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Gabor Wavelet based Detection of Architectural Distortion and Mass in Mammographic Images and Classification using Adaptive Neuro Fuzzy Inference System

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ABSTRACT
Breast cancer is a leading cause of cancer death among women. Many studies have shown that mammography is the most effective method for early detection of abnormalities such as microcalcification and mass. In the study on breast cancer, it is observed that architectural distortion is the most commonly missed abnormality in false-negative cases. Mass detection also poses a big challenge in detection because of its varying shape and density, as it is highly connected to the surrounding parenchymal tissue density. This paper proposes a new method for improving detection of architectural distortion and mass in mammographic images using Gabor wavelets and Adaptive Neuro-Fuzzy based classification. Segmentation of the abnormality is done using Otsu's thresholding. The segmented image is operated with Gabor filter. Feature extraction is done from the output images by forming Gray Level Co-occurrence Matrix (GLCM). Classification is done using Adaptive Neuro-Fuzzy Inference System (ANFIS). The Regions of Interest (RoI) of 40 images are used for training and testing using ANFIS. The sensitivity obtained is about 80% in case of images with architectural distortion and 50% in case of images with mass. The specificity obtained is about 83% for both the cases.

Keywords
ANFIS, Architectural Distortion, Breast cancer, Gabor wavelet, Mammography, Mass.

1. INTRODUCTION
Over the past two decades, cancer has been one of the biggest threats to human life and it is expected to become the leading cause of death over the next few decades. Of all the known cancers, breast cancer is a major concern among women and its incidence has increased in recent years [1]. At present there is no effective way to prevent breast cancer, because its cause remains still unknown. However efficient diagnosis of breast cancer in its early stages can give women a better chance of recovery [11].

Mammography is a special type of x-ray imaging used to create detailed images of the breast. Mammography uses low dose x-ray, high contrast, high resolution film specifically for imaging the breasts. Mammography plays a major role in early detection of breast cancer [15] [12]. Once the lump is discovered, mammography can be a key component in diagnosing the lump to determine whether it is cancerous or not. Masses are defined as space occupying lesions that are described by their shape and margin properties. A benign is smoothly marginated, whereas a malignancy is characterized by an indistinct border that becomes more spiculated with time [4]. Architectural Distortion is the change in normal oriented texture of the breast which contains several linear structures such as ligaments, ducts and blood vessels that cause directionally oriented texture in mammograms. If an abnormality is found, image guided biopsy and other types of diagnostic imaging can be done. There are two types of mammography namely: screening mammography and diagnostic mammography. The goal of screening mammography is to detect cancer when it is still too small to be felt by the physician. Diagnostic mammography is for evaluation of various abnormalities in mammographic images [8].But the presence of architectural distortion in mammographic images is not identified by the presence of increased density in mammograms. Detection of architectural distortion is performed by the identification of presence of spiculations and distortion of normal oriented texture pattern of breast.

According to E.Catanzarti et al software architecture of Computer Aided Detection (CAD) system for Microcalcification based on Gabor transform known as GNN-CAD (Gabor Neural Network CAD systems) is used [13]. Rangaraj M. Rangayyan et al suggested that the analysis of curvilinear structures may improve the performance of algorithms for detection of spiculated masses and architectural distortion [2]. Upon the detailed survey of the existing literatures it is observed that there is a need for improvement in the detection of architectural distortion and mass. This paper proposes a technique for detecting architectural distortion and mass in mammographic images using gabor wavelets and ANFIS.

This paper is organized into six sections including this introduction section on breast cancer, mammography and the survey on existing techniques. Section 2 deals with the proposed technique to improve the detection of architectural distortion and mass. The extraction of features from the output images by forming GLCM is explained in section 3. Section 4 describes the classification of images into normal and malignant images using ANFIS. The results and discussion are explored in section 5. Conclusion and future scope of the work are drawn in Section 6.

2. PROPOSED METHOD FOR THE DETECTION OF ARCHITECTURAL DISTORTION AND MASS
The proposed method for the detection of architectural distortion and mass using gabor filter is shown in Fig 1. The mammographic images from the Mammographic Image Analysis Society (MIAS) database are used. The

mammographic image with architectural distortion and mass are shown in Figure 2 and Figure 3 respectively.

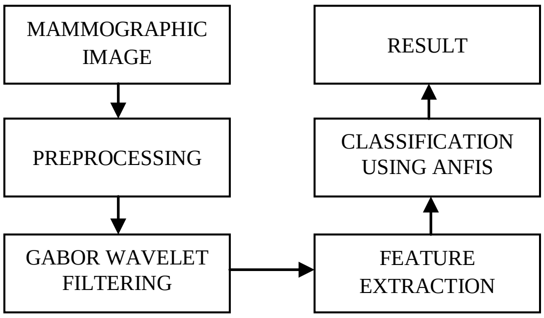


Figure 1.Proposed Block Diagram for the Detection of Architectural Distortion

Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. All filters are generated from a filter which is considered as mother wavelet by scaling and rotation [14]. Thus the set of filters are called set of wavelets. Gabor filter has both multi-resolution and multi-orientation properties. Gabor filters was presented in several works on image processing which are related to segmentation and analysis of texture [9].

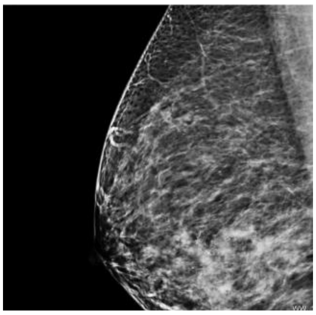


Figure 2. Mammographic Image with Architectural Distortion

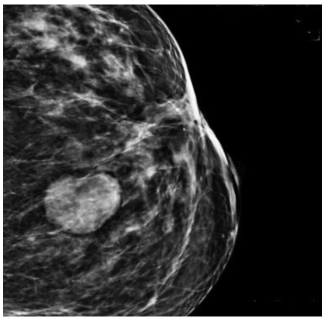


Figure 3.Mammographic Image with

The mathematical representation of Gabor filter function is given by the equation (1).

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)} \cos(2\pi f x) \qquad (1)$$

where,

$$x = x1\,cos\theta + y1\,sin\theta$$
$$y = -x1\,sin\theta + y1\,cos\theta$$
$$x1 = -\sigma_x\,to + \sigma_x$$
$$y1 = -\sigma_y\,to + \sigma_y$$

In equation (1), the parameters namely σ_x, σ_y are the variance of Gaussian function along x-direction and y-direction respectively and f is the frequency of the sinusoid. The parameters of the Gabor filter equation namely, variance of Gaussian function along x-axis and y-axis and frequency of the sinusoid are calculated according to the design rules as follows

Variance along x-axis,

$$\sigma_x = \frac{\tau}{2\sqrt{2ln2}} \qquad (2)$$

Variance along y-axis,

$$\sigma_y = l\sigma_x \qquad (3)$$

Frequency,

$$f = \frac{1}{\tau} \qquad (4)$$

where,

τ- period of cosine term in filter equation

l- elongation of Gabor filter along orientation direction

θ-orientation of filter

These parameters are given as inputs to the filter function. The Gabor filter function will be convolved with the image to be processed. Gabor functions are the only filters with orientation selectivity.

The mammographic image is initially preprocessed. The preprocessing steps include cropping, histogram equalization and segmentation. An approximate segmentation of the abnormal part of breast in the mammographic image is performed using Otsu's thresholding [3]. The threshold values between the ranges 0 to 1 are chosen according to the abnormality in the mammographic image. The segmented image is convoluted with Gabor filter function. The edges of the segmented image are oriented according to the angle at which the images are filtered. In the filter function the parameters namely σ_x, σ_y and f are calculated as per the design rules specified in equations (2) to (4). The values of l and τ are determined empirically as 8 and 4 respectively: by observing the spicule width and length in mammograms with architectural distortion in the MIAS database [3]. Thus the values of σ_x, σ_y and f used in the function are calculated and determined as 2, 16 and 0.25 using the formulas mentioned in equations 2, 3 and 4.

3. FEATURE EXTRACTION

In mammography the spatial resolution of x-ray which is in the order of few microns permits to visualize masses. But the conventional mammograms are highly textured and complex. This makes the interpretation difficult. For this reason, it is necessary to extract features from the mammogram to improve performances of the diagnosis in terms of precision and reliability. Extraction of features is done by the formation of GLCM [5]. GLCM is a 8×8 matrix for all set of input images. Five co-occurrence matrices are constructed in four different spatial orientations.

A fifth matrix is constructed by computing the mean of the preceding four matrices. From the co-occurrence matrix features are extracted. The main features include contrast, correlation, energy, homogeneity, autocorrelation, variance, dissimilarity, cluster shade and entropy. Among these features, five features are selected as inputs for classifying the mammographic images into normal images, images with architectural distortion and images with mass. The features selected are contrast, correlation, homogeneity, dissimilarity and cluster shade. The selected features are listed in Table 1.

Table 1.Features given as testing data for ANFIS

Features / Image Type	Contrast	Correlation	Homogeneity	Dissimilarity	Cluster shade
NORMAL IMAGES	0.627	0.9775	0.9499	0.1945	85.689
	0.7947	0.9753	0.9351	0.2081	71.194
	0.6472	0.9823	0.9452	0.2171	84.75
	0.6328	0.9834	0.9474	0.2062	82.13
	0.6496	0.9763	0.9424	0.1989	82.73
	0.6315	0.9721	0.9405	0.2076	83.72
IMAGES WITH AD*	1.3752	0.9334	0.8894	0.4018	22.432
	1.5527	0.9269	0.8715	0.4215	21.63
	1.2792	0.9303	0.8805	0.429	29.929
	1.5636	0.924	0.9036	0.4172	22.18
	1.522	0.9341	0.894	0.4092	22.768
IMAGES WITH MASS	0.9716	0.9614	0.9088	0.3152	55.51
	0.9842	0.9571	0.9121	0.3124	53.62
	0.9957	0.9584	0.8841	0.3029	53.35
	0.9807	0.9546	0.8987	0.3022	57.62

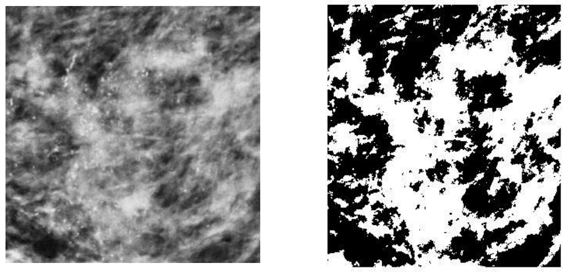
*-Architectural Distortion (AD)

4. CLASSIFICATION

The mammographic architectural distortion and mass are classified by using ANFIS with a set of features extracted from the images. The inputs for the system are five features that are extracted from the mammographic images. The features for normal images, images with architectural distortion and images with mass are taken as inputs. The targets are assigned according to the input features given. In ANFIS the input will be defined in the form of matrix and the last column of the matrix defines the output [6]. Here the last column contains 0, 1 or 2 depending on whether the image is normal, image is with architectural distortion or image is with mass respectively. 25 images are used for training and 15 images for testing in ANFIS. After the training dataset is loaded a Fuzzy Inference System (FIS) is generated. The system is trained by specifying the number of epochs. Finally the system is tested with test inputs. Thus totally 40 images are used for training and testing in ANFIS.

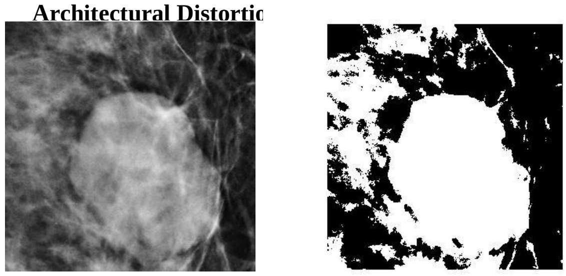
5. RESULTS AND DISCUSSION

The original mammographic image from the MIAS database is preprocessed. The preprocessing steps include cropping the original mammographic image to size of 300×300 and histogram equalization of the image. The RoI is segmented from output image using Otsu's thresholding [10]. The segmented image with architectural distortion and mass are respectively shown in Figure.4 and Figure.5.



a) **b)**

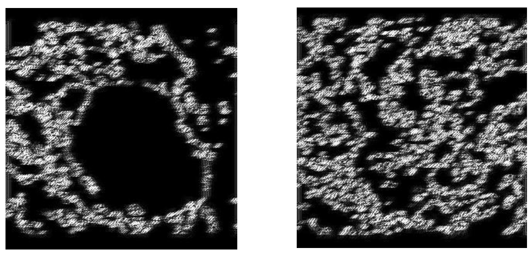
Figure.4 a) RoI of Mammographic Image with Architectural Distortion b) Segmented Image with Architectural Distortic



a) **b)**

Figure.5 a) RoI of Mammographic Image with Mass b) Segmented Image with Mass with threshold value

The segmented image is operated with Gabor filter. The filter detects the edges of the segmented region. The Gabor filtered mammographic images with mass and architectural distortion are shown in Figure.6. Hybrid learning algorithm is used for training the images in ANFIS. It uses a combination of gradient descent algorithm and least squares method for training the data. It requires the dataset of desired outputs for the set of inputs to make the training dataset. In ANFIS three Membership Functions (MFs) are assigned to each input. Here, the Gaussian bell type MF is used for inputs since it gives minimum training error and the output is a constant type. The classification results using ANFIS are given in Table 2.



a) b)

Figure.6 a) Gabor Filtered Mammographic Image with Mass b) Gabor Filtered Mammographic Image with

Table 2.Classification Results of ANFIS

Image Category	No of Training Imgs	No of Testing Imgs	Error
Normal	9	6	1
Architectural Distortion	9	5	1
Mass	7	4	2

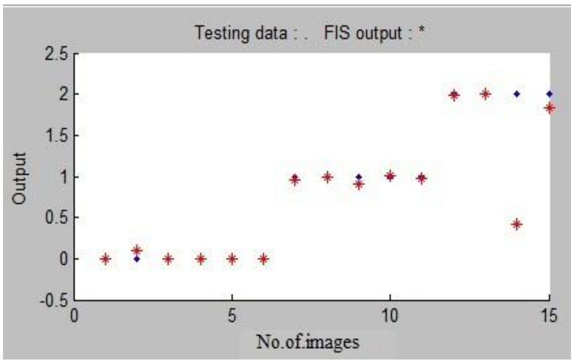


Figure.7 Classification Results using ANFIS

The sensitivity obtained is about 80% in case of images with Architectural Distortion and 50% in case of images with Mass. The specificity obtained is 83% for both the cases. Figure.7 shows the classification result obtained in ANFIS.

6. CONCLUSION

A technique for the detection of architectural distortion and mass in mammographic images using Gabor wavelet is performed. Features are extracted from the RoI. The suitable features are selected from the set of extracted features and given as input to ANFIS for classification. From the classification results of ANFIS it is inferred that there is 4% increase in sensitivity for images with architectural distortion comparing with the existing works whereas the sensitivity for images with mass need to be improved.

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