A Review of Breast Density Classification Methods

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Abstract: Breast cancer is the most common life-threatening disease found in women in the developed countries. The risk factor of breast cancer is related to breast density, which is estimated with the help of mammography. Breast density can be evaluated by qualitative as well as quantitative methods. Few CAD systems have been designed for the automated classification of breast density. These CAD system designs have either used the segmented breast tissue or a predefined ROI; therefore these CAD designs can be broadly classified as Segmentation-based approaches or ROI-based approaches as described in this article. After that the BI-RADS classification is performed based on the extracted texture features.

Keywords: Breast cancer, Breast density, Classification, Feature extraction, Feature selection, Mammograms.

NOMENCLATURE

DDSM	Digital Database for Screening mammography
MIAS	Mammographic Image Analysis Society
CAD	Computer-Aided Diagnosis
MRI	Magnetic Resonance Imaging
ROI	Region of Interest
SBT	Segmented Breast Tissue
BIRADS	Breast Imaging-Reporting and Data System

I. INTRODUCTION

With the advancement of society, Indian women are also adopting the Western culture; due to that risk of breast cancer has increased rapidly [1-6]. It is the most frequent form of cancer being found among women in the United States, African countries, and European countries and also in metro-cities of India [7]. Detection of breast tumor in initial phase is really a challenging task. Computer aided diagnostic (CAD) systems are used in the medical imaging as a second opinion tool for the radiologists to gain confidence in their diagnosis. A lot of CAD systems and imaging modalities, namely mammography, ultrasound, MRI [8-9] etc. are developed for the detection and prediction of breast tumor. Among these, mammography is the most effective approach for screening of breast tumor that can be helpful to detect a malignancy up to two years before a lump can be felt.

Mammography [8, 10] is the technique to predict and detect breast cancer. It is based on different levels of X-ray absorption for the various breast tissue components such as fat, calcifications and tumors. The sensitivity and specificity of mammography are high, so small tumors and micro calcifications can be detected easily. The two most common forms for breast projection are Medio-Lateral Oblique (MLO) and Cranio-Caudal (CC). In MLO projection almost the whole breast is visible, often including lymph nodes. The CC view is taken from above, resulting in an image that sometimes does not display the area close to the chest wall.

The risk factors of breast tumor in women are development of hormones, genetics, age of first pregnancy, number of pregnancies, hormones replacement therapy (HRT), breast density, age, obesity, smoking, drinking, late night work, menarche, menopause, drugs, alcohol etc. [11-14]. Among these, breast density [15] is thought to be a major risk factor of breast cancer [16-18]. Fundamentally, breast density is a comparison of the relative amounts of fibro-glandular tissues versus fatty tissues in the breast. Women with dense breast have higher percentage of fibrous tissue and less fat tissue. In the past, many approaches have been developed to divide the breast tissue into well defined classes. Wolfe was one of the first researchers to present the correlation between breast density and the possibility for the risk of breast cancer [19]. He proposed that the breasts can be divided into four categories on the basis of density as mentioned in Table I.

TABLE I: BI-RADS CLASSIFICATION [15]

BI-RADS Class	Density (%)	Breast density
TYPE-I	00-25	Entirely fatty
TYPE-II	26-50	Some fibro-glandular tissue
TYPE-III	51-75	Heterogeneously dense breast
TYPE-IV	76-100	Extremely dense

Typical cases of breast density can be easily classified in respective classes from their classic appearance but some cases are a confusing task for radiologists to classify

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accurately; these cases are called atypical cases. Both the cases are shown in Fig. 1 for different BI-RADS classes. The lower frame of Fig. 1 shows the atypical cases of breast density. For atypical cases, it is not easy to predict the BI-RADS classification; therefore, a CAD system is required for assessment of these types of cases.

The rest of the paper is organized as: section II presents a brief summary of the existing work on breast density classification on the basis of segmented and Region of Interest (ROI) of mammograms. Extracted features for classification purpose by different authors are also listed in same section, and finally conclusion is drawn in section III.

II. LITERATURE REVIEW

The use of intelligent CAD system designs results in increase in diagnostic accuracy specifically in atypical cases where there is considerable overlap in terms of radiological appearances between different image classes [20-29]. However, in case of mammographic images, lesions are masked by denser tissues in certain cases. It has also been reported that increase in breast tissue density is associated with malignancy and therefore a lot of intelligent CAD systems have also been proposed for breast tissue density classification using mammographic images. These CAD system designs have either used the segmented breast tissue or a predefined ROI for further processing; therefore these CAD designs can be broadly classified as segmentation-based approaches or ROI-based approaches as depicted below.

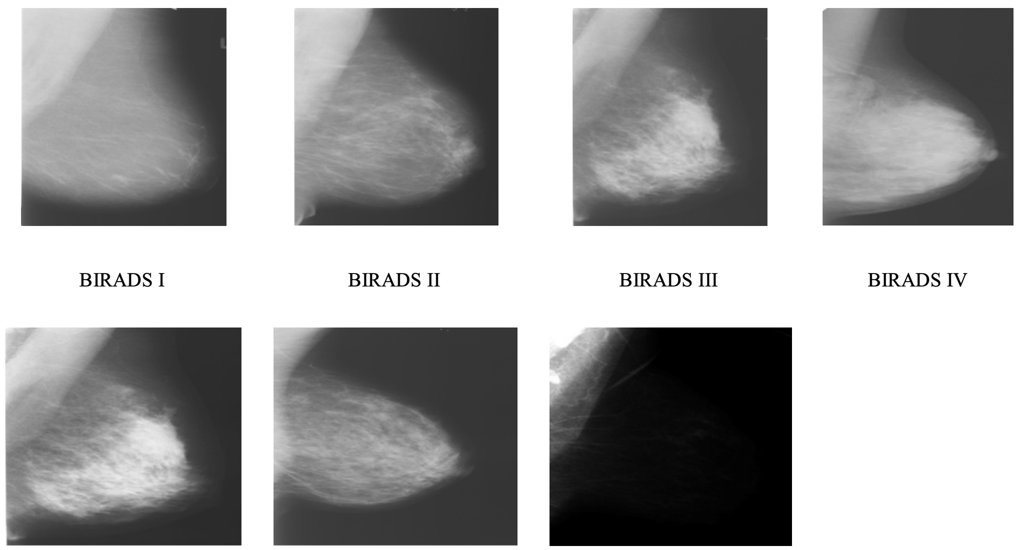

Fig.1. Typical cases of BIRADS Classification in upper frame and atypical cases in lower frame

A. Segmentation Based Approaches

Torrent, *et al.* [30] presented a technique to compare the clustering-based and region-based algorithms for segmentation of mammographic images as per density. The first algorithm was based on a multiple thresholding obtained by excess entropy; the second approach used fuzzy C-Means clustering and the third was based on the statistical analysis of the breast. The performance of the algorithms was evaluated using a database of full field digital (FFD) mammograms containing 150 CC and 150 MLO images and it was finally concluded that the use of region information is useful for the homogeneous region segmentation and clustering algorithms obtained better sensitivity.

Petroudi, *et al.* [31] proposed an algorithm for breast density classification. The set of texton [32] histograms was used that defines the breast parenchymal density models for different input images. For classification, an input test mammogram was first segmented, filtered with the maximum response (MR8) filter bank [33]. The reported accuracies were 91 %, 64 %, 70 % and 78 % for BI-RADS I to BI-RADS IV class, respectively. This work was extended in [34] for two class classification and 70% accuracy was achieved.

Kallenberg, *et al.* [35] proposed a combination of segmentation and ROI-based technique for breast density classification. He tested the proposed method using 750 digitized film mammographic images acquired from different sources and got better result with respect to the user-assisted threshold method. For the density classification, firstly the images were pre-processed and then texture features were extracted. For classification of pixels, separate training set of 500 manually labeled Cumulus images was used. Then k-nearest neighbor (KNN) classifier was used for the classification of breast density as fatty or dense category.

Papaevangelou, *et al.* [36] developed an automatic breast density classification method that was tested on 83 randomly selected mammograms from radiology department of

Thriasio Hospital. They considered MLO and CC views of each mammogram for the evaluation of that method. Firstly, the images were segmented for removal of pectoral muscles and background, then texture and statistical features from each image were extracted and images were then classified in two classes and four classes. An accuracy of 94% and 92.8% was obtained for MLO & CC views respectively in two-class BIRADS classification. Overall accuracy of 84.3% and 79.5% for MLO & CC views was achieved, respectively using four-class BIRADS classification.

Ciatto, *et al.* [37] classified the digital mammograms on the basis of *k*-statistic value in two and four class. All the experiments were performed on 100 images, out of which 69 were negative mammogram and 31 were cancerous. By varying the kappa (*k*) value, the different classes of breast density were obtained and the risk factor for different classes was measured and it was concluded that breast density is the major risk factor of breast tumor.

Tagliafico, *et al.* [38] developed a system known as MedDensity based on maximum entropy. Spatial information was used for automatic thresholding and segmentation of breast into fatty and dense tissue. Segmented area's pixel value was used to estimate the area of the dense tissue and total breast area. Breast density calculated using this was positively correlated with BI-RADS breast density measures [39, 40].

Zhou, *et al.* [41] developed an automated tool for the breast density estimation. In this study, CC and MLO views of 260 mammograms of 65 patients were used. The complete process of breast density estimation consists of three steps: In the first stage whole breast region was segmented from the background and pectoral muscle by an automated breast boundary-tracking algorithm, then an adaptive dynamic compression technique was applied to the breast image for the improvement of contrast and brightness to extract the gray level texture features. Lastly, rule-based classification was used to classify the mammograms into four classes as per their texture features. For the correct classification, computer-estimated percent dense area and the "truth" was 94% and 91% for CC and MLO views, with a mean bias of less than 2%.

Chatzistergos, *et al.* [42] developed a system to automatically provide parenchymal breast density category estimation based on local texture features of the image, known as texton. The method was tested on a set of 59 digitized mammographic images of MLO view and achieved success rates of 98.3% and 93.2% for two-class and four-class classifications, respectively.

Oliver, *et al.* [43] presented a review of different techniques for extracting features in tissue classification systems, and demonstrated the feasibility of estimating breast density using CAD system, as well as the benefits of segmentation of the breast based on internal tissue information. The proposed approach was tested on the MIAS database classified as per BIRADS standard, and an agreement of 82% was obtained between automatic and manual classification. This work was extended in [44].

Wenda, *et al.* [45] developed an automatic mammographic density segmentation approach using a novel binary model based Bayes classifier. The MIAS database was used for evaluation. Texture features were extracted that contain periodic, spatial and geometric information for different tissues. The accuracy rates of 93% and 88% were reported for fatty and dense classes.

Vallez, *et al.* [46] presented a review of different classification techniques for two datasets namely Digitized Screen-Film Mammography (SFM) and Full-Field Digital (FFDM) Mammography, classified as per BI-RADS standard. The authors also designed a method called tree classification that was based on the combination of two classifiers. Statistical analysis was used to test the normality and equal statistical variance of the features. Thus, features that are significantly influenced by the tissue type were considered. This method was tested on 322 mammograms of SFM dataset and 1137 mammogram of the FFDM dataset, and 80% of mammograms were correctly classified.

B. ROI-Based Approaches

Li, *et al.* [47] proposed a method to demonstrate the effect of ROI selection and ROI size on mammograms for the breast density estimation. In this approach, texture features were extracted from the selected ROI, not the entire image and the result of variation in the size of ROI was estimated. Finally, it was concluded that the performance varied if the ROI is selected from the region behind the nipple.

Mustra, *et al.* [48] proposed a method for classification of breast density based on the ROI selection. He firstly selected the ROI and applied Gabor filter for the detection of blood vessels and then applied region growing segmentation method for the estimation of tissue to be fatty or dense. All images were taken from the MIAS database.

Mustra, *et al.* [49] designed a CAD system for classification of fatty and dense tissue from mammograms. In this work, the MIAS database was used and mammograms classified them by suppressing scattered structure, which does not represent any type of tissue. Gabor filters of different sizes were used for suppressing the blood vessels and edge detection. Morphological operation was used for the suppression of unwanted tissue on filtered image with enhanced contrast. Thresholding was used to avoid false detection. Once again the results were compared with different extracted texture features of selected ROI and the authors achieved 6% better result with respect to the segmented experiment [50, 51].

Kim, *et al.* [52] designed an automated method for the breast density classification. For evaluation, 170 pairs of CC-view images of patients were taken from the Seoul National University Hospital. From the selected ROI, intensity mean and standard deviation were calculated using histogram and then contour was used for the tissue separation and dense and fatty tissues were successfully classified.

Kutluk, *et al.* [53] developed a method for classification of breast tissue density from mammographic images. The scale invariant feature transform (SIFT) algorithm was used to extract texture features and learning vector quantization (LVQ) algorithm was used for the supervised classification of mammograms into fatty, fatty-glandular and dense-glandular classes. The method was tested on the MIAS dataset and an accuracy of 90 % was achieved.

The next section, describes the studies carried out by different authors on different datasets. Some authors have worked on local database that was collected from different radiologists or different local hospitals, DDSM dataset and some worked on the MIAS dataset. These studies are listed below in Table II, Table III and Table IV respectively.

TABLE II: STUDIES CARRIED OUT ON DIFFERENT LOCAL DATABASE

Author(s), Year	Segmented Breast Tissue/ROI	No. of images	Name of Database	Classifier	Accuracy (%)	Considered class
Karssemeijer , 1998 [54]	SBT	615	Nijmegen	KNN	65.00	BIRADS I-IV
Petroudi, *et al*. 2003 [31]	SBT	132	Oxford database	KNN	75.75	Fatty, dense
Mustra, *et al*. 2012 [55]	ROI	144	KBD-FER	KNN, Naive Bayesian	79.30	Fatty, Dense
Masmoudi, *et al*. 2013 [56]	SBT	2052	EL FARABI	K-NN	79.00	BIRADS I-IV
Liu, *et al*. 2011 [57]	ROI	88	Tianjin tumor hospital	SVM	86.40	BIRADS I-IV

Note: SBT-Segmented breast tissue

TABLE III: BRIEF STUDY CARRIED OUT ON DDSM DATABASE BY DIFFERENT AUTHORS

Author(s), Year	Segmented Breast Tissue/ROI	No. of images	Classifier	Accuracy (%)	Considered Class
Oliver, *et al*. 2005 [58]	SBT	300 R-MLO	KNN, Decision tree	47.00	BIRADS I-IV
Oliver, *et al*. 2008 [59]	SBT	831	SFS+KNN	77.00	BIRADS I-IV
Bovis, *et al*. 2002 [60]	SBT	377	ANN	71.40	BIRADS I-IV
Bosch, *et al*. 2006 [61]	SBT	500	KNN, SVM	84.75	BIRADS I-IV
Oliver, *et al*. 2010 [62]	SBT	831	LDA-PCA	79.00	Fatty, dense

TABLE IV: BRIEF STUDY CARRIED OUT ON MIAS DATABASE BY DIFFERENT AUTHORS

Author(s), Year	Segmented Breast Tissue/ROI	No. of Images	Classifier	Accuracy (%)	Considered Class
Muhimmah, *et al*. 2006 [63]	SBT	321	DAG-SVM	77.57	Fatty, fatty-glandular, dense-glandular
Oliver, *et al*. 2005 [58]	SBT	270	KNN	67.00	BIRADS I-IV
			Decision tree	73.00	BIRADS I-IV
Oliver, *et al*. 2008 [59]	SBT	322	SFS, KNN	86.00	BIRADS I-IV
Subashini, *et al*. 2010 [64]	SBT	43	SVM	95.55	Fatty, fatty glandular, dense glandular
Sharma, *et al*. 2014 [65]	ROI	322	SMO	96.46	Fatty, Dense
Tzikopoulos, *et al*. 2010 [66]	SBT	322	SVM	85.70	Fatty, fatty-glandular, dense-glandular
Blot, *et al*. 2001[67]	SBT	265	KNN	65.00	Fatty, fatty glandular, dense glandular
Qu, *et al*. 2011[68]	SBT	322	E-FELM	72.67	BIRADS I-IV
Bosch, *et al*. 2006 [61]	SBT	322	KNN, SVM	95.42	BIRADS I-IV
Z. Chen, *et al*. 2011[69]	SBT	322	KNN, Bayesian	75.00	BIRADS I-IV
Oliver, *et al*. 2010 [62]	SBT	322	LDA-PCA	94.00	Fatty, dense
Mustra, *et al*. 2012 [55]	ROI	322	KNN, Naive Bayesian	82.00	Fatty, Dense

Note- SBT: Segmented breast tissue

C. Feature extraction, selection and classification

Texture features are extracted from the selected regions of interest (ROIs) using the gray level difference statistics GLDS) [70], first order statistics (FOS) [71], statistical feature matrix (SFM) [72], Haralick's spatial gray level co-occurrence matrix (SGLCM) [73], Law's texture energy measure (TEM) [74], fourier power spectrum (FPS) [75]. Since intensity levels are different for dense and fatty tissues, various texture feature extraction models are helpful, as mentioned earlier. These features give the information about the spatial distribution of intensity value with the brightness, which can be helpful in breast density assessment [15]. After feature extraction, all the features are normalized to zero mean and unit variance. Performance evaluation of feature extraction algorithm and selected features by different authors are listed in Table V.

TABLE V: FEATURE EXTRACTION ALGORITHM AND EXTRACTED FEATURES BY DIFFERENT AUTHORS

Author(s)	Algorithms/Models	Extracted features	Database Used
Petroudi, *at al.* [31, 34]	Texton features	Statistical Distributions, Gray Level Based Features	Oxford database
Kallenberg *et al.* [35]	Location based features	Euclidean distance to the nipple, Skin, Pectoral muscle	EPIC Research lab, Netherland
	Intensity based features	Pixel value in the original image, Pixel value in the enhanced image, Pixel value in the normalized image, Difference between the normalized pixel value and the median pixel value of the pectoral muscle, Median pixel value of the breast tissue	
	Texture features	Gaussian derivatives, Entropy, Homogeneity, Variance	
Papaevangelou, *et al.* [36]	Statistical and textures features	Mean value, Standard deviation, Kurtosis, Skewness, Entropy, Median absolute deviation 1 and 0, Inertia, Cluster Shade, Cluster prominence, Correlation, IDF	Thriasio Hospital
Zhou, *et al.* [41]	Texture features	Energy, Standard deviation	University of Michigan
S. Chatzistergos, *et al.* [42]	Texton features	Mean value, Standard deviation, Kurtosis, Skewness, entropy, Inertia, Cluster Shade, Cluster Prominence, Correlation, Inverse Difference Moment, Mean absolute deviation, Median absolute deviation, Interquartile range	Local Database
Oliver, *et al.* [43, 44]	Morphological features	Relative area, Centre of masses, Intensity of both clusters	MIAS, DDSM
	Texture features	Contrast, Energy, Entropy, Correlation, Sum average, Sum entropy, Difference average, Difference entropy, Homogeneity	
H. Wenda, *et al.* [45]	Texture features	Contrast, Energy, Skewness, Kurtosis, Entropy, Homogeneity, Standard deviation, Moments up to the fourth order	MIAS
N. Vallez, *et al.* [46]	Morphological and texture features	Cuartil, Contrast, Sum Variance, Variance, Difference Entropy, Difference Variance, Correlation, Homogeneity, Cluster Shade, Autocorrelation, Dissimilarity	SFM
	Morphological and texture	Range, Maximum, Minimum, Asymmetry, Variance, Intercuartile Range, Correlation, Autocorrelation, Difference Variance, Sum Variance, Cluster Prominence, Cluster Shade	FFDM
Li *et al.* [48]	GLCM features	Balance and skewness	Department of Radiology, University of Chicago
	Spatial gray level features	Contrast and coarseness	
	Fourier Analysis	Root mean square of power spectrum, First moment of power spectrum	
	Fractal analysis	Fractal dimension	
Y. Kim *et al.* [52]	Statistical features	Mean intensity, Standard deviation	Seoul National University Hospital
Karssemeijer [54]	Grey level histogram features	Skewness, Variance	Nijmegen
Mustra, *et al.* [55]	GLCM features	Higher intensity than muscle region, Mean intensity, Standard deviation, Higher intensity than Otsu's threshold, Entropy, Skewness, Kurtosis	Mini-MIAS KBD-FER
Masmoudi, *et al.* [56]	LBPV features	Mean intensity, Standard deviation	EL FARABI
Liu, *et al.* [57]	Statistical features	Variance, Skewness, Kurtosis	Tianjin tumor hospital
Oliver, *et al.* [58, 59]	Morphological features	Relative area, Centre of masses, Intensity of both clusters	MIAS DDSM
	Texture features	Contrast, Energy, Entropy, Correlation, Sum average, Sum entropy, Difference average, Difference entropy, Homogeneity	
Bovis, *et al.* [60]	SGLD features	Angular second moment, Contrast, correlation, Inverse different moment, Sum average, Sum variance, Sum entropy, entropy, Difference average, Difference variance, Difference entropy, Information measure of correlation-1, Information measure of correlation-2,Inertia, Variance.	DDSM
	Fourier transform	Total Spectral Energy	
	Laws' texture features	total texture energy	
	DWT features	Standard deviation, Mean, Skewness, Kurtosis	
Bosch, *et al.* [61]	SIFT features	Edge Directions	MIAS, DDSM
	Texton features	Statistical Distributions, Gray Level Based Features	
Sharma, *et al.* [65]	SGLCM	Second moment, Contrast, Correlation, Sum of squares, Inverse difference moment, Sum average, Sum variance, Sum entropy, Entropy, Difference variance, Difference entropy, Information measure of correlation-1, Information measure of correlation-2, Maximal correlation coefficient.	MIAS
	GLDS	Homogeneity, Contrast, Mean, Energy, Entropy	
	FoS	Mean, variance, skewness, kurtosis	
	SFM	Coarseness, Contrast, Periodicity, Roughness	

	Law's	Edge-Level, Spot-Level, Wave-Level, Ripple-Level, Spot-Edge, Wave-Edge, Ripple-Edge, Wave-Spot, Ripple-Spot, Ripple-Wave, Edge-Edge, Spot-Spot, Wave-Wave, Ripple-Ripple	
	Fractal	Hurst coefficient at resolution 1 and 2	
	FPS	Radial sum, Angular sum	
Tzikopoulos et al. [66]	Intensity based features	Mean and variance of the pixel intensity values,	MIAS
	Intensity	Pixel value in the original image, Pixel value in the enhanced image, Pixel value in the normalized image, Difference between the normalized pixel value and the median pixel value of the pectoral muscle, Median pixel value of the breast tissue	
	Texture	Gaussian derivatives, Entropy, Homogeneity, Variance	
Blot et al. [67]	GLCM features	Mean intensity, Standard deviation, Entropy, Skewness, Kurtosis	MIAS

III. CONCLUSION

Mammographic images contain useful information for breast density estimation, which is a risk factor of breast cancer. For breast density classification, many CAD systems were developed but they still lack accuracy. These CAD system designs have either used the segmented breast tissue or a predefined ROI for further processing therefore, these CAD designs can be broadly classified as segmentation-based approaches and ROI-based approaches as described in this paper. Since BI-RADS categories are standard for measuring the breast cancer risks, so in near future, an automated system for the breast density classification has to be developed for early prediction of breast cancer in women on the basis of BI-RADS breast density type.

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