Research Article
Breast Cancer Detection Using Multi-resolution Diatric Microarray Curvelet Transform

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Abstract: In this study, a computer aided breast cancer diagnosis framework to group masses in the Mammography Image Analysis Society (MIAS, 2012) database mammogram images utilizing Improved Square Centroid Lines Gray level distribution Method (ISCLGM) is presented. Breast cancer is the heading reason for non-preventable cancer passing among women. Early discovery of the cancer can lessen death rate. Studies have demonstrated that radiologists can miss the identification of a noteworthy extent of anomalies not withstanding having high rates of false positives. In this study, he key peculiarities utilized for the characterization of ISCLGM is extracting the features through three dimensional magnetic resonance based Texture Detection algorithm and get classified using the Multi-resolution Diatric curvelet Transform by Gradient field analysis and they are fed into SVM classifier to classify mass/non-mass image and also benign/malignant images. This System enables the radiologists to assist the breast cancer cells more effectively through the SVM (Support Vector Machine) based Microarray feature selection technique. The proposed method provides classification accuracy of 98% and yields greater efficiency in detecting the breast cancer.

Keywords: Computer aided diagnosis, mammogram, multi-resolution diatric curvelet transform, square centroid lines gray level distribution method

INTRODUCTION

Breast cancer is a proliferation of malignant cells that arises in the breast tissue, specifically in the terminal ductal-lobular unit. Scientists are exploring how the tumour growth cells may affect breast cancer risk. A large, long-term study funded by Gaza, is the breast cancer which is the most common malignancy, accounting for more than 30% of all cancer in females. The incidence rate among the women in Gaza is 15.6/100,000 persons, is now being done to help find the causes of breast cancer and it has enrolled 340,460 women with breast cancer in the recent years.

Early detection of cancer treatment impact in the main requirement for computational methods to detect micro calcifications in mammograms is to keep the shape and the size of individual image structures of cancer cells (Eltoukhy *et al*., 2009). The challenge is to employ Computer Aided Detection (CAD) techniques for the purpose of assisting radiologists in the early detection of cancer, by processing and analyzing images. The techniques used in CAD schemes are diversified. Several types of filters and techniques using region growing, thresholding, mathematical morphology and segmentation have been applied.

The computer aided detection techniques are used for radiologists to detect mammogram which required magnified lenses (Christoyianni *et al*., 2002). The

images obtained in this technique examine the malignant or benign tumors growth cells and results in 50-60% of false positives (Elfarra and Ibrahim, 2012). It may lead to inefficient in some cases in identifying the tumor's growth in interior veins of blood cells. To overcome this, Mammography Image Analysis Society (MIAS, 2012), utilizing the method of dyadic wavelet transform which allows radiologists to view the breast in small slices providing more detailed images of specific areas, of the malignant growth cells. The computer aided Detection technique in this research work carries the five step process in detecting the image: Feature Extraction, Feature Selection Technique and Segmentation and classified the cancer cells by Gradient Field analysis in Improved Square Centroid Lines Gray Level Distribution Method.

The Mammography image produced may results in existence of invisible noise which results in reducing the examining of the malignant cells. To overcome this Multi-resolution Diatric curvelet Transform through three dimensional magnetic resonance based Texture Detection algorithm has been proposed in which produces efficient result in detecting the features of malignant cancer cells (Brown *et al*., 2009). After removing the noise disturbances, Support vector machine classifier can differentiate benign and malignant cancer cells growth size which helps in

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determining the optimal size of the training set and perform feature selection.

The main goal of this research implies in identifying the breast cancer exist in the minute tissue of the body. The Research of this study proposes Improved Square Centroid Lines Gray Level Distribution Method using Gradient Field Analysis which provides potential efficient in recognizing the breast cancer and it becomes the valuable technology in identifying the cancer cells even in the interior tissues of breast. It results in identifying and preventing the breast cancer at early starting stage and reduces the fatality rate in breast cancer.

LITERATURE REVIEW

Essential work has done in identifying the breast cancer cells. Some researcher defined the process for finding the breast cancer cells, but it cannot be an effective method in decreasing to a maximum extent in fatality rate of breast cancer disease.

The author Keller *et al.* (2012) investigated the amount of fibro glandular tissue content in the breast as estimated mammographically, commonly referred to as breast Percent Density (PD%), is one of the most significant risk factors for developing breast cancer. Development of an algorithm in this study which effectively estimates breast in both raw and post processed digital mammography images would be beneficial in terms of direct clinical application and retrospective analysis yet it has limitation in density analysis on a single type of digital mammographic image.

In the paper Sadeghi-Alidbadi *et al.* (2013) proposed the features of the valid streaks along with the color and texture features of the entire breast cancer cells, an accuracy of 76.1% and weighted average Area Under ROC Curve (AUC) of 85% is achieved for classifying cancer images into streaks The data set has also been applied to the two-class sub-problems of Absent/Present classification (accuracy of 78.3% with AUC of 83.2%) and to Regular/Irregular classification (accuracy 83.6% with AUC of 88.9%). When the method was tested on a cleaned subset of 300 images randomly selected from the 945 images, the AUC increased to 91.8, 93.2 and 90.9% for the Absent/Regular/Irregular, Absent/Present and Regular/Irregular problems, respectively. This challenging dataset is the largest validation dataset for streaks detection and classification published to date but it is impractical while applying streak classification in higher density analysis of breast cancer.

In D'Aloia *et al.* (2013) which is intended in Computer-Aided Detection (CAD) systems, which automatically detect signs of illness in its early stage, are important and necessary for breast cancer control. They provide a second opinion to help physicians detect abnormalities. Micro-calcifications and masses are the two most important indicators of illness malignancy and their automated detection is very valuable for early breast cancer diagnosis. The high correlation between the appearance of micro calcification clusters and diseases suggests that CAD systems for the automated detection of Micro-calcifications clusters can be very useful and helpful for avoiding misdiagnosis and for early stage cancer detection. The present study summarizes the various methods adopted for micro calcification cluster detection and compares their performance. This study results in difficulty for radiologists to provide both accurate and uniform evaluation particularly because of the large number of mammograms to be analyzed.

The author Minavathi *et al.* (2013) dissected the work of detection of abnormalities in breast is done in different phases using different modalities and different biomedical techniques. These techniques and modalities are able to furnish morphological, metabolic and functional information of breast. Integrating these information assists in clinical decision making. This study concentrates on early detection of breast cancer which characterizes the breast mass as malignant or benign by investigating the features retrieved from dual modalities mammograms and Ultrasound using SVM classifier. Architectural Distortion (AD) with Speculated mass is an important finding for the early detection of breast cancer. SVM classifiers achieved 95.6% sensitivity in characterizing the breast masses using the features retrieved from two modalities. But it is difficult to retrieve all these information from single modality.

Piliouras *et al.* (2004) proposed an efficient classification algorithm is proposed for characterizing breast lesions. The algorithm is based on the cubic least Squares Mapping and the Linear-kernel Support Vector Machine (SVMLSM) classifier. Ultrasound images of 154 confirmed lesions (59 benign and 52 malignant solid masses, 7 simple cysts and 32 complicated cysts) were manually segmented by a physician using custom developed software. Texture and outline features and the SVMLSM algorithm were used to design a hierarchical tree classification system. Classification accuracy was 98.7%, misdiagnosing 1 malignant and 1 benign solid lesion only. This system may be used as a second opinion tool to the radiologists. It developed a developed a high performance and accuracy classification technique, but not discovered about comprised images of simple cysts, complicated cysts, benign and malignant lesions.

Tzikopoulos *et al.* (2011) presented fully automated segmentation and classification scheme for mammogram, based on breast density estimation and detection of asymmetry images. First, image pre-processing and segmentation technique are applied, including a breast boundary extraction algorithm and an improved version of a segmentation scheme, features for breast density categorization are extracted, including a new fractural dimensional related feature. A SVM are employed for classification, achieving accuracy of up to 85%. It detects the breast cancer cells

yet inefficient in finding the origin of breast cells in the interior of the tissue.

MATERIALS AND METHODS

The radiologists while diagnose a breast cancer in mammogram, they look for some significant features that discriminate malignant from benign masses due to the advancement and developing technology in medical science. These visual features which are based on shape, size, thickness of the breast cancer cell and margin-could have different interpretation based on radiologist's opinion and experience. To overcome the problem of these different interpretations, more discriminative features should be extracted. Mammography Image Analysis Society provides multiple methods for obtaining these discriminative features, which can be done in five steps.

Feature extraction: Features are extracted for each suspected area representing textures, statistical properties, spatial domain, fractal domain or wavelet bases (Fu *et al*., 2005). Feature extraction is an important factor which directly affects the classification result. Most systems extract features to detect abnormalities and classify them as benign or malignant. There are various feature extraction methods that serve to condense input data and to reduce redundancies by highlighting important characteristics of the image (West *et al*., 2001) proved that the use of multi resolution analysis of mammograms improves the effectiveness of any diagnosis system based on wavelet coefficients. The classification of benign and malignant cancer image is still a difficult and challenging problem for researches. To overcome this problem, the proposed feature extraction can be done by three dimensional Multi-resolution magnetic resonance based texture detection algorithm (Dehghani and Dezfooli, 2012). The extracted feature is fed in to the SVM classifier.

Breast cancer cells have higher x-ray attenuation coefficient than normal soft tissues, which means higher intensity in mammography image. The extraction of features is an important step that affects the classification process in pattern recognition and CAD systems. Current CAD systems relay heavily on sophisticated methods in machine learning to address the area of pattern recognition and classification which has high computational load, leading to longer time for Multi-resolution analysis (Christoyianni *et al*., 2002). The early detection of breast cancer cells features can be identified by using the three dimensional Magnetic Resonance based Texture Detection algorithm.

Three dimensional magnetic resonance based texture detection algorithm: MRI has exceptional sensitivity for the detection of breast cancer and can depict cancers that are entirely occurs on conventional imaging. Reported sensitivities for invasive cancers using Statistical Texture Detection algorithm are consistently produce efficiency greater than 90%. Magnetic Resonance based Texture Detection algorithm is clinically used to provide volumetric three-dimensional anatomical information and physiologic information that are indicative of increased vascular density and vascular permeability changes associated with angiogenesis (Luzzatto, 2011). One of the most widely used indications for imaging is to preoperatively evaluate known tumors for size of tumor, extent of disease, multi-centricity and multi-focality.

Texture-based algorithms divide the image into regions yielding different statistical properties. Such methods assume that the statistics of each region are stationary and that each region is extended over a significant area (Eltoukhy *et al*., 2012). The Magnetic resonance is included to generate an image reference for cancer cells with high intensity. This Multi-resolution image using three dimensional magnetic resonance results in identifying the early detection of cancer image and the detection area of breast cancer can be shown in Fig. 1.

In this study, a computer aided breast cancer diagnosis framework to group masses in the Mammography Image Analysis Society (MIAS) database mammogram images utilizing Improved Square Centroid Lines Gray level distribution Method (ISCLGM) is displayed.

In Fig. 2 shows a weighting for each optical parameter per its importance for malignancy. The statistical features can be detected by using the mean [$<H_na(0)>H$] and standard deviation (g [[$<H_na(0)>H$]) of healthy tissue from the earliest available time point (T = 0) during the process.

Normal breast tissue and log-transformed in each subject reconstructed parameter such as total hemoglobin concentration Ha_t, blood oxygen saturation Bs; and reduced scattering coefficient $M_{s\ and}$ tumor cell thickness B. The log-transformed data were then normalized using healthy-tissue averages to derive a 'C$_a$-Score' for each parameter in each tissue voxel (e.g., the difference of tissue voxel property "Hn (X)" and its corresponding mean in the healthy-tissue region was determined and the result was then divided by the standard deviation of "Ln (X)" in the healthy region). The subscript index H_n specifies the healthy tissue region. The denominator is the standard deviation (g) of the log-transformed voxel data in the patient's healthy tissue.

For example, the 'C$_a$-Score' for total hemoglobin is given by:

$$C_a H_{at} = \frac{H_n[H_{at}] - < H_n[H_{at}] > H_1}{g[H_n[H_{at}]]H_1} \tag{1}$$

The malignant parameter μ can be calculated at each position r can be given by:

$$\mu(r) = [zHa_t(r), zBs(r), Ms(r), B(r)]\alpha \tag{2}$$
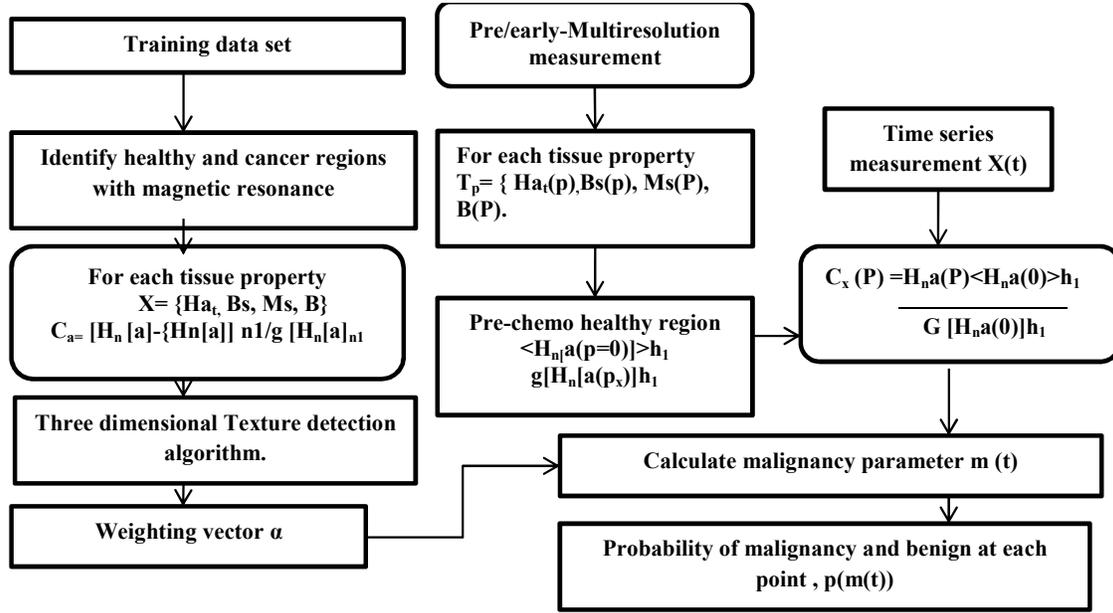
Fig. 1: Proposed Data Processing Flowchart for detecting breast cancer with multiple measurements
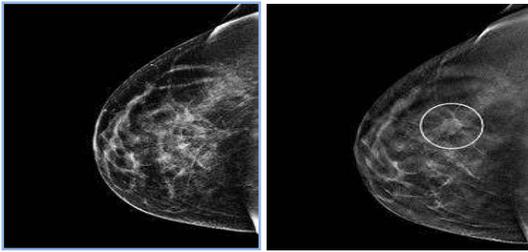
Fig. 2: Defected breast cancer cell is identified with the features obtained by three dimensional magnetic resonance based texture detection algorithm

The tissue malignancy/benign can be computed using a probability of malignant function:

$$\frac{P(\mu)=1}{1+e^{-\mu(r)}} \qquad (3)$$

The Eq. (3) optimize *r* such that the difference between healthy ($P(\mu_H) \sim 1$) and malignant ($P(\mu_M) \sim <1$) tissues in our training set is identified.

Feature selection technique: The next step in CAD tool is Feature selection and the technique applied for extracting the feature selection is SVM based Microarray feature selection technique (Ponraj *et al.*, 2011). In this technique, the extracted feature can be selected and organized in to array structure. The datasets has been taken from the SVM based microarray which carries the subsamples data and it can be calculated by using the algorithm.

SVM based microarray feature selection algorithm:
Array R = [] and *S′* = Make subsamples [Ha$_t$, Bs, Ms, B]; *t* = 1, *T*

While *S′* ≠ [] do
Train *T* SVMs, with features in set *S′*
for *j* = 1 to *T* do
DJj = *DJj*×μ (r) end for
for all feature *l* ∈ *S′* do
Compute the ranking score *cl* using Eq. (1)
end for
e = *argminl* (*cl*) where *l* ∈ *S′*
R = [*e*, *R*]
S′ = *S′* - [*e*]
end while
return *R*.

Feature segmentation: Segmenting the breast cancer image is an important factor and it classifies the breast tissue under various categories. The algorithm evaluates the region properties of the mammogram image and thereby would classify the image into important segments. Images from MIAS database (Mammogram Image Analysis Society database (UK)) have been considered to conduct experiments and the segmentation thus obtained is comparatively better than the other normal methods. The validation of the work has been done by visual inspection of the segmented image by an expert radiologist (Soltanian-Zadeh *et al.*, 2004). This is our basic step for developing a Computer Aided Detection (CAD) system for early detection of breast cancer.

Extended Expectation Algorithm (EEA): The proposed algorithm used for segmenting the image is Extended Expectation Algorithm (EEA) algorithm assigns each pixel in the mammogram membership to one of an eight number of classes depending upon the statistical properties of the pixel and its neighbors. The individual pixel classifications form a two-dimensional
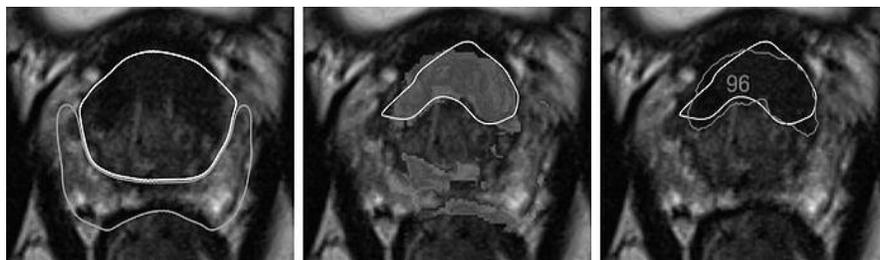
Fig. 3: The segmentation results of a breast cancer mammogram by using the extended expectation algorithm

Table 1: Comparison of different data samples (segmented by extended expectation algorithm) with a radiologist results

Data sample no.	Area (malignant tissue)	Area (benign tissue)	Detection efficiency for radiologists in existing system	Detection efficiency for radiologists by proposed EEA algorithm
331	27.8	24.2	4.9	5.2
296	58.3	60.8	1.8	6.3
100	75.6	83.3	8.2	9.6

labelled which must be estimated from the observed image. Both the mammogram and its labelled fields are modelled as discrete-parameter random fields. We estimate the pixel classes by minimizing the expected value of the number of misclassified pixels; this is known as the marginal estimate. The texture class labels X as a Markov Random Field (MRF) with a four-point nearest-neighbor system and probability mass function is defined as:

$$PX(x) = 1 \exp((zHa_t(r), zBs(r), Ms(r), B(r)) - gxr) \quad (4)$$

where, gxr are MRF model parameters, z is a normalizing constant and t (m; n) = 0, if m = n; t (m; n) = 1, if m is not equal to n. We will assume that the pixels in the observed image Y can be modelled as conditionally independent Gaussian random variables given the pixel labels X and that the conditional probability density function of the pixel at location r given X depends on the value of pixel location:

$$f\left(Y, X\left(\frac{y}{x}, q\right)\right) = pf\left(\frac{y_r}{x_r}\right)\left(\frac{y_r}{x_r}, q\right) \quad (5)$$

The value of q = [mi, s2i], with mi and s2i being the unknown mean and variance for texture class and ranges the value i = {1…L}, where L is the number of texture classes. We must assign each pixel in the mammogram membership in one of the L classes subject to minimizing the expected value of the number of misclassified pixels. The estimate which minimizes this expected value is estimate of X. The EEA estimate at pixel S is given by:

$$X_S = \arg\max(S) + P_{X/Y}\left(\frac{x}{y}, q\right) \quad (6)$$

Images used in this research were obtained from MIAS mammogram database. In this experiment, images were assumed to consist of three classes: background, normal tissue and tumor. For the spatial interaction parameter, its value is 3:6. A tumor is usually associated with higher grayscale values than the other regions, by sorting the grayscale values in the observed image and uses the sample mean and variance of the largest grayscale values as the initial parameter estimates for the tumor class (Nakayama *et al.*, 2006). The remaining values are then used to obtain initial estimates of the parameters for the normal tissue and background region. In addition to segmenting abnormalities, algorithm can also indicate the reliability of each classified pixel by using the marginal conditional probability mass function of the labelled estimated by Eq. (4). This information is displayed as an image where each pixel value is proportional to the marginal conditional probability associated with classified pixel, i.e., larger gray-level indicates higher reliability of classification. The proposed Extended Expectation algorithm detected 100% of the abnormal tissues in the 7 mammograms that contain circumscribed masses, 65% of the 17 mammograms that have malignant tissues, but only 58% of the 12 mammograms that have benign lesions and the produced segmentation results are shown in Fig. 3.

The images can be used by the radiologist directly. This creates a synthetic 'second reader', allowing every image set to be read by two readers, the radiologist and the computer. It reduces the workload for the radiologists while increasing their detection performance and gives an efficiency of 96% in detecting the breast cancer in early stage and it is resulted in Table 1.

Feature classification: Computer-Aided Diagnosis (CAD) is a technology used for detection and characterization of cancer. Although CAD is not limited to a single type of cancer, a large number of CAD systems to date have been designed and used for breast cancer. Various classification methods have been used for classifying mammogram masses into malignant or benign. The Proposed feature classification can be obtained by:

- Multi-resolution Diatric curvelet Transform by Gradient field analysis

- Improved Square Centroid Lines gray Level Distribution Method (ISCLADM)
- SVM classifier to classify mass/non mass images and also benign/malignant images.

RESULTS AND DISCUSSION

Multi-resolution diatric curvelet transform by gradient field analysis: A computer-aided diagnosis system using the Multi-resolution Diatric Curvelet Transform (MDCT) algorithm is proposed for interpreting mammograms in early stage and the proposed system for mammogram diagnosis is shown in Fig. 4. The purpose is to develop a method for the characterization of the mammography as both mass and non-mass regions and to determine its diagnostic performance to differentiate between malignant and benign. The Multi-resolution Diatric curvelet Transform that was recently derived is used to differentiate among 220 mammograms: 60 malignant, 60 benign and 120 normal. A support vector machine is used as classifiers to build the diagnostic model. A dataset from the Mammographic Image Analysis Society database is used for testing the method.

The proposed Diatric curvelet Transform is a multistate and multidirectional transform that provides a better representation of the objects with edges. It also involves coefficients to represent the curves. After that, the frequency plane is divided into wedges. The wedges have a parabolic shape as a consequence of dividing the plane into radial and angular partitions. Finally, gradient field is applied to each wedge to find the curvelet coefficients. Radial divisions are responsible

for decomposing the image into multiple gradient scales and angular partitions corresponding to different angles. Because of this, addressing the particular wedge is necessary to determine the angle and the scale. Each wedge corresponds to a particular curvelet according to a specific scale and angle in the spatial domain through gradient field analysis. It performs classification tasks by constructing optimal separating radial division that maximizes the margin between the two nearest data points belonging to two separate classes. Given a training set $\{(x_i, x), I = 1, 2,..., m\}$, where the input and class labels ($x_i \in \{+1, -1\}$), the separation of gradient scales classification is given by:

$$k(X, X_i = ((x_i, x) + 1)^d \tag{7}$$

where x, xi represents input data in training set and d is the polynomial factor in which different samples of data from the training set and testing set is calculated. In the first step of the work, the dataset is classified as normal and abnormal. The dataset is divided into a sample in 220: 110 for training and 110 for testing. The training set has 60 abnormal and 60 normal mammogram samples. The testing set also has 60 abnormal and 60 normal mammogram samples. The sensitivity and specificity analyses are done for the same data:

$$Sensitivity = \frac{TP}{TP + FN} \tag{8}$$

$$Specificity = \frac{TN}{FP + TN} \tag{9}$$
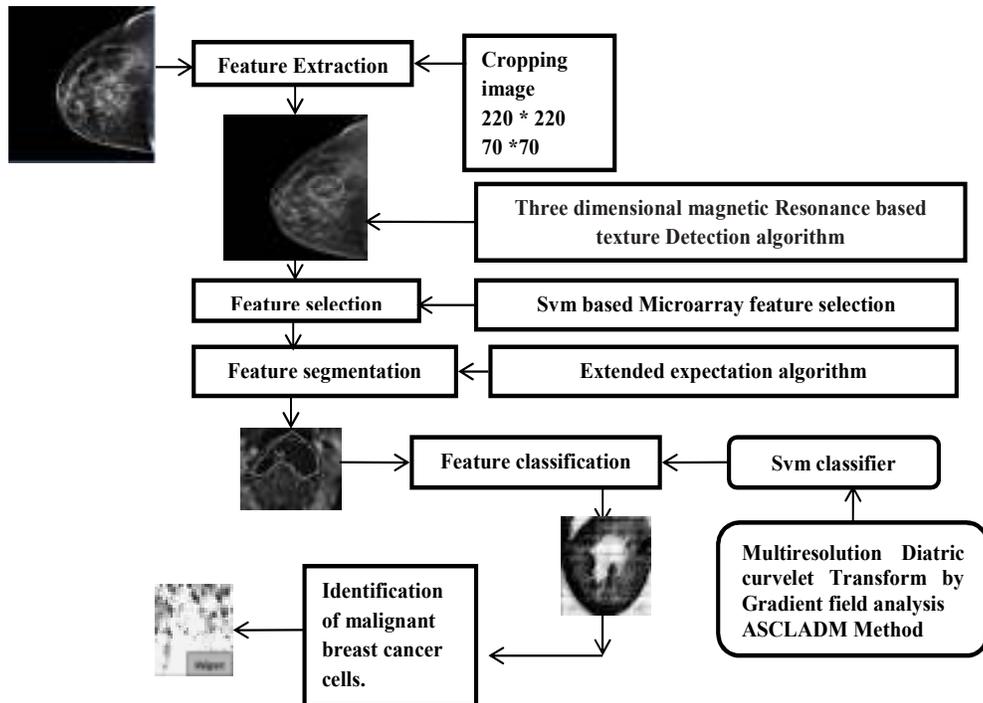
Fig. 4: The proposed System for mammogram diagnosis

Table 2: Classification success rates and sensitivity and specificity values for separating the mammogram images as malignant/benign and mass/non mass via SCLGLDM and (ISCLGLDM+MDCT)

	Existing system of Square Centroid Lines Gray Level Distribution Method (SCLGLDM)			Proposed system of Improved Square Centroid Lines Gray Level Distribution Method (ISCLGLDM) + Multi-resolution Diatric Curvelet Transform (MDCT)		
Pixels	Success rates (%)	Sensitivity (%)	Specificity (%)	Success rates (%)	Sensitivity (%)	Specificity (%)
120*120	58	58	58	98	100	96
	63	75	47	98	100	96
60*60	42	52	34	92	92	96
	57	67	67	90	92	96
60*60	48	53	44	90	90	92
	54	80	80	91	92	92
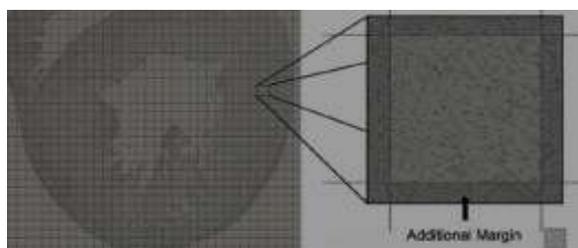
Fig. 5: Visualizing the breast cancer at each interior cell pixel range (120*120, 60*60 and 60*60) by applying the improved square centroid lines gray level distribution method
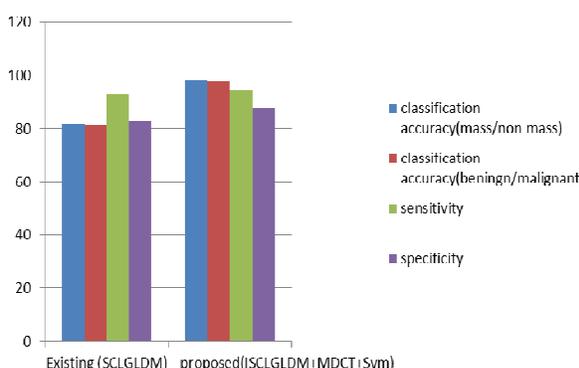
Fig. 6: Predicting Efficiency in detecting breast cancer with an Existing SCLGLDM and Proposed system

where, TP, TN, FP and FN indicate the true positives, true negatives, false positives and false negatives, respectively.

Improved Square Centroid Lines gray level Distribution Method (ISCLADM): The classified tumor obtained from the Multi-resolution Diatric Curvelet Transform is further classified in to a new feature proposed method as "improved Square Centroid Lines Gray level distribution Method (SCLGM)". In this method the smallest square that includes the segmented mass and the relations between the pixels of each centroid line provide discriminative information about the mass type and it is shown in Fig. 5. The proposed method consists of six centroid lines (Ci): C1 at $\theta = 0$, C2 at $\theta = \pi/4$, C3 at $\theta = \pi/2$ and C4 at $\theta = 3\pi/4$, C4 at $\theta = 3\pi/2$, C4 at $\theta = 2\pi/2$ which is the lines that pass through the square's centre point. The gray level points at each centroid line are represented by Ic_g as:

Table 3: The classification accuracy rate of mass and non-mass (in percentage)

Class	Proposed (ISCLGLDM + MDCT) (%)	Previous (SCLGLDM) (%)
Mass	97.10	76.70
Non mass	100	86.67
Classification accuracy	98.55	81.69

Table 4: The classification accuracy rate of benign and malignant (in percentage)

Class	Proposed (ISCLGLDM + MDCT)	Previous (SCLGLDM)
Benign	100	62.50
Malignant	96	100.00
Classification accuracy	98	81.25

Table 5: The results of sensitivity and specificity obtained during the training and testing stage using SVM classifier

Stage	Sensitivity (%)	Specificity (%)
Training stage	92.9	94.3
Testing stage	88.0	83.0

$$Ic_g = \forall (X,Y,Z) p : x_1 \sin\theta - y_1 \cos\theta - x_2 \sin\theta + y_2 \cos\theta + x_3 \sin\theta - y_3 \cos\theta = 0,$$

$$where (x_c, y_c, z_c) \ is \ the \ square \ centre \ XY, Z \in \theta \left\{ 0, \frac{\pi}{4}, \frac{2\pi}{4}, \frac{3\pi}{4}, \frac{2\pi}{2}, \frac{3\pi}{2} \right\}$$

(10)

SVM classifier to classify mass/non mass images and also benign/malignant images: The set of images provided by the Mammographic Image Analysis Society (MIAS, 2012) dataset is used in applying the proposed technique. These images are previously investigated and classified by an expert radiologist based on Improved Square Centroid Lines Gray Level Distribution Method and Multi-resolution Diatric curvelet transform. This dataset is selected according to the various cases it includes and it is classified through SVM classifier to perform training and testing stage. This data set is composed of 322 mammograms of right and left breast, from 161 patients, where 60 were diagnosed as Malignant, 60 Benign and 120 Normal.

The data set was divided into two groups, 50% for constructing for training and 50% for testing (Rashed *et al.*, 2007). Table 1 presents the data set distribution between mass and non-mass and also the distribution of abnormalities between benign and malignant. After performing the SVM classifier, the result is tabulated in Table 2 to 5.

Figure 6 illustrates the efficiency and early identification of breast cancer in classifying the mass/non mass and benign/malignant cancer image.

CONCLUSION

Breast cancer diagnosis using a digital mammogram is a practical field for medical application. In this study, implemented a CAD system and investigate the performance of the Multidimensional Diatric curvelet Transform method in the problem of recognizing breast cancer in the three dimensional magnetic resonance based Texture Detection algorithm of digital mammograms. A different classification scheme is applied in the classification of breast cancer. The presented results demonstrate that MDCT is a useful tool to discriminate malignant/benign and mass/non mass breast cancer tissues. The proposed System yields greater efficiency of 98% in detecting breast cancer. Based on these results, the proposed system is observed that features provide significant support for more detailed clinical investigations and the results are very encouraging when tissues are classified. It decreases the fatality rate due to breast cancer and provides early identification in detecting breast cancer.

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