and 0.99, respectively. The initial contour position has great impact on the active contour and in (Wirth *et al*., 2004) this active contour is used to segment the breast tissue from mammography image. To obtain the breast boundary from the background, the combination of morphological operation and global threshold method is utilized (Wei *et al*., 2005). The segmentation accuracy achieved by this method is 94.9% with the inclusion watershed transform. The segmentation of skin line from the stroma (i.e., it is fatty tissue in the breast with high contrast) edge and the tag in the patient's body is segmented out from the Region of Interest (RoI) is sown in Fig. 3.

The Discrete Cosine Transform (DCT) is used to define the features of spectral domain that will result in high classification (Farag and Mashali, 2003) performance of the mammogram images. In this method, the classifier is applied by utilizing the back propagation neural network. This method reduces the computational complexity and improves the classification accuracy than conventional methods. The Region of Interest (RoI) is extracted from the mammography image by Hunter algorithm and the feature descriptor is used to classify the disease using a neural network algorithm (Cascio *et al*., 2006). This method achieves a sensitivity rate of 82% with improvement in classification. The benign breast disease has oval, smooth and round contours whereas malign breast disease has speculated and rough contours. The physician should be careful in diagnosis, hence, in (Guliato *et al*., 2008), the polygonal contour feature is sort out, since there is lesser accuracy in global contour features. The resulting evaluation shows that this method achieves 0.94 classification accuracy. Sameti *et al*. (2009), the researcher developed the detection of breast disease based on the two Region of Interest (RoI) namely, development of subsequent mass and similar to subsequent mass. About 72% classification accuracy is achieved by this method by examining the 62 mammography images. The malignant and benign masses are classified by a computer aided system based on the texture and gradient analysis (Mudigonda *et al*., 2000). About 82.1% classification accuracy achieved by the posterior probability algorithm. The efficient approach for classification by using Support Vector Machine (SVM) and this approach is developed in (Naqa *et al*., 2002), this method achieves a sensitivity rate of 94% and found to be promising techniques for future enhancement. The classification of cancer disease from other fatty tissue is shown in Fig. 4. This study proposes

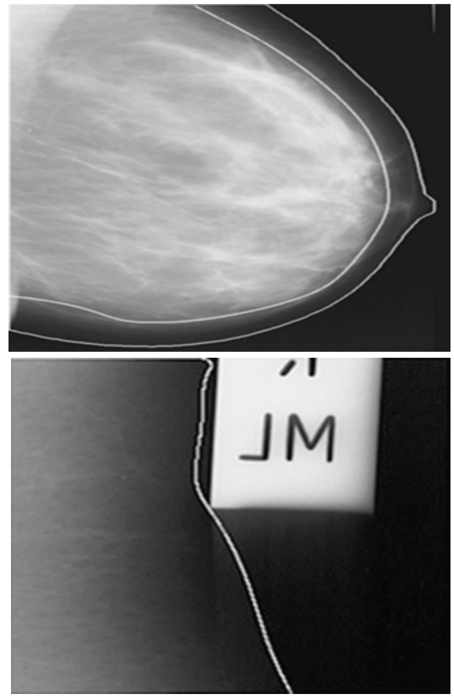

Fig. 4: Segmentation of RoI

a mammographic analysis model based on efficient transformation, segmentation and classification methods.

MATERIALS AND METHODS

Image transformation: The mammographic image is filtered using median filter (Vidhya *et al*., 2011) to remove the noise followed by Non Subsampled Shearlet Transformation (NSST). This transformation will be useful multidirectional and multidimensional analysis as it is the extension of wavelet Transform (WT). This transformation separately combines the multi direction and multi scale analysis. This transformation is achieved by combining the directional filters and Laplacian Pyramid (LP). The high and low frequency components of the mammography image are obtained by decomposing with Non Subsampled Laplacian Pyramid (NSLP). Then the shearlet coefficients and subbands are obtained using the directional filters. The NSST is formed by assigning the composite dilation (Hou, 2012; Easley *et al*., 2008) of a 2D affine system as in Eq. 1:

$$A_{DS} = \left\{ \Psi_{j,k,m}(x) = \left|\det D\right|^{j/2} \Psi \times (S^K D^j - m) : j,k \in z,\ m \in z^2 \right\} \tag{1}$$

Where:
S = Shearlet matrix
D = Anisotropic matrix
m = Shift parameter
j = Scale parameter
k = Directional parameter

$$D = \begin{bmatrix} d & 0 \\ 0 & d^{1/2} \end{bmatrix} \tag{2}$$

$$D = \begin{bmatrix} d^{1/2} & 0 \\ 0 & d \end{bmatrix} \tag{3}$$

Here, $|\det S| = 1$ and 2x2 invertible matrix can be formed from 'S' and 'D'. From Eq. 2 and 3, we can have the anisotropic dilation matrix having 'd' value greater than zero. The value of 'd' has greater impact on the frequency scale of shearlet transform. Also, the direction of shearlet transform is controlled by the shear matrix as in Eq. 4 and 5:

$$S = \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix} \tag{4}$$

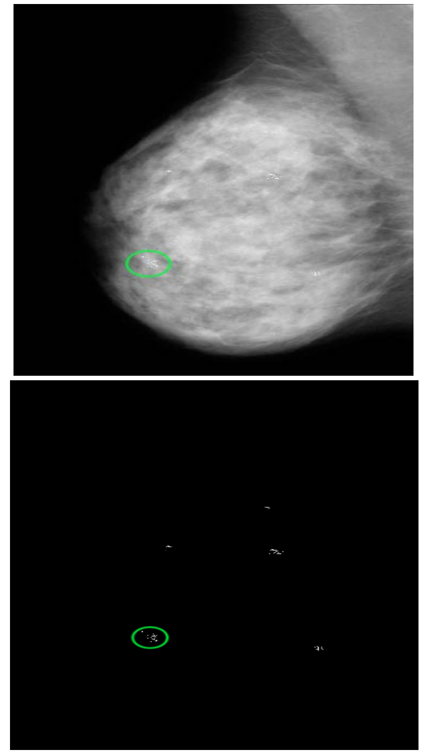

Fig. 5: Classification RoI

$$S = \begin{bmatrix} 1 & 0 \\ s & 1 \end{bmatrix} \tag{5}$$

Finally, the Shearlet Transform (ST) function is formed by Eq. 6 and 7 as (Easley *et al*., 2008):

$$\Psi_{j,k,m}(x) = 2^{j\,(3/2)} \Psi^{(1)} (S_0^k D_0^j x - m) \tag{6}$$

$$\Psi_{j,k,m}(x) = 2^{j\,(3/2)} \Psi^{(0)} (S_1^k D_1^j x - m) \tag{7}$$

As a result, multidirectional and multiscale decomposition is achieved by utilizing NSLP and shearlet filter. A low frequency and high frequency sub images are resulted by NSLP decomposition at each level. Again the iterative decomposition of the low band image is executed based on the decomposition level as shown in Fig. 5.

Segmentation: Support vector Machine (SVM) is the powerful algorithm for segmentation problems as it shows remarkable performance improvement than the conventional algorithms. The maximum margin with the optimal hyper plane is found to have the better generalization ability as shown in Fig. 6.

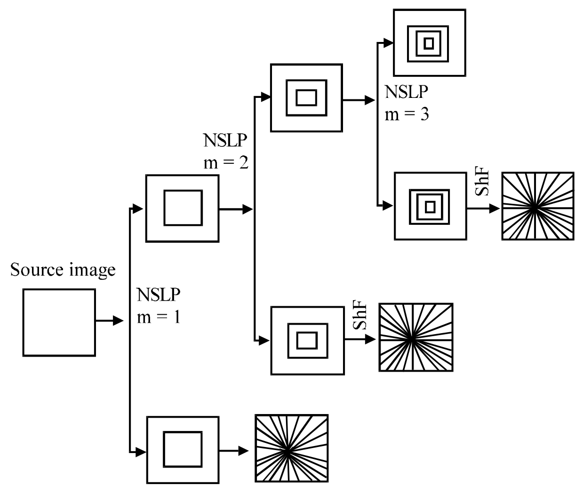

Fig. 6: Proposed NSST decomposition

Here, the training set is used to find the optimal hyper plane, let us consider that training sample as $\{(x_i, y_i): I = 1, 2, ..., n\}$, then the optimal hyper plane is computed using the following expression Eq. 8:

$$f(x) = w.x + b = 0 \tag{8}$$

Where:

$x_i Є\{-1, +1\}$ = Feature descriptor

$y_i Є\{-1, +1\}$ = Feature descriptor

Here, 'b' and 'w' are obtained using segmentation problem. Kernel trick is used to separate the feature vector linearly as in Eq. 9:

$$f(x) = \Sigma_{i \in \Omega} \alpha_{i y_i} k(x, x_i) + b \tag{9}$$

Even though, the SVM shows better performance for segmentation, the improper computation of hyper plane will degrade the performance of the segmentation which also reduces the performance of classification. In order to handle the medical image; we use Robust Support Vector Machine (RSVM) (Liu and Tang, 2014). The hyper plane of the closest sample is obtained by solving the optimization problem as expressed in Eq. 10:

$$\begin{gathered} \min_{w,p} \left(\frac{1}{2} \| w \|^2 + \Sigma_{i=1}^{N} \xi i \right); s.t. \\ : \forall_{1=1}^{N} : y_i (w^T x_i - \rho) \; {}_{\forall_{i=1}^{N} : \xi i \geq}^{\geq} {}_{0}^{1} - \xi_i \end{gathered} \tag{10}$$

The adjustable factor 'μ' between the positive and negative hyper plane can be expressed as in Eq. 11 by substituting Eq. 11 in Eq. 10, we can have the optimization problem as in Eq. 12:

Table 1: Features for breast disease analysis

Feature	Sub-type
Texture	Regional, Boundary descriptor and Density descriptor; Histogram and Laplacian moment; Histogram and Laplacian entropy; Local binary pattern; Fractal dimension
Intensity	Corrected
	Original
Morphology	Distance from skin; Position; Nipple angle; Nipple distance

$$m^+ = \mu m^- \tag{11}$$

$$\begin{gathered} \max_{w,\rho} (m^+ m^-); s.t.: m^+ = \mu m^-; \; m^+ = \min_{yi=-1} \left(\frac{yi(w^T x_i - \rho)}{\|w\|} \right) \\ ; m^- = \min_{y_i=-1} \left(\frac{yi(w^T x_i - \rho)}{\|w\|} \right) \forall_{i=1}^{N}; y_i (W^T x_i - \rho) \geq 0 \end{gathered} \tag{12}$$

The RSVM can be derived from the optimization problem as expressed in Eq. 13. Finally, by assuming the OCSVM (Liu and Tang, 2014) and SVM, the optimal value for RSVM adjustment factor (μ) can be computed by Eq. 14:

$$\begin{gathered} \max_{w,\rho} \left(\frac{1}{2} \|w\|^2 \right); s.t.: \forall_{j=1}^{N} y_i = 1: \\ y_i (w^T x_i - \rho) \geq \frac{2\mu}{\mu + 1}; \forall_{i=1}^{N} y_i = -1: \\ y_i \left(w^T x_i - \rho \right) \geq \frac{2}{\mu + 1} \end{gathered} \tag{13}$$

$$\begin{gathered} \max_{a} \left(\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_j x_i^T x_j a_i a_j - \Sigma_{i=1}^{N} \alpha_i \right); \\ s.t.: \Sigma_{i=1}^{N} y_i \alpha_i = 0; \forall_{i=1}^{N} y \leq \alpha_i \leq C \end{gathered} \tag{14}$$

The decision function to compute the optimal decision hyper plane is proposed in algorithm-1.

Classification: ANFIS algorithm is proposed for classification. The most basic and powerful building block of any classification system is feature selection. The proper feature selection will reduce the number of input feature, computational cost and improve the prediction of the system (Scholkopf *et al*., 2001; Zhang, 2000).

Hence, the proposed classification method defines the precise feature selection method which is used for the further classification process. The types of feature available for breast disease analysis from mammography images are listed in Table 1. For better performance and easy implementation so this paper is going to utilized three feature descriptor namely, regional, boundary and density for further classification problems. The continuous function can be converted to any degree of accurate compact set by Adaptive Neuro-Fuzzy Inference

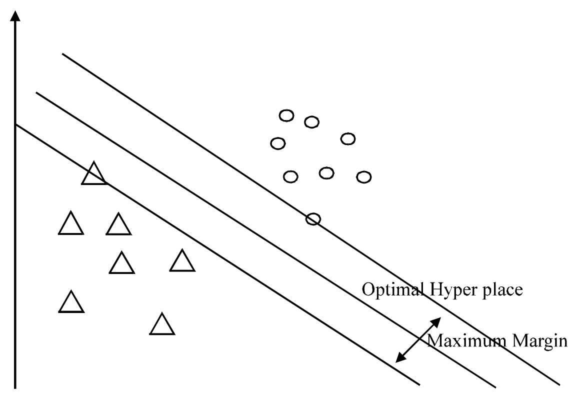

Fig. 7: Hyper plane in SVM

System (ANFIS) (Papadimitriou and Terzidis, 2005). The first order fuzzy model of Sugeno (Jang, 1993) will be exactly equivalent function of ANFIS system. The Artificial Neural Network (ANN) shows better performance but when it comes to medical imaging ANFIS outperform the ANN. The main advantages of the ANFIS system are, handling uncertainty and imprecise image information. These two criteria should be present in the analysis, since the medical images are affected by noise, measurement errors and patients physics (Mitra and Hayashi, 2000).

The proposed ANFIS classification is shown in Fig. 7. The hybrid learning rule is applied on the mammography input images. The hybrid learning model is formed by combining the gradient-descent, least square algorithm and back selection. The ANFIS model has five processing layers as shown in Fig. 8. The five layers are described as:

- Membership grade generation
- Fuzzy operation
- Firing strength 'w' scaling
- Input summation and
- Output summation.

The summation of input is expressed by Eq. 15:

$$Y = w(PX + r) \tag{15}$$

Where, r, p are adaptable parameters. The process of ANFIS is divided among a certain time period called as the epoch. Two various processes will occur at each epoch; they are experienced at layer 4 and layer 5. Initially, layer 4 will compute the output of each node and in layer 5 least square regression methods are used to compute the resulting parameters. Finally, the accuracy of the classification is computed and the errors are updated for further classification process.

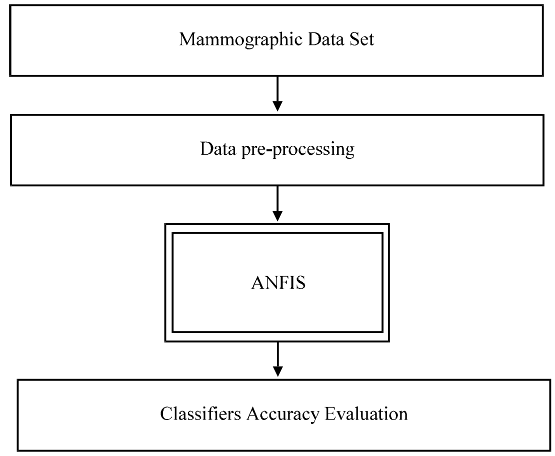

Fig. 8: Proposed ANFIS classification

RESULTS AND DISCUSSION

Performance evaluation: The MLO (Medio-Lateral oblique) and CC (Cranial-Caudal) image for various breast cancers are taken from medical image databases such as DDSM (Digital Database of Screening Mammograms) (Heath *et al*., 2001) and MIAS (Mammographic Image Analysis Society) (Suckling *et al*., 1994). To have the extensive evaluation process, we have examined the proposed system with various images such as MLO images of right breast, the MLO image of left breast, CC image of right breast and CC image of left breast. The proposed system is evaluated under two scenarios, namely visual evaluation and quantitative analysis. The visual evaluation shows that the proposed system classifies the cancer area efficiently. The in-depth visual shows that the proposed system has a slight difference in classified area when compared to existing methods. The proposed system evaluates 183 various images out of which 10 randomly selected images are shown in Fig. 9. From Fig. 9 and 10, it is clear that the proposed system classify the cancer affected area with negligible difference when compared to already defined area are:

$$\text{Sensitivit} = \frac{TP}{TP + FN} \tag{16}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{17}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

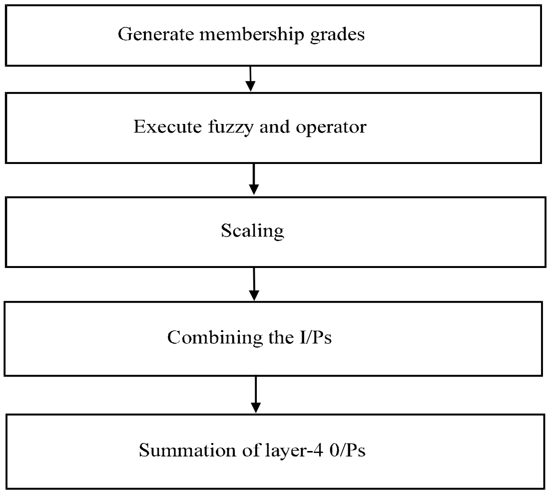

Fig. 9: Five Layers of ANFIS classification

Table 2: Quantitative evaluation of proposed system

Parameters	Nomenclature	Result (%)
Sensitivity	TP = Cancer patient with cancer	98.73
Specificity	FP = Normal patient with cancer	96.15
Accuracy	TN = Normal patient without cancer	98.36
-	FN = Cancer patient without cancer	-

To complicate the evaluation process and to justify the efficiency of the proposed system is evaluated under quantitative scenario. The quantitative evaluation of the proposed system is made in terms of sensitivity, specificity and accuracy. The sensitivity is defined as the ratio of True Positive (TP) and the summation of true positive and False Negative (FN) as expressed in Eq. 16. In similar, the specificity is defined as the ratio of True Negative (TN) to the summation of true negative and False Positive (FP) as expressed in Eq. 17. Finally, the accuracy is defined as the ratio of summation of true positive and true negative to the summation of true positive, true negative, false positive and false negative as expressed in Eq. 18. The proposed system achieves a sensitivity, specificity and accuracy of 98.73, 96.15 and 98.36%, respectively as shown in Table 2.

CONCLUSION

A new mammographic image analysis is proposed in this study. The proposed system comprises of three major processes, namely, transformation, segmentation and classification. The transformation is carried out by Non Subsampled Shearlet Transform (NSST), followed by Robust Support Vector Machine (RSVM) based segmentation and Adaptive Neuro-Fuzzy Inference System (ANFIS) based classification. The proposed system is evaluated under two scenarios such as visual evaluation and quantitative analysis. The images are

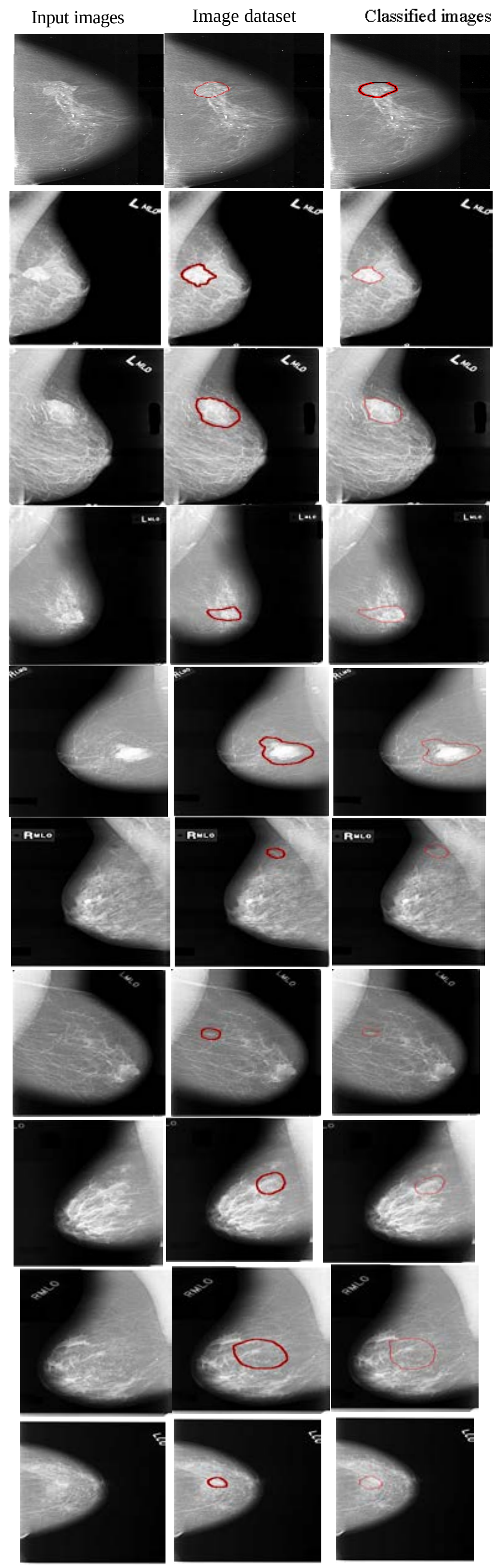

Fig. 10: Performance evaluation of proposed system

obtained from various medical image databases such as DDSM and MIAS. The quantitative analysis is made in terms of sensitivity, specificity and accuracy and tabulated. The proposed system shows remarkable improvements and in the future, various algorithms are utilized to achieve more that 99% in terms of sensitivity, specificity and accuracy, moreover to reduce the development complexity.

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