Automated Characterization of Mammographic Density for Early Detection of Breast Cancer Risk

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***Abstract*---Mammographic density provides significant amount of information about breast cancer risk. Therefore, automated appraisal of mammographic density could help the radiologist to assess the risk of developing breast cancer. This paper presents fully automated breast tissue characterization methodology for mammograms, which consists of three phases: i) preprocessing ii) feature extraction and iii) classification. To remove the high frequency artifact such as labels and wedges, Otsu's global thresholding method and connected component labeling is employed. This paper incorporates a new straight line method proposed by us in our earlier work to remove the pectoral muscle from the breast area which is our region of interest. Haralick's texture descriptors and Zernike moment descriptors are extracted from the region of interest. SVM and BPNN classifiers are used to classify the extracted features into one of the three breast parenchyma classes viz., dense, glandular and fatty tissue. The work reported an accuracy of 95.83%.**

Keywords: Mammograms, Breast parenchymal density, Pectoral region, Haralick texture measures, Zernike Moments

I. INTRODUCTION

Breast cancer is a common cancer worldwide. As per the reports of Indian Council of Medical Research (ICMR), it is emerging as number one cancer when compared to cervical cancer. IARC has warned that India could see a predominant number of new cases of breast cancer by 2015 which is estimated to be around 250,000. Mammogram, the X-ray image of the breast is now the most widely used screening technique for early breast cancer detection. The different breast tissue namely dense, glandular and fatty is X-rayed differently due to the fact that fatty breast allow X-rays to permeate things it forming dark areas on a mammogram which allows better lesion detection. However the glandular and dense breast blocks X-rays and so appear as white areas on the mammogram, making it difficult to detect tumors as they also appear as white regions on the mammogram. Computer Aided Diagnosis (CAD) tools are now being researched that would help radiologist in detecting the region of interest and also that could act as a second reader in diagnosing the diseases. Digital mammography and CAD system plays a major role for detecting breast cancer in the recent years. Studies reveal that women having dense breast are at a high risk of breast cancer and their tumors are likely to be associated with more aggressive characteristics than women with fatty breasts. CAD helps to detect breast cancers at the benign stage itself when it is difficult to analyze breast tissue by the radiologist in the case of women with dense breasts [1]. Radiologists classify breast densities by their visual perception and experience of the medical images. This project work tries to automatically characterize the breast density and this would help the radiologist to assess the risk of breast cancer.

II. PREVIOUS WORK

The number of techniques for breast density pattern classification is shown in the literature. The work in [2] applies variance histogram analysis and discriminant analysis for dividing the mammogram images into three regions. Then using this regions breast density is classified into four categories, namely (i) fatty, (ii) mammary gland diffuseness, (iii) non uniform high density, and (iv) high density. Histogram features were extracted and classified using BPNN in [3]. A new approach was proposed to model and classify breast tissue using probabilistic Latent Semantic Analysis (pLSA) in [4].

The work in [5] computes six statistical features and classifies the breast tissue based on the histogram and obtained 80% classification accuracy. Histogram and accumulative histograms were utilized to estimate the breast density based on gray scale statistics in [6]. Statistical technique to segment the mammograms based on the breast density is applied in [7], where Karhunen Loeve based model and linear discriminant model was employed to classify breast density, taking neighborhood pixels into account. They obtained better results with the principal component analysis model. Fractal related features and SVM classifier is employed for characterization of breast density in [8]. The work in [9] utilizes morphological and texture descriptors and sequential forward selection classifier for classification. Scale invariant feature transform, local binary patterns and texton histograms are extracted and modeled with SVM classifier for breast density classification [10]. In [11] features were calculated from the statistical measures and features are classified using SVM. K-nearest neighbor was used to characterize the breast tissue density in [12,13,14,15]. Bayesian classifier was applied in [16]. Whole breast with pectoral region is considered as a region of interest for feature extraction and classification in many of the research papers. In our proposed work artifactless and pectoral muscle removed breast parenchyma alone is taken as a region of interest. Haralick's texture features and Zernike moment features are extracted from the region of interest. Then the performance is calculated using the features is fed into the SVM classifier and BPNN classifier.

III. METHOD

The main aim of this study is to classify breast tissue density for detecting breast cancer at the benign stage itself. The various phases of the proposed method is given in Figure 1. The initial step in this work involves artifact removal, image enhancement and pectoral muscle removal. All these are done as a preprocessing step before extracting the features. In this study, Haralick texture features and Zernike moment features are extracted. The extracted features are fed into the SVM and BPNN classifiers. This method has been tested on freely available Mini-Mias database [17].

A. Preprocessing phase

The original mammogram which contains artifacts and the pectoral muscle is first preprocessed to remove them. Radio opaque artifacts presents in the mammogram can result in misclassification and so it becomes vital to remove them before further processing. Further the mammogram image quality is improved by noise reduction. The pectoral muscle is seen as a high density region in mediolateral oblique views mammograms, and it hinders the accurate detection of breast densities [18]. Thus the pectoral muscle removal is inevitable for selecting the region of interest.

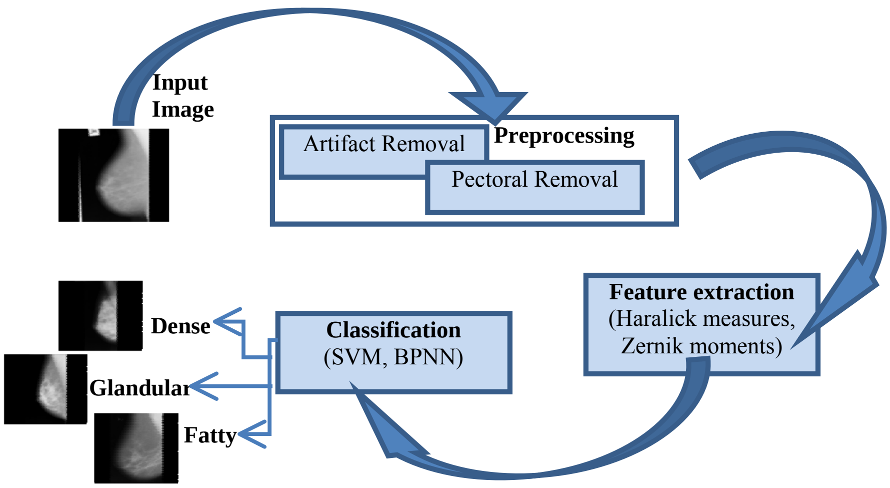

Figure 1. Various phases of the proposed method.

A mammogram contains two regions: breast region and non-uniform background region. Most of the background region holds high intensity artifacts. In this work, first Otsu's global thresholding method is used for binarizing the image. Between class variance is maximized by the Otsu's global thresholding method which makes well thresholded classes to be distinct with respect to the pixel intensities [19]. Next, connected regions are found out and the largest connected region which includes the pectoral muscle is recovered. This region is further processed to segment the breast region which is the region of interest from the pectoral muscle region. Connected component labeling scans an image, pixel by pixel (from top to bottom and left to right) in order to locate the connected pixel regions, i.e., region of pixels that share the same intensity values. Artifact removed image is shown in Figure 2. After artifact removal, median filtering is applied for removing noise and morphological techniques are used for enhancing the image. Median filtering has been found to be very powerful in removing noise from 2D signals without blurring edges. This makes it particularly suitable for enhancing images. The pectoral muscle is removed using our previous work [11] which uses a straight line method proposed by us. Pectoral muscles lie on the left or right top corner depending on the view of the image.

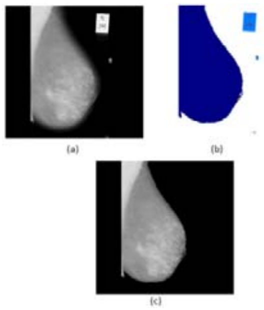

Figure 2. a) Original Image. b) Connected component labeled image. c) Artifacts removed image.

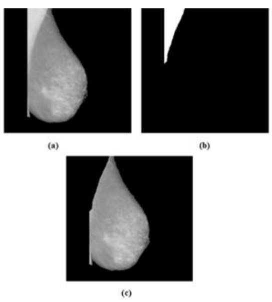

Figure 3. a) Original image. b) Segmented pectoral muscle region. c) Pectoral muscle eliminated breast region.

To make processing easy the right MLO mammogram is first flipped to the left side before removing the pectoral region. To remove the pectoral muscle a new straight line method is applied to the top left quadrant which contains the pectoral region [11, 20]. Figure 3. shows the pectoral muscle removed image.

B. Feature extraction phase

A specific combination of features is required for classification in any image processing and analysis applications. Texture is one of the most important features in pattern recognition area. Though many statistical methods are available in the literature [11] to extract the texture, Haralick features and Zernike moment features are widely used for texture description so this work employ these features for classification.

1) Haralick texture feature

Texture features are extracted from co-occurrence matrices. A co-occurrence matrix element $p(i, j)$ is the joint probability of the occurrence of grey-levels i and j for pixel pairs which are separated by a distance d and at a direction θ [21]. For obtaining the fine texture details d=4 and 8 are tried, but d=4 provides better results and the direction $\theta = 0^\circ$ is used because there is no significant dependence of the discriminatory power of the texture features on the direction of the pixel pairs for mammographic textures. Gray level co-occurrence matrices (GLCM) are used to extract second order statistics from an image. Out of 14 texture measures suggested by Haralick [22], the most relevant 11 features are used in this work. Table I. lists these features and their expressions.

2) Zernike moment feature

In CAD system, shape plays a vital role for analyzing mammogram images. The mammogram acquisition method produces a two-dimensional image of the three-dimensional interaction process between breast parenchyma and X-rays. This may lead misevaluation of breast density. For example, the mammogram of the women having small breasts and low amounts of glandular tissue may appear to have high density but mammogram of the women having large breasts and substantial amount of glandular tissue may appear to have low breast density. Therefore, shape feature is important for density evaluation [23].

Similar shape may belong to the same tissue category. Zernike moments have been suggested to be a good descriptor for shape feature extraction [24-27]. Zernike moments are computed by projecting the image onto a set of complex Zernike polynomials which satisfy the orthogonal property. The orthogonally implies that the image has no redundancy or overlap of information between the moments [28]. Computations of the Zernike moments do not require knowledge of the precise boundary of an object [26].

The Zernike moments are based on a set of complex valued orthogonal polynomials that form a complete polynomial set over the interior of the unit circle $U : x^2 + y^2 \leq 1$.

TABLE I. HARALICK TEXTURAL FEATURES.

No.	Texture Features	Expressions
1	Correlation	$t1 = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} \frac{(ij)\,p(i,j) - (\mu_x \mu_y)}{\sigma_i \sigma_j}$
2.	Contrast	$t2 = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} \lvert i-j \rvert^2 \, p(i,j)$
3.	Energy	$t3 = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} p(i,j)^2$
4.	Entropy	$t4 = -\sum_{i=0}^{Ng} \sum_{j=0}^{Ng} p(i,j) \log(p(i,j))$
5.	Inverse Difference Moment	$t5 = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} \frac{1}{1+(i-j)^2} p(i,j)$
6.	Sum of squared variance	$t6 = \sum_{i=0}^{Ng} \sum_{j=0}^{Ng} (i-\mu)^2 \, p(i,j)$
7.	Sum average	$t7 = \sum_{i=2}^{2Ng} i p_{x+y}(i)$
8.	Sum entropy	$t8 = -\sum_{i=2}^{2Ng} px+y(i) \log(px+y(i))$
9.	Sum variance	$t9 = \sum_{i=0}^{Ng} (i-t8)^2 \, px+y(i)$
10.	Difference variance	$t10 = \sum_{i=0}^{Ng-1} i^2 \, p_{x-y}(i)$
11.	Information measure of correlation 2	$t11 = \sqrt{1 - \exp -2(HXY2 - t4)}$ $HXY2 = -\sum_{i=0}^{Ng} \sum_{j=0}^{Ng} px(i)py(j) \log(px(i)py(j))$

Ng=Number of grey-levels in the image.

Zernike moment for an digital image function $f(x,y)$ is expressed as

$$V_{n,m}(\rho,\theta) = R_{n,m}(\rho)\, e^{jm\theta}$$

Where,

$Z_{n,m}$ are the Zernike moments and $V_{n,m}$ is a two dimensional Zernike polynomial and

Here, n is a non-negative integer, m is non-zero integer subject to constraints n-|m| is even and $|m|<n$, j is the imaginary unit $\sqrt{-1}$, ρ is the length of the vector from origin to (x,y), θ is the angle between vector ρ and the x-axis in a counter clock wise direction and $R_{n,m}(\rho)$ is the radial polynomial, which is defined as

$$R_{n,m}(\rho) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!\,(((n+|m|)/2)-s)!\,(((n-|m|)/2)-s)!} \rho^{n-2s}$$

The list of Zernike polynomials upto 4^{th} order implemented in this work is given in Table II.

TABLE II. LIST OF ZERNIK POLYNOMIALS UPTO 4^{TH} ORDER.

Index	N	M	Zernike Polynomials
0	0	0	1
1	1	-1	$2\rho\sin\theta$
2	1	1	$2\rho\cos\theta$
3	2	-2	$\sqrt{6}\rho^2\sin 2\theta$
4	2	0	$\sqrt{3}(2\rho^2-1)$
5	2	2	$\sqrt{6}\rho^2\cos 2\theta$
6	3	-3	$\sqrt{8}\rho^3\sin 3\theta$
7	3	-1	$\sqrt{8}(3\rho^3-2\rho)\sin\theta$
8	3	1	$\sqrt{8}(3\rho^3-2\rho)\cos\theta$
9	3	3	$\sqrt{8}\rho^3\cos 3\theta$
10	4	-4	$\sqrt{10}\rho^4\sin 4\theta$
11	4	-2	$\sqrt{10}(4\rho^4-3\rho^2)\sin 2\theta$
12	4	0	$\sqrt{5}(6\rho^4-6\rho^2+1)$
13	4	2	$\sqrt{10}(4\rho^4-3\rho^2)\cos 2\theta$
14	4	4	$\sqrt{10}\rho^4\cos 4\theta$

C. Classification phase

1) BPNN

A Backpropagation neural network (BPNN) uses a supervised learning method and feed-forward architecture. The BPNN is based on the gradient descent technique for solving an optimization problem, which involves the minimization of the network cumulative error. Error is the difference between the target output and the actual output. This BPNN is designed in such a way as to update the weights in the direction of the gradient descent of the cumulative error. This is done in an iterative way. A feedback signal i.e. error is then backward propagated to the neural network for updating the weights of the layers, thereby minimizing the mean squared error between the network output and the target output [29]. In this work sigmoid function is used as a activation function.

2) Support Vector Machine (SVM)

SVM is a supervised learning algorithm, for binary classification is the simplest form. From the training samples SVM tries to models the two different classes. So that it generalize well to test data. The principle of SVM is to find the hyperplane which maximize the distance between the two classes. The hyperplane generated depends on the samples which are a subset of the two classes. The samples which lie near the hyperplane are called support vectors [30,31]. Support vectors are the training samples that define the optimal separating hyperplane and are difficult patterns to classify. Where the training samples are linearly separable it is easy to classify them. However then the samples are linearly inseparable then the kernel function is used to separate the two classes. Some common kernels are Polynomial (homogeneous), Polynomial (inhomogeneous), Gaussian radial basis function, Sigmoid. In this proposed work polynomial and radial basis function kernel of SVM is used.

IV. EXPERIMENTS AND DISCUSSIONS

An organization in UK called Mammography Image Analysis Society (MIAS) has created a mammogram database with ground truth such as tissue types, class of abnormality and severity of abnormality and location of abnormality. The mammogram in this database is digitized to a resolution of 50m x 50m, 8 bits represents each pixel. This database is used in this study. It contains both the right and left breast images of the same patient with a uniform size of 1024 x 1024 pixels [17].

The Haralick texture features and Zernike moment shape features are extracted from 120 normal mammograms from the MIAS database. Of these, 49 mammograms have dense tissue, 36 mammograms have glandular tissue and 35 mammograms have fatty tissue. The SVM is trained in multiclass mode to provide a value of 0 for dense tissue, 1 for glandular tissue and 2 for fatty tissue mammograms.

In our work initially, out of the 14 Haralick texture features the most dominant 11 features namely correlation, contrast, energy, entropy, inverse difference moment, sum of squared variance, sum average, sum entropy, sum variance, difference variance and information measure of correlation 2 are extracted. First, SVM with polynomial kernel and radial basis function kernel is used for classification. Next the efficacy of Haralick feature for classification of breast density using BPNN was carried out. A three layer network is used for this purpose. The performance of the classifier is checked for different network structure and the best performance is achieved with the network structure having 11 input neurons and 7 hidden neurons. Table III gives the classification results obtained using Haralick texture measures.

TABLE III. RESULTS OF BREAST TISSUE CLASSIFICATION USING HARALICK TEXTURE MEASURES.

Type		**Dense (%)**	**Glandular (%)**	**Fatty (%)**
SVM	Polynomial kernel	87.50	87.50	87.50
	RBF kernel	93.50	87.50	99.50
BPNN		85.76	78.22	93.30

Then, Zernike moment shape features were extracted. Using the 14 Zernike polynomials upto 4^{th} order 14 Zernike moment features were obtained. First, SVM with polynomial kernel and radial basis function kernel is used for classification. Next the efficacy of Zernike moment features for classification of breast density using BPNN was carried out. A three layer network is used for this purpose. BPNN with network structure having 14 input neurons and 9 hidden neurons gives the best performance. Table IV gives the classification result found using Zernike moment features.

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TABLE IV. RESULTS OF BREAST TISSUE CLASSIFICATION USING ZERNIKE MOMENTS.

Type		Dense (%)	Glandular (%)	Fatty (%)
SVM	Polynomial kernel	81.25	87.5	93.75
	RBF kernel	68.75	81.25	75.00
BPNN		77.22	83.26	80.24

The performance of the classifier was then tested by fusing Haralick and Zernike moment features. 11 Haralick texture features and 14 Zernike moment features are combined and the combinations of 26 HarZer features are fed into SVM classifier and BPNN classifier. SVM with polynomial kernel and radial basis kernel is used for classification. Next the efficacy of HarZer features for classification of breast density using BPNN was carried out. The performance of the classifier is checked for different network structure and the best performance is achieved with the network structure having 26 input neurons and 15 hidden neurons. The results based on HarZer features are given in Table V.

TABLE V. RESULTS OF BREAST TISSUE CLASSIFICATION USING COMBINATION OF HARALICK MEASURES AND ZERNIKE MOMENTS.

Type		Dense (%)	Glandular (%)	Fatty (%)
SVM	Polynomial kernel	93.75	93.75	100
	RBF kernel	91.50	89.50	100
BPNN		87.25	85.24	100

TABLE VI. OVERALL BREAST TISSUE CLASSIFICATION RESULTS.

Classifier		Haralick measures (%)	Zernike moment (%)	Haralick + Zernike (HarZer) (%)
SVM	Polynomial kernel	87.50	87.50	**95.83**
	Radial basis kernel	93.50	75.00	93.66
BPNN		85.76	80.24	90.83

Table VI and Figure 4 shows the overall performance of Haralick texture features, Zernike moment shape features and its combination HarZer features with SVM and BPNN classifiers. When compared to BPNN, SVM is found to be given better performance using Haralick measures, Zernike moment features and HarZer features. Further it can also be seen from the Table VI that the HarZer features outperforms Haralick features and Zernike features in classification of breast density using both SVM and BPNN. Table VII gives a comparison of our work with other works for breast tissue density using different features and classifiers.

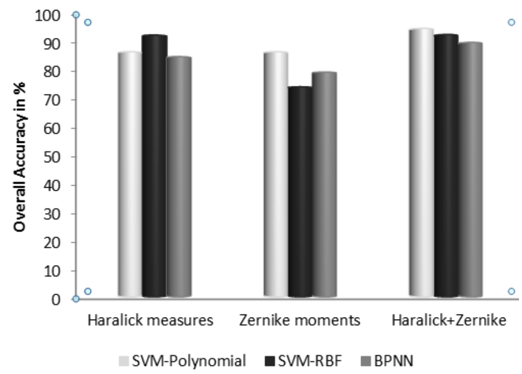

Figure 4. Graph showing the comparison of Haralick features , Zernike features and HarZer features performance using SVM with polynomial and RBf kernel classifier and BPNN classifier.

V. CONCLUSION

This paper proposes an automated appraisal of mammographic density into three classes of breast tissue viz., fatty, glandular or dense. The mammogram is first binarized using Otsu's thresholding and connected component labeling method is then applied to obtain the biggest connected region. This region is then processes using the proposed straight line method to remove the pectoral muscle. Haralick texture features, Zernike moment features and combination of Haralick and Zernike (HarZer) features were extracted from the pectoral removed breast region. Supervised classifiers such as SVM and BPNN are applied to Haralick texture features, Zernike moment features and HarZer features for classification of breast tissue density. The study shows HarZer features using SVM outperforms and obtained the best classification accuracy of 95.83%. The mammogram images were processed using Matlab. This proposed method is beneficial for clinical decision support systems in the early detection of breast cancer risk.

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TABLE VII. COMPARISON BETWEEN OTHER WORKS WITH OUR PROPOSED WORK.

Features	Classifier	Accuracy	Reference
Histogram featues	BPNN	71%	Wang et al. [3] 2003
Statistical features		80%	Sheshadri et al. [5] 2007
Morphological and texture	SFS+KNN	91%	A.Oliver et al. [9] 2008
Histogram	Thresholding	80% - 90%	Tagliafico et al. [6] 2009
ROI	PCA / LDA	90%	Oliver et al. [7] 2010
Statistical features	SVM	95.44%	T.S.Subashini et al. [11] 2010
Fractal features	SVM	85.7%	S.D.Tzikopoulos et al.[8] 2011
SIFT, LBP, texton histogram	SVM	93.548%	G.Liasis et al. [10] 2012
GLCM, Statistical, Histogram	k-NN	82.5%	M.Mario et al., [32] 2012
Haralick + Zernike moments (HarZer)	BPNN	90.83%	Proposed work
Haralick + Zernike moments (HarZer)	SVM	**95.83%**	**Proposed work**

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