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Computer Aided Classification of Architectural Distortion in Mammograms Using Texture Features

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***Abstract*—**Computer aided diagnosis systems provide vital opinion to radiologists in the detection of early signs of breast cancer from mammogram images. Architectural distortions, masses and microcalcifications are the major abnormalities. In this paper, a computer aided diagnosis system has been proposed for distinguishing abnormal mammograms with architectural distortion from normal mammogram. Four types of texture features GLCM texture, GLRLM texture, fractal texture and spectral texture features for the regions of suspicion are extracted. Support vector machine has been used as classifier in this study. The proposed system yielded an overall sensitivity of 96.47% and an accuracy of 96% for mammogram images collected from digital database for screening mammography database.

***Keywords*—**Architecture Distortion, GLCM Texture features, GLRLM Texture Features, Mammograms, Support Vector Machine.

I. Introduction

MAMMOGRAPHY is a reliable screening tool for early detection of breast cancer. Early detection increases the chance for proper treatment and thereby increases the chances for survival. There are three signs of abnormalities that can detected in screening mammogram images, that are masses, microcalcifications and architectural distortions [1], [2].

In mammograms with architectural distortion, the normal architecture of the breast is distorted with no definite mass visible. Speculations radiating from a point and focal retraction at the edge of the parenchyma are also visible for mammograms with such abnormality. Architectural distortions are difficult to detect because their parenchymal features, its subtlety and changeable presentation. As a result, 12% to 45% of this type of abnormality is missed in screening of mammograms [3].

The classification rate of architectural distortion or subtle signs of manual reading of mammogram images is very low. The computer aided diagnosis system can help radiologists with a second opinion. Significant improvements have been made in computer aided diagnosis for but still work needs to be done to improve the accuracy of the diagnosis systems. So in a way to overcome the shortcomings of existing computer aided diagnosis systems and in order to improve accuracy and sensitivity a computer aided diagnosis system, a methodology has been proposed to classify normal and architectural distortion images. A methodology has been proposed to detect and distinguish regions with architectural distortion from normal regions based on texture analysis. Gray level co-occurrence matrix (GLCM) texture, gray level run length matrix (GLRLM) texture, fractal texture and spectral texture features have been extracted for each region which is input to support vector machine (SVM) for classification.

The remaining part of the paper is organized as follows. Section II discusses related work of researchers in brief. The details of database and datasets used in this research are discussed in Section III. The proposed methodology is explained in Section IV. Results and discussions are presented in Section V which is followed by conclusions.

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II. Literature Review

A few numbers of researchers have worked on detection and classification of mammograms with architectural distortion as compared to the masses and the microcalcifications. The related work of the researchers is discussed briefly.

Ichikawa et al. [1] proposed to detect areas of architectural distortion with spiculations. The region of suspicion was detected by concentration indexes of line-structures. They used discrimination analysis to distinguish regions with architectural distortion with the accuracy of the classification 76%.

Guo et al. [4] used Hausdorff fractal dimension to characterize regions with architectural distortion and used support vector machine (SVM) to distinguish regions with architectural distortion from normal regions. They achieved an accuracy of 72.5% for mammograms of mammographic image analysis society (MIAS) database.

Sampat et al. [5] proposed a system for detection of spiculated masses and architectural distortions based on their physical characteristics. They used radon transform to enhance the images and used radial speculation filters to detect spiculated lesions. For their work, they used images from digital database for screening mammography (DDSM) database. A sensitivity of 80% was obtained with 14 false positives per image in the detection of architectural distortion and sensitivity of 91% at 12 false positives per image for spiculated masses.

Nakayama et al. [6] decomposed the image into subimages at three scales by a novel filter bank based on wavelets and the Hessian matrix. For classification, quadratic discriminant functions was used, with convergence indices of linear structures at scale 1 to 3 and distributions of linear structures as input to this function. They achieved the sensitivity of 71.3% at 3.01 FP/image.

Rangayyan et al. [7] proposed a method for detection of architectural distortion of mammograms of interval cancer cases. They used Gabor filters, phase portrait analysis, fractal analysis, and texture analysis. They extracted fractal dimension and Haralick's texture features for each suspected region. Stepwise logistic regression was used for feature selection. They achieved an area under receiver operating characteristic (ROC) curve (AUC) as 0.77 with artificial neural networks (ANN) based on radial basis functions (RBF), as well as with SVM. The proposed method was tested on the mammograms collected from Aberta program.

Biswas and Mukherjee [8] proposed a model for recognizing architectural distortion in mammograms based on distinctive texture properties. They modeled different textures in mammograms by a mixture Gaussian distribution. Multiscale oriented filter bank was used for analyzing mammograms to form texture descriptor of vectorized filter responses. For the research they used MIAS as well as DDSM databases. They achieved 81.6% accuracy for mammograms from MIAS database and 88.3% accuracy for DDSM database.

Handa et al. [9] proposed a detection system by selecting those lesions whose intensities are higher as well as lower than those of the surrounding regions. They used difference of Gaussian (DoG) based filter and then they used a thresholding technique to reduce false positives. They achieved a sensitivity of 81% at 7.9 false positives per image for the mammograms taken from DDSM database.

Kamra et al. [10] proposed a methodology that detects the architectural distortion in mammograms by using a combination of Gabor filter with directional filters over the directional spectrum for the detection and the extraction of orientation fields. They achieved a sensitivity of 89% for mammograms taken from MIAS database.

Phadke and Rege [11] proposed a system to classify architectural distortion abnormality from other malignant abnormalities and normal regions. They extracted Gabor features and Law's texture energy measures features. For classification, SVM with RBF kernel function was used. For training and testing they used mammogram images from MIAS database. They achieved 90% sensitivity, 80% specificity and 82.86% accuracy.

Yoshikawa et al. [12] made an analysis of mammary gland structure, detection of the distorted region and reduction of false positive. They used Gabor filter for analyzing the mammary gland structure. They applied thresholding, based on breast density, to determine the initial guess of architectural distortion region. For reduction of false positive, SVM with 23 types of characteristic features was used. They achieved 82.72% sensitivity at 1.39 false positives per image for mammograms from DDSM database.

Bailur et al. [13] proposed a procedure to distinguish normal and architectural distortion regions through graphs, image plots and numerical values by drawing Andrew plot, mesh plot, contour plot and by Control chart. Images from MIAS database were used for testing, and efficiency of 89.4 percent was achieved.

Most of the researchers have determined the spiculated lesions and their orientation fields to analyze patterns for identification of mammograms with architectural distortion. But the approach that has been adopted in this research is based on simple procedure where first the suspicious looking region is extracted from the mammogram image. Thereafter texture features are extracted and classifier determines whether the region is abnormal or normal.

III. Database Used

Mammograms from digital database for screening mammography (DDSM) database have been taken for this work. This is a publically available database in which mammograms are digitized from screen film and it is assembled by a research group at the University of South Florida [14].

Two image sets have been prepared from 129 normal mammograms, 108 malignant mammograms and 21 benign mammograms have been collected from DDSM database. Set1 consisting of 39 normal, 39 malignant architecture distortion and 5 benign architecture distortion mammogram images has been used for training. The rest of the images have been grouped in Set2 and has been used for testing of the proposed methodology as shown in Table I.

TABLE I
Datasets Used for Classification

Image Set	Normal	Architectural Distortion	
		Malignant	Benign
Set1	39	39	05
Set2	90	69	16

IV. Proposed Procedure

Most of the methods proposed by researchers are based on detection of spiculated lesions, and a few are texture based. The proposed methodology for differentiation of normal mammogram and abnormal mammograms with architectural distortion as abnormality is based on identifying distinct texture features. The suspicious regions of mammogram images are extracted manually as square regions that may vary in size.

A. Preprocessing

These regions are enhanced with Contrast Limited Adaptive Histogram Equalization (CLAHE), which is a special case of the histogram equalization technique that functions adaptively on the image to be enhanced [15]. These regions are used for extraction of texture features. Four types of texture features have been extracted.

B. Feature Extraction

Texture features are considered important in computer aided diagnosis systems for mammograms. Filipczuk et al. [16] suggested that texture features are important in application to breast cancer detection. They used GLCM and GLRLM texture features to distinguish malignant tumor from a benign tumor. Best accuracy was achieved with GLRLM as texture statistic, by [17] for classification of mass and non mass mammogram images. It was concluded by [18] that texture analysis based on GLCM and GLRLM can produce considerably better results to distinguish malignant image and benign. Different techniques have been proposed by researchers to identify mammograms with architectural distortion. The method which has been proposed in this research is based on the extraction of texture features, since the texture of normal region and a region with architectural distortion is different. Rangayyan et al. [7] used GLCM based Haralick texture features, [11] extracted Laws' texture measures, [12] used Gabor texture features. Different texture features have been tried and a set of following four types of texture features has been proposed that result in better accuracy.

GLCM Texture Features: Texture features based on gray level co-occurrence matrix (GLCM) are widely used technique for texture analysis. This gives an estimation of second order statistics of an image since it collects information about pixel pairs. GLCM is a matrix of frequencies of pixel brightness values of an image.

The GLCM information is extracted on the basis of coefficients Haralick coefficient [19], [20]. Table II shows the list of GLCM based texture features. GLCM features have been extracted for four distances at four angles, 0°, 45°, 90°, 135°. These features are averaged for four angles, thereby giving 52 features.

TABLE II
DETAILS OF GLCM FEATURES

S.No.	GLCM Texture Features
1.	Correlation
2.	Cluster Prominence
3.	Cluster Shade
4.	Dissimilarity
5.	Energy
6.	Entropy
7.	Homogeneity
8.	Sum of squares: Variance
9.	Sum average
10.	Sum variance
11.	Sum entropy
12.	Information Measures of Correlation I
13.	Information Measures of Correlation II

GLRLM Texture Features: Gray level run length matrix (GLRLM) provides the information related to spatial distribution of gray level runs. GLRLM is a measure of the number of pixels that have the same intensity in a particular direction. GLRLM is a statistical texture measure that produces good classification results. The texture features extracted with GLRLM gives the distribution of short runs and long runs. The run length is the number of pixels in the run and run length value is the number of times such run length occurs in the image [21]. Seven GLRLM based features have been extracted as shown in Table III.

TABLE III
DETAILS OF GLRLM FEATURES

S.No.	GLRLM Texture Features Extracted
1.	Short Run Emphasis (SRE)
2.	Long Run Emphasis(LRE)
3.	Gray Level Non-Uniformity (GLN)
4.	Run Percentage (RP)
5.	Run Length Non-Uniformity (RLN)
6.	Low Gray Level Run Emphasis (LGRE)
7.	High Gray Level Run Emphasis (HGRE)

Spectral Texture Features: Spectral features compute the spectral energy distribution as a function of radius from center of spectrum. Spectral texture features are useful in differentiating periodic and non periodic texture patterns. These features are based on Fourier spectrum. The spectrum is expressed in polar coordinates to give a function $S(r,\theta)$, where S is spectrum function, r and θ are the variables of this coordinate system. For each direction θ, $S(r,\theta)$ is a 1D function, $S(r)$ that gives the pattern of behavior along a radial direction from the origin, for different values of θ. For each frequency r, $S(\theta)$ is a 1D function that gives behavior along a circle centered on the origin, for a fixed value of r [22]. $S(r)$ and $S(\theta)$ have been computed for all the regions of suspicion that have been resized to 128×128 to reduce the computational complexity and two features are extracted for these regions.

Fractal Texture Features: Fractal based texture features give an analysis of geometric complexity to describe spatial patterns of textures. Fractals indicate complex patterns that recur at various scales. Costa et al. [23] proposed Segmentation-based Fractal Texture Analysis (SFTA) procedure to extract texture features from grayscale image, in which image is decomposed into a set of binary images by using Two-Threshold Binary Decomposition (TTBD). For each of these binary images, fractal dimension from its region's boundaries are extracted. 12 SFTA based texture features have been extracted for each region of suspicion.

C. Classification

In order to classify the mammogram regions into normal and abnormal regions, the features extracted have been input to Support Vector Machine (SVM). SVM is based on the principle of optimal hyperplane. It predicts the output into best of two possible classes. It is different from other classifiers which try to minimize the training error and tend to overfit the training data [24]. In contrast to other classifiers SVM minimizes the empirical risk and maximizes the margin of data points from corresponding linear distance boundaries [25]. Guo et al. [4] worked on detection of architectural distortion and concluded that SVM produced better results in comparison to radial basis function neural networks. SVM with linear kernel function and sequential minimal optimization method has been used that resulted in better accuracy.

V. Results and Discussions

A methodology has been proposed to distinguish abnormal mammogram images with architectural distortion of the normal mammogram images. Feature set consisting of texture features has been prepared for each region of interest. SVM has been used to build a classifier model with Set1 and an output of Set2 is predicted. The performance evaluation parameter considered are sensitivity (Se), specificity (Sp), accuracy (Acc), positive predictive value (PPV), negative predictive value (NPV) and Youden's index. A classification system results a False Positive (FP) if the system labels a negative point to a positive point, False Negative (FN) if the system labels a positive point to a negative point, True Positive (TP) and True Negative (TN) if the system predicts the label correctly [26].

In this proposed detection system, TP is taken as number of abnormal image classified as abnormal (malignant as well as benign), TN value is number of normal images correctly identified, FP is number of normal images classified as abnormal and FN is abnormal images classified as normal. The output of testing set is compared with the original class attribute to get the values of true positive, true negative, false positive and false negative. Table IV shows the sensitivity, specificity, accuracy, PPV, NPV and Youden's index for Set2. The overall accuracy of the proposed detection system is 94.29%. PPV, that indicates system's ability to show the abnormality if classifier results positive, is 0.9213. NPV, that indicates system's ability to show normal if the disease is not there, is 0.9651. Youden's index that indicates system's ability to dodge failure is 0.8869. The area under the receiver operating characteristic (ROC) curve (AUC) is 0.9435.

TABLE IV
Performance Parameters for Proposed System

S.No.	Parameter	Output
1	Misclassified Abnormal	3
2	Misclassified Normal	7
3	Sensitivity	0.9647
4	Specificity	0.9222
5	Accuracy	0.9429
6	PPV	0.9213
7	NPV	0.9651
8	Youden's Index	0.8869

Four types of texture features have been used in this paper. The contribution of these texture features individually has been analyzed. Sensitivity, specificity, accuracy, PPV, NPV and Youden's index of these texture features is shown in Table V. AUC for spectral, GLCM, GLRLM, and fractal features is 0.7471, 0.7703, 0.8415 and 0.8899 respectively. A plot of ROC for these features is shown in Fig. 1.

The performance of all the possible combinations of these features has also checked and it has been observed that best output has been achieved when a combination of all of these features has been considered.

The proposed system is also checked for its performance and its generalization capability with K-fold cross validation procedure. K-fold cross-validation has been applied on testing set (Set2) to compute values of sensitivity, specificity, accuracy. The value of K is varied from 5 to 15 and results are shown in Table VI for each value of K, average of 10 iterations is considered. Accuracy varies from 94.11% to 96.77%. Best results are achieved at K=10, having an accuracy of 96.37% with sensitivity 97.83% and specificity 94.82%.

TABLE V
Performance Parameters for Different Features

Features	Se	Sp	Acc	PPV	NPV	Youden's index
Spectral	0.4941	1.0000	0.7543	1.0000	0.6767	0.4941
GLCM	0.7294	0.8111	0.7714	0.7848	0.7604	0.5405
GLRLM	0.6941	0.9889	0.8457	0.9833	0.7739	0.6830
Fractal	0.8353	0.9444	0.8914	0.9342	0.8586	0.7797

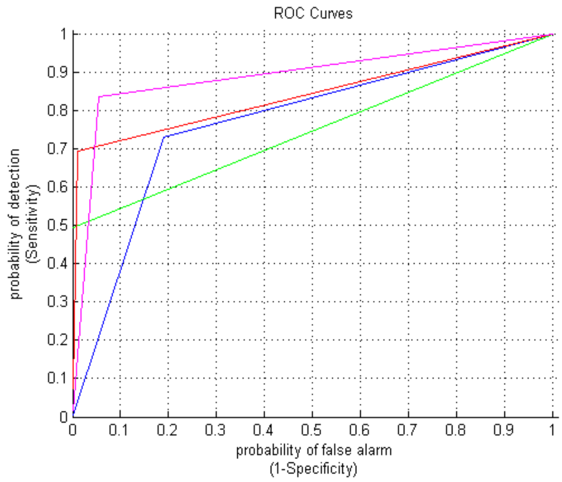

Fig. 1 Contribution of various features

TABLE VI
Results after K-Fold Cross-Validation

Value of Cross Validation	Se	Sp	Acc
5	0.9873	0.9009	0.9453
6	0.9751	0.9085	0.9428
7	0.9956	0.8982	0.9483
8	0.9898	0.8981	0.9446
9	0.9849	0.9223	0.9545
10	**0.9783**	**0.9482**	**0.9637**
11	1.0000	0.8931	0.9475
12	0.9605	0.9202	0.9411
13	0.9879	0.9177	0.9548
14	0.9899	0.9075	0.9501
15	0.9983	0.9142	0.9569

To improve the classification performance, the box constraint C for the soft margin in SVM has been considered. The performance of the system has been checked by varying the value of C from 0.2 to 1.5 as shown in Table VII. It has been observed that best performance has been achieved at C=0.4 as well as C=0.5 where accuracy of classifier achieved is maximized. Only three abnormal images have been misclassified as normal. The accuracy achieved at these two values of C is 96% with sensitivity 96.47% and specificity

95.56%. AUC at these values is 0.9601. The ROC curve at C=1 and at C=0.4 or 0.5 is shown in Fig. 2.

TABLE VII
PERFORMANCE PARAMETERS FOR DIFFERENT VALUES OF C

C	Sensitivity	Specificity	Accuracy
0.2	0.9529	0.9333	0.9429
0.3	0.9529	0.9333	0.9429
0.4	**0.9647**	**0.9556**	**0.9600**
0.5	**0.9647**	**0.9556**	**0.9600**
0.6	0.9647	0.9444	0.9543
0.7	0.9647	0.9444	0.9543
0.8	0.9647	0.9444	0.9543
0.9	0.9647	0.9333	0.9486
1.0	0.9647	0.9222	0.9429
1.1	0.9647	0.9222	0.9429
1.2	0.9647	0.9222	0.9429
1.3	0.9647	0.9222	0.9429
1.4	0.9647	0.9222	0.9429
1.5	0.9647	0.9111	0.9371

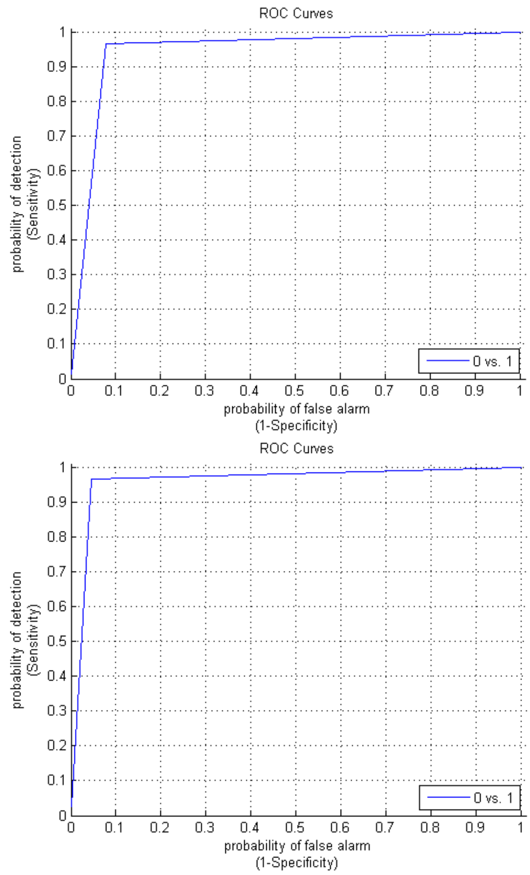

Fig. 2 ROC using SVM at C=1 and at C=0.5 or C=0.4

The work of this paper has also been compared with the work of the other researchers. The exact comparison however is not possible due to variation in the use of the database, the datasets or the regions taken from that database. A brief comparison in terms of sensitivity, specificity, accuracy and AUC is made as shown in Table VIII. It has been observed from the table that there is an improvement in the performance of the proposed detection system.

TABLE VIII
A COMPARISON OF PROPOSED SYSTEM WITH OTHER SYSTEMS

Paper and author	Year	Se (%)	Sp (%)	Acc (%)	AUC
Ichikawa et al.[1]	2004			76.00	
Guo et al.[4]	2005			72.50	
Sampat et al.[5]	2005	91.00			
Nakayama et al.[6]	2008	71.30			
Rangayyan et al.[7]	2010				0.77
Biswas& Mukherjee[8]	2011	89.20	86.70	88.30	
Handa et al.[9]	2012	81.00			
Kamra et al.[10]	2012	89.00			
Phadke and Rege[11]	2013	80.00	90.00	82.86	
Yoshikawa et al.[12]	2013	82.72			
Bailur et al.[13]	2014			89.40	
Proposed Methodology	2015	96.47	95.56	96.00	0.96

VI. CONCLUSIONS

The goal of this work is to provide the radiologists/experts a second opinion in the form of the computer aided diagnosis system that is more reliable and has higher accuracy. A methodology has been suggested to distinguish mammograms with architectural distortion from normal mammograms. The methodology proposed is a simple and effective in discriminating this abnormality. The texture features used in this work are able to distinguish the abnormal regions from normal ones. Some of the abnormal images, however, could not be detected due to their normal like appearance or their presence in the dense breast area. Work is being done to further to include the other abnormalities along with architectural distortion and an optimal set of features that may distinguish the abnormal region from a normal one.

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