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# Classification of Architectural Distortion from Other Abnormalities in Mammograms

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**ABSTRACT**

***Screening mammograms is a repetitive task that causes fatigue and eye strain. For thousands of cases analyzed by a radiologist, not more than ten are cancerous and thus an abnormality may be overlooked. Computer-aided detection (CAD) algorithms are developed to assist radiologists in detecting mammographic abnormalities. In this paper, a CAD system is developed to classify Architectural Distortion abnormality from other malignant abnormalities and normal mammogram samples. Gabor features and Law's Texture Energy measures are used to detect architectural distortion. Classification is done using Support Vector Machines (SVM). SVM identifies the architectural distorted sample from other samples. SVM is implemented using RBF kernel function. Algorithm is tested for two datasets one set which includes all abnormalities except speculated masses and other set includes all abnormalities along with speculated masses.***

**Keywords:** Computer-Aided Detection (CAD), Mammograms, Architectural Distortion, Support Vector Machines (SVMs), Kernel Functions

## 1. INTRODUCTION

Breast cancer is among the most common and deadly of all cancers, observed in most of the women in developed cities. Breast Cancer is a type of cancer where cells in the breast divide and grow without normal control. A tumor can be benign (not dangerous to health) or malignant (has the potential to be dangerous). Normal, Benign and Malignant mammograms are shown in Fig. 1(a), 1(b) & 1(c). Mammography is a standard medical imaging modality used to screen for breast cancer, although there are many others. All women who are suspected of cancer go through mammography screening procedures for early detection and diagnosis of tumor. Early detection leads to early diagnosis and better plan of action for effective treatment. Mammography is simple, low cost and non-invasive. CAD systems are developed to aid radiologists to provide a second opinion and may be used in the first stage of examination. The final decision is left to the radiologists. A typical mammogram is an intensity x-ray image with gray levels showing levels of contrast inside the breast which characterize normal tissue and different calcification and masses. Some of the important signs of breast cancer that radiologists look for are clusters of microcalcifications, circumscribed masses, spiculated masses and architectural distortions. Fig 2 shows Architectural Distortion, Spiculated Mass, Microcalcification & Circumscribed mammogram images.
An architectural distortion is one with no definite mass visible. This includes spiculations radiating from a point, and focal retraction or distortion of the edge of the parenchyma. Masses and calcium deposits are easy to see by x-ray because they are much denser than all other types of soft tissues around.

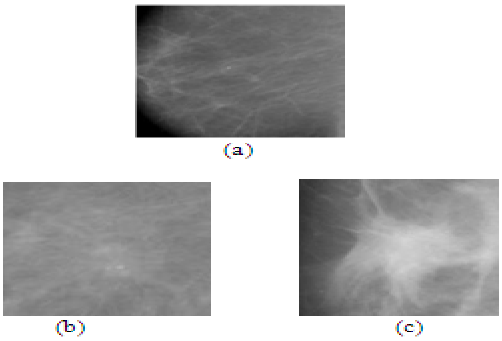


**Fig. 1** (a) Normal, (b) Benign & (c) Malignant Mammograms

A mammogram, due to the presence of several piecewise linear structures, such as ligaments ducts, and blood vessels, can be considered as an image with oriented texture. The normal oriented texture pattern, which typically converges toward the nipple, is distorted in the presence of architectural distortion. No definite mass is visible in case of architectural distortion. A limited number of research publications exist on the analysis of the performance of commercial CAD systems in detecting architectural distortion. Algorithm for detection of architectural distortion using Gabor features and Laws Texture Energy measures is implemented.

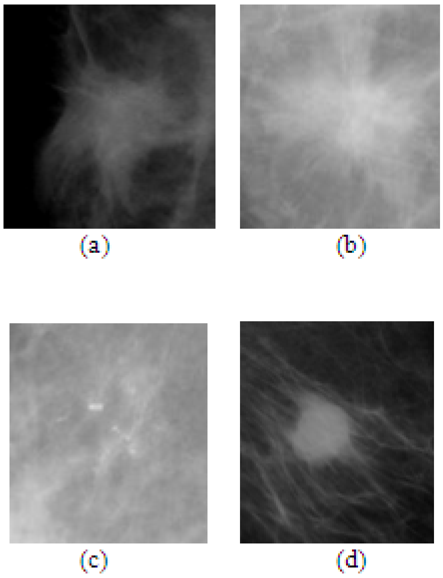


**Fig. 2** (a) Architectural Distortion, (b) Spiculated Mass (c) Microcalcification & (d) Circumscribed

Architectural distortion is defined in the Breast Imaging Reporting and Data System (BI-RADS) as follows: "The normal architecture (of the breast) is distorted with no definite mass visible. This includes speculations radiating from a point and focal retraction or distortion at the edge of the parenchyma. Architectural distortion can also be an associated finding." Architectural distortion is the third most common mammographic sign of nonpalpable breast cancer, but due to its subtlety and variable presentation, it is often missed during screening. Whereas many publications have been directed toward the detection and analysis of calcifications and masses, relatively few have been published on the detection of architectural distortion in mammograms.

U.S.Ragupathyet et al discuss use of Gabor filter for detection of architectural distortion [1]. They use Adaptive Neuro Fuzzy Inference System for classification of mammograms. Minavathi, et al use model based approach for detection of architectural distortion [2]. The model is based on Gabor filters. Shantanu Banik et al make use of angular spread of power spectral density for detection of architectural distortion [3]. Amit Kamra & Jain propose a hybrid methodology that combines a Gabor filtration with directional filters over the directional spectrum for detection of architectural distortion in digitized mammograms [4]. Sujoy Kumar Biswas and Dipti Prasad Mukherjee propose a generative model for constructing an efficient set of distinctive textures for recognizing architectural distortion in digital mammograms [5]. Rangayyan & Leo present methods for the detection of architectural distortion in mammograms of interval cancer cases taken prior to the detection of breast cancer using Gabor filters, phase portrait analysis, fractal analysis, and texture analysis [7]. Desautels Shormistha Prajnaet al use texture and fractal features for detection of architectural distortion [9]. Ayres and Rangayyan applied Gabor filters and phase portrait maps to characterize oriented texture patterns in mammograms to detect architectural distortion [10]. T. Matsubaraa, et al developed two detection approaches for architectural distortions existing around skinline and within mammary glandular tissues [11]. Dheeba J and Tamil Selvi S make use of SVM classifier to classify microcalcification into benign and malignant [6].

## 2. METHODOLOGY

The objective of this work is to develop a system which can help classify the architectural distortion abnormality from other abnormalities and normal samples at a very early stage. Fig. 3 shows the block schematic of the same. Architectural distortion commonly exhibits a node-like pattern with speculations that appear to radiate from a point. However, curvilinear structures related to ligaments, ducts, vessels, and edges of parenchymal regions that overlap in the mammographic projection image could also give rise to similar patterns. The derivation of features related to the textural patterns and characteristics of the regions of architectural distortion to assist in separating them from normal region is described in the following sections.

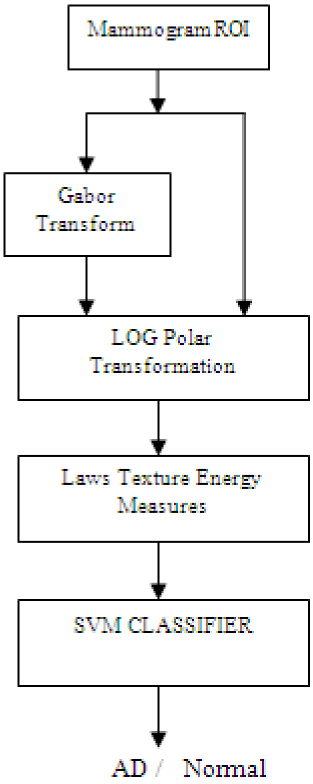



**Fig. 3** System Block Diagram

**2.1 Gabor filter features**

Potential sites of architectural distortion in the prior mammograms were detected initially by the analysis of oriented texture patterns with the application of Gabor filters and linear phase portrait models, as follows:
Gabor filters were used as detectors of oriented features; the real Gabor filter kernel oriented at the angle is given by,

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

Kernels at other angles were obtained by rotating this kernel. The parameters in 1, namely $\sigma_x$, $\sigma_y$ and f were derived using the design rules proposed by Rangayyan and Ayres [10]. A set of 180 Gabor kernels with angles spaced evenly over the range [-Π/2, Π/2] was used. For each image, a magnitude response and orientation field was obtained by using the response and angle of the Gabor filter with the highest response at each pixel.

**2.2 Laws' texture energy measures**

Laws' texture energy measures are based on convolution kernels that emphasize specific structural patterns, and could be used to generate useful features related to the intersecting tissue structures, spiculations, and node-like patterns of architectural distortion. Laws used several 1-D and 2-D convolution kernels to classify each pixel in an image based on measures of local texture energy. 1-D operators of length five pixels, such as L5 = [1 4 6 4 1], R5 = [1 -4 6 -4 1], W5 = [-1 2 0 -2 1] are used to generate 2-D convolution masks of size 5 x 5 pixels to emphasize center-weighted local average (L5L5 = $L5^T$ L5), ripples (R5R5 = $R5^T$ R5) and wave patterns (W5W5 = $W5^T$ W5), respectively. Laws' L5L5, R5R5, W5W5 masks are shown in Fig. 4. The rectangular ROIs detected automatically and their Gabor magnitude responses of the same size were transformed to the polar coordinates. This geometric transformation converts speculated patterns into ripple or wave patterns. Because architectural distortion is expected to include speculations radiating from a point at or near the center of the corresponding ROI and node-like patterns, we hypothesize that Laws' 5 x 5 convolution masks for the wave detector (W5W5), the ripple detector (R5R5), and the center weighted local average (L5L5) should provide discriminant information.
The transformed ROIs and the transformed Gabor magnitude responses were convolved with Laws' 5x5 convolution masks designed for the detection of waves (W5W5), ripples (R5R5), and the center-weighted local average (L5L5). In addition, two other masks, W5W5 rotated by 45 and R5R5 rotated by 45, were used. Following the application of the selected filters, texture energy measures were derived from each of the filtered images by computing the average of the squared values in a 15x15 sliding window.

Finally, the sum of each of the energy measures normalized by the area of the transformed image was used to derive ten features (five from the transformed ROIs and five from the transformed Gabor magnitude responses) for feature selection and pattern classification.

$$\text{L5L5} \quad \begin{array}{ccccc} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{array} \qquad \text{R5R5} \quad \begin{array}{ccccc} 1 & -4 & 6 & -4 & 1 \\ -4 & 16 & -24 & 16 & -4 \\ 6 & -24 & 36 & -24 & 6 \\ -4 & 16 & -24 & 16 & -4 \\ 1 & -4 & 6 & -4 & 1 \end{array}$$

$$\text{W5W5} \quad \begin{array}{ccccc} 1 & -2 & 0 & 2 & -1 \\ -2 & 4 & 0 & -4 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & -4 & 0 & 4 & -2 \\ -1 & 2 & 0 & -2 & 1 \end{array}$$

**Fig. 4** Laws' Texture Energy Masks

### 2.3. Support Vector Machine (SVM)

SVM is a constructive learning procedure rooted in statistical learning theory. It is based on the principle of structural risk minimization, which aims at minimizing the bound on the generalization error (i.e., error made by the learning machine on data unseen during training) rather than minimizing the mean square error over the data set. As a result, this leads to good generalization and an SVM tends to perform well when applied to data outside the training set. SVM schemes use a mapping into a larger space so that cross products may be computed easily in terms of the variables in the original space making the computational load reasonable. The cross products in the larger space are defined in terms of a kernel function K(x,y) which can be selected to suit the problem. The hyperplanes in the large space are defined as the set of points whose cross product with a vector in that space is constant. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters αj of images of feature vectors which occur in the data base. With this choice of a hyperplane that points x in the feature space which are mapped into the hyperplane are defined by the relation,

$$\sum_{i=1}^{N_s} \alpha_i K(x, s_i) = b \qquad (2)$$

Where Si,, i= 1,2,…N is the subset of training samples, {xi, i=1,2,…N} are the support vectors and b is a constant. By introducing the kernel, SVMs gain flexibility and SVMs can be robust, even when the training sample has some bias. The support vectors in the Fig. 5 are elements of the training set that lie exactly on or inside the decision boundaries of the classifier [12]. The classifier uses these borderline examples to define its decision boundary between the two classes (i.e 'Architectural Distortion' or 'Other') [12].

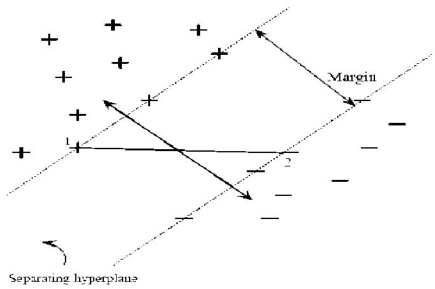



**Fig. 5** Support Vector Machine with a hyperplane

## 3. SYSTEM IMPLEMENTATION

### 3.1 Database resource

The mammogram images used in this experiment are taken from the mini mammography database of MIAS (Mammogram Image Analysis Society). The database contains 322 mammogram images in mideolateral oblique view. The original MIAS Database (digitized at 50 micron pixel edge) has been reduced to 200 micron pixel edge and clipped/padded so that every image is 1024 pixels × 1024 pixels [13].

**3.2 Sub-images generation**

MIAS images are very large in size hence there is a need to crop and resize the images. MIAS database provides center and radius of abnormality for all the images. So according to the given center, we crop the images to size 128 x 128 squared around the given center.

MIAS database provides ten cases of Architecural Distortion abnormility. Out of these ten cases six are used for training the SVM classifier and all ten are used to test the classifier. Two sets of samples are used to test the classifier. Set1 consists of four architectural distortion, four Normal, ten Microcalsification, four circumscibed masses, seven misscelaneous samples. Set2 consists of four architectural distortion, four Normal, ten Microcalsification, four circumscibed masses, seven misscelaneous and eight spiculated lesion samples.

**3.3 SVM classifier**

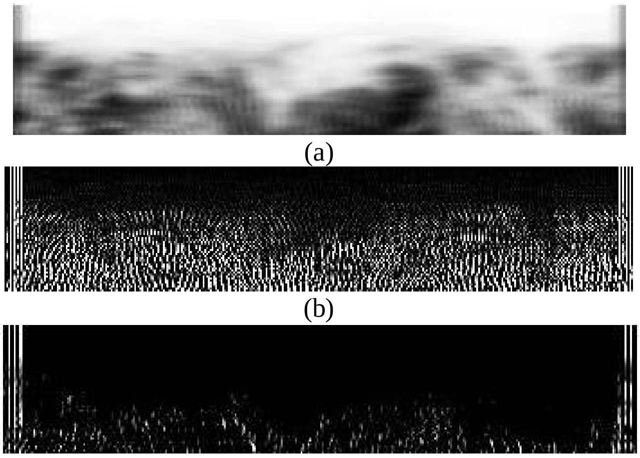
Total ten features are determined for each image of the training set and these features are used to train a SVM classifier for discriminating Architectural Distortion samples and normal or other abnormalities. The key attribute of SVMs is to map the data into the feature space where a hyperplane (decision boundary) separating the classes may exist. This mapping is achieved via the use of kernels, which are the functions which return the scalar product in the feature space by performing calculations in the data space. The simplest is the linear SVM trained to classify linearly separable data. The distance between the two parallel hyperplanes on which the support vectors for the respective classes lie is called the margin. SVM finds a decision boundary that maximizes the margin. For non-linear classification, kernels are used to map the data into a higher dimensional feature space in which a linear separating hyperplane can be found. The kernel function used is radial basis function with sigma value 0.6.

## 4. RESULTS

**4.1 Performance measures**

The performance measures enable appropriate evaluation of the classification technique. The performance of the proposed approach for the classification of normal and abnormal images is measured by Classification Accuracy, Sensitivity and Specificity.

**4.2 Analysis of result**



(a)

(b)

(c)

**Fig. 6** Results of applying Laws filter on Log-Polar Transformed ROI on image mdb155

The selected ROI is transformed using Log-Polar transform. Then Laws texture energy measures are determined by filtering this image using Laws filters. The geometric transformation as described above converts speculated patterns into ripple or wave patterns as illustrated in Figs. 6 (a), (b), (c). Fig. 6(a) is result of applying L5L5 Laws filter to the Log-Polar transformed image. Fig. 6(b) is result of applying R5R5 Laws filter to the Log-Polar transformed image. Fig. 6(c) is result of applying W5W5 Laws filter to the Log-Polar transformed image.

Two sets Set1 and Set2 of samples are used to test the SVM based classifier. Classifier classifies the samples into architetural distortion and others. Set1 includes all abnormalities except speculated masses and Set2 includes all abnormalities along with speculated masses. Results of classification of Set1 and Set2 are given in Tabel 1 and Tabel 2.

**Table 1:** Result table for Set 1

| Type of Image | Total Number of Images | Correct | Wrong |
|---|---|---|---|
| Other | 25 | 20 | 5 |
| Architectural distortion | 10 | 09 | 1 |
| Total | 35 | 29 | 6 |

**Table 2:** Result table for Set 2

| Type of Image | Total Number of Images | Correct | Wrong |
|---|---|---|---|
| Other | 33 | 23 | 10 |
| Architectural distortion | 10 | 09 | 1 |
| Total | 43 | 32 | 11 |

## 5. CONCLUSION

The work is done on a standard known database MIAS, which is readily available on the internet. In this work, Gabor features and Laws' texture energy measures are used to classify Architectural Distortion. SVM classifier with RBF kernel function is used.

Results for detection of architectural distortion are given in Table 1 and Table 2. Table 1 shows results for Set 1 which includes all types of abnormalities except speculated lesions. With Set1 we get 90 % sensitivity, 80 % specificity and 82.86 % accuracy. Table 2 shows results for Set 2 which includes all types of abnormalities. With Set 2 we get 90 % sensitivity, 69.70 % specificity and 74.42 % accuracy. From these results it is clear that our algorithm gives less accuracy when we use speculated lesion samples along with other types of abnormalities for classification. So we can conclude that our algorithm can not differentiate well between architectural distortion and speculated lesions. So in order to differentiate between these two types of abnormalities additional features need to be explored.

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