Classification of Digital Mammograms Into Masses and Non-Masses using Texture Combination Features and SVM

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Abstract: This paper presents a framework for grouping of mammogram images into carcinogenic and non- carcinogenic images. In this paper, image is enhanced using nonlinear contrast enhancement algorithm and then segmented using internal and external mask segmentation. The features used in the proposed work are based on the texture feature which means that the segmentation results will have minimal impact on the classification results of mammograms into masses and non – masses. The features used are Contrast, Energy, Homogeneity, Entropy, Mean Intensity, Standard Deviation, Taxonomic distinctness, Taxonomic distance and learning takes place by Support Vector Machine. The algorithm was applied on Mammographic Image Analysis Society database and when compared with contemporary techniques , the results were improved.

Keywords: Mammograms, Content Based Image Retrieval (CBIR), Support Vector Machine(SVM), Segmentation.

I. INTRODUCTION

Breast cancer unending reason for expiration of females in European nations. The disclosure of cancer of breast at initial stage can minimize the breast cancer fatality. The European nations are working hard to detect malignancy at an early stage. The early stage disclosure can be achieved with mammography. The mammograms can't restrain breast cancer, but they can save the life of the patient by discovering breast cancer at earlier stage. Medicinal images play an imperative role in the disease analysis, education and exploration. The progression of computer vision and digital image tone has engendered a mammoth extent of digital images in medical territory [1].

The susceptibility of the mammograms varies approximately between 70's and 90's that rely on the parameters like location and lesion size, the density of breast tissue, exam quality, patient age and interpretation ability of radiologist. To guarantee that the particular region is cancer, medical check-up is being required.

Thus, as of late, there has been magnified enthusiasm for the advancement and utilization of mammographic picture handling strategy, with the crucial goals of outspread symptomatic accuracy and giving a moment sentiment to the doctors. These procedures have been utilized to create PC supported identification/PC symptomatic (CAD/CADs) frameworks

CBIR denotes the preview of mammograms in the data store that are significant to a query, utilizing the information that are derived from the images themselves ,instead of depending on textual information or any other labels. The system importance has got increased as a consequence of the accessibility of large image databases including, military commerce, medicines and the science. CBIR is intended to remove the various problems with the retrieval of text image based upon text as it is time consuming and labeling each and every image in large database is a time taking process. Secondly, the labeling is highly subjective and differs from user to user [2].

II. LITERATURE WORK

Various techniques are being established for the developed tools that help the radiologists in the premature cognition and diagnosis of cancer. The process of detection of cancer that is concerned with the breast starts with the enhancement of the mammographic image followed by segmentation. In [3] a comparative study of indirect contrast enhancement of mammographic images was provided. Histogram equalization and its many variant were applied on mammographic images for indirect contrast enhancement and performance was calculated using efficient measure of Peak Signal to noise ratio (PSNR) and enhancement. In[4] a new method for edge enhancement and suppression of the noise of mammographic images using haar wavelet was discovered. The results obtained even in image regions that contain low contrast and the tissues that are dense were better.

After enhancement of mammographic image, the next step considers the identification of the masses from the mammographic images. In [5] review of the different existing ways of the segmentation of masses and the automatic detection in the image of mammographs was done. The execution of seven mass detection procedures is being looked at by database of two dissimilar mammographic images and the results were given according to the terms of Free –response Receiver Operating Characteristic (FROC) analysis and Receiver Operating Characteristic (ROC).

For the division of mammogram into breast and background ,

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author anticipated a novel strategy by examining the area surrounded by outline based on iso intensity[6]. Results were assessed by examination by manual outskirts drawn by different professionals for an arrangement of many mammograms. The thickness of pectoral muscle locale is like tumor cells in the MLO vision of the mammograms which makes it crucial to segment it from breast region before further processing. A procedure in view of positional characteristic of pectoral muscle in the locale of breast to join the repetitious grey thresholding based on inter class variance and morphological operations to find boundary of pectoral muscles was given in [6]. The different regression model are utilized onto the unpleasant fringe so as to acquire a precise division of the pectoral muscle and results got by the calculation matches with that of master radiologist

After segmentation of breast masses, next step is to group the masses as malignant and benign. In [7], author then apply the filter called as iris at a variety of scales and segmented the suspicious region by the methods of thresholding based on neighbor pixels. The segmented areas were portrayed by output of iris filter, texture, intensity and morphological features. To lessen the number of false positives the back propagation neural network is used. In [8] a three step procedure for recognition of mammographic masses was introduced. Firstly, enhancement of image is done to improve the contrast of an image depending on the statistical parameters. Then region of interest were segmented from the enhanced region using thresholding and malignant masses images were ordered by region ranking system based on the features computed.

In [9], researcher contemplated a system using breast density features to extract mammography using BIRADS standards and images were retrieved using support vector machines. Two dimensional principal component analysis was utilized for breast thickness texture characterization, so as to adequately considers the texture and take into consideration dimensionality decrease. In[10], an algorithm was proposed in which artifacts including the pectoral muscles were removed before processing the Region of Interest extracted from mammograms. Statistical features were extracted to represent the breast tissue which was fed into support vector machines in order to classify them into glandular, dense and fatty tissues.

In [11], an advanced CAD system for detecting abnormalities based on common information depending on matching of templates with templates selected precisely. The algorithm chooses the most useful template using substantial database of earlier collected and labeled mammograms. In [22] , a computational strategy was presented to guide the professionals in identifying the masses of breast in mammogram images. Mammographic images were preprocessed prior to segmentation using cellular network. The shapes and textures of the region of interest was analyzed using shape descriptors and geostatic functions and delegated as non-masses or masses using SVM.

In [12], a system was developed which employed an input image to examine for comparative mammograms in the database. The mammographic abnormalities were deciphered in light of their medical qualities determined in BIRADS standards. The features were arranged in terms of hierarchy based on their relevance and distance measure was used to compute the similarity. Relevance feedback was employed to examine the information needed by user's so as to extract the target images more precisely.

In[13] , a system was developed which permitted doctors to find lesions in mammograms that are similar to a given illustration. The similarity measure was made consistent with the radiologists by employing mammographic features in a tree like structure and computing distance based on weights. In [21], a system was proposed for distinguishing calcified area by deciding definite asymmetric areas among the sets of mammograms of both breast. After that the variogram capacity is used to every dissimilar area independently for characterization as malignant or benign.

Prior detection of breast cancer can decrease the casualties due to breast cancer. Masses and micro calcification are initial symptoms of breast cancer but due to subtle appearance and ambiguous margins, they are difficult to distinguish as masses and non-masses. In[14] , a classification approach by PSO Wavelet Neural Network was developed. The system extracted abnormalities from the measures computed by Law Texture Energy on Laws Texture Energy from the mammograms and categorizing the doubtful area of interest by using a pattern classifier.

One of the main barriers in employing neural networks to the medical field is that it's terribly tough to interpret in terms of physically substantive ways because result of the learned data is numerically encoded within the trained conjunction weights. In [15], a PSO based mostly Fuzzy Hyper-Rectangular Composite Neural Network that applies particle swarm optimization to carve the rules produced by the trained Hyper Rectangular Composite Neural Network while maintaining the recognition performance or even improving it was developed.

The next challenge was to develop a learning framework for heterogeneous medical retrieval. In [16], authors proposed an evolutionary strategy for constructing a decision system and to asses and compare the results of medical databases with existing techniques. A unified learning frame of reference for heterogeneous medial image retrieval based on a Full Range Autoregressive Model with the Bayesian approach was developed in [17]. Using the unified approach, the color autocorrelogram, edge orientation autocorrelogram and micro-texture information was extracted. Adaptive binary tree based SVM for effective as well as fast categorization of medical images in feature vector space was used. The performance was analyzed by Precision and Recall graph and results showed that the recommended system for heterogeneous medical image database is fitter than the existing systems at low computational and storage cost.

In [18], researcher classified areas extracted from breast images as non-masses or masses by means of taxonomic distinctness and taxonomic diversity index as texture features for the areas of interest. Depending upon phylogenetic trees the indexes were computed, that are applied to depict the pattern in the areas of mammograms. The results demonstrated promising performance of texture extraction technique with the support vector machine. In [19], a CAD system was presented using Wavelet Co-occurrence Feature set and maximized classification accuracy using Genetic Fuzzy System.

After converting mammogram images into corresponding wavelet coefficient using db8 wavelet function, Wavelet Co-occurrence feature were computed from wavelet coefficients of detail sub-bands from mammogram decomposition. The highest classification accuracy was achieved with sixteen discriminative features from four level of mammogram decomposition. In [20], author presented a novel method to evaluate the irregularity and property of rough textures by modeling pictures as realizations of some intrinsic random fields that behave as fractional anisotropic Brownian fields at high frequencies. From the straight line properties of those variations, two textural indices calculating each irregularity and aniosotropy property were accustomed to discover lesions in mammograms. Results tested that the indices captured vital data concerning tissues of mammograms and served for detection of all lesion sorts.

III. MATERIALS AND METHODS

In the given part, the various steps of the methodology used are elaborated which includes acquisition of images, pre-processing, extraction of features, classification of the masses and validation of the results. Fig. 2 represents the order of steps in terms of flow chart. The objective of the algorithm is to find out whether the input image given is cancerous or non-cancerous. If the image is classified as a cancerous, then it is called mass and if the image is classified as non-cancerous image, then it is called non-mass. The various steps used for the classification process have been elaborated in the next section .

A. Acquisition of Images

The images used for the system are acquired from the MIAS database. The MIAS database is shorthand for Mammographic Image Analysis Society which consists of total of 322 mammographic images comprising of Cranial-Caudal and Medio Lateral view images of 161 women. The images in the MIAS database corresponds to various types of images which represents masses and calcification which has different labeling indicating different things about mammograms. In MIAS the first column indicates the reference number of MIAS database, second column indicates the character of the background tissue, third column represents the class of the abnormality present in the image and fourth column depicts the abnormality severity present i.e. image is cancerous or non-cancerous. In addition to this, other information includes the x and y image coordinates of the abnormality center along with the approximate radius of the circle encompassing the abnormality. The dimesnions of all the images is 1024 X 1024 pixels. The class distribution and distribution of type of abnormalities in MIAS database are shown in Fig. 1(a) and Fig. 1(b)

Fig. 1(b) Distribution of type of abnormalities in MIAS

Fig. 2 Flowchart for the Classification of Image as Mass/Non –Mass

Fig. 1(a) Class Distribution of MIAS Database

B. Image Enhancement

To segment the image abnormality precisely, the preprocessing step performed before segmentation is image enhancement. In this, Logarithmic nonlinear contrast enhancement method is used to raise the quality of the image so that the fine details from the mammograms can be extracted which was not possible with the mammogram with some noise or lack of clarity. It is a nonlinear model for image processing which is used to keep the grey level values within a particular range and to process the images more accurately from human visual view point.

C. Region of Interest (ROI) Extraction

After enhancement of image, the next step is extraction of the region of interest from which various features will be extracted. The image acquired from the MIAS database are converted into grey level image and then converted into smaller range of output values which closely approximates the original image. For segmentation, firstly quantization of image is performed which means converting the large range grey level values into small range grey level values. The image is quantized into five different grey level values i.e. 256, 128,64,32,16. After that for region extraction, thresholding of image is performed which is process of converting grey level image into binary level image by means of Otsu's thresholding technique. After thresholding, the final part is ROI extraction from the image which means extraction of the part of the region which is contributional to a particular application. The region obtained after segmentation will output the image part that is to be checked for cancer. The ROI is divided into layers to perform local analysis , which is utile because pixels at the center of the region will give origin of mass and boundary pixel will elaborate that mass has developed. Thus we find the texture feature by constructing a diversity tree in each layer. Internal and external masks are used for separately finding these layers.

D. Quantization

After preprocessing, the next step is to represent the image with lesser number of grey levels. The image which is represented with M number of pixels , after quantization will be represented by N number of pixels where M>N. The input grey level sets is mapped into smaller number of grey level values. Then the image is analyzed and represented at different grey levels. In our proposed work, the images are quantized into 5 grey level values: 256, 128, 64, 32 and 16.

E. Region of Interest and Feature Extraction

After quantization, the succeeding step is to divide the ROI into layers namely external and internal mask which is then presented to feature extraction sub stage of texture feature extraction using diversity trees. The aim of region of interest division into different layers is to perform local analysis, which is utile because these layer areas may supply information which differentiates between non – masses and masses. For example, the pixel at the center may indicate mass origin whereas the pixel at the border will indicate how mass has grown. The texture features are described by means of diversity trees. Internal and external masks are used to find these layers. The first internal mask is decided by binarization of the measure ROI. The second internal mask was firm by binarization of the measure ROI. The second internal mask is predicated on sequential reductions of the dimensions of the ROI with relation to the primary one whereas maintaining the center of mass. The concept of Region of Extraction of Mammographic images are given in Fig. 3. Fig. 3(a), Fig. 3(b) and Fig. 3(e) represents the segmentation of mammogram which are non-cancerous. Fig. 3(c) and Fig. 3(d) exemplify the segmentation of the image which are cancerous. The output of the Region of Interest Extraction using internal and external mask as specified in the procedure is shown in the each phase.

There are many conventional techniques of image segmentations. One of the technique is edge detection by means of prewitt, sobel, Laplacian of Gaussian and Canny edge detection techniques. If the comparison is made between the used algorithm and the contemporary techniques, used method show far better results against the existing conventional techniques.

Fig. 4 shows the comparison of the designed segmentation approach with the segmentation approaches like Laplacian of Gaussian, Canny edge detection. The first column Fig. 4(a) represents the original image. Fig. 4(b) represent the Laplacian of Gaussian edge detection. Fig. 4(c) show the Canny edge detection whereas the last column Fig. 4(d) represent the segmentation with the proposed method.

F. Feature Extraction

Posterior quantization, ensuing step is to divide the ROI into layers particularly internal and external mask which is then presented to feature extraction sub stage of texture feature extraction by diversity trees. The target of breaking the region of interest into different layers is to perform local analysis, that is helpful as these areas of the layer may provide data which differentiates between non – masses and masses. For example, the pixel at the center may indicate mass origin whereas the pixel at the border will indicate how mass has grown. The texture features are described by means of diversity trees. Internal and external masks are used to find these layers. The first internal mask is decided by binarization of ROI which is quantized. The second internal mask is resolved by binarization of the measure ROI. The second internal mask relies on ordered curtailment of the dimensions of the ROI with regard to the primary one whereas maintaining the mass center.

G. Diversity Trees

Diversity trees find application in Biology to represent the hierarchical relationship between the various species of the organisms. The species are represented by leaves and the ancestor to the species is represented by internal nodes. Hence it is possible to depict the relationship between different species i.e. finding out which species belong to which organism. The difference between any two organisms within a community is elaborated by taxonomic distinctness and taxonomic diversity. The indexes encompass species number, individual number and connectivity structure of the species. The taxonomical diversity
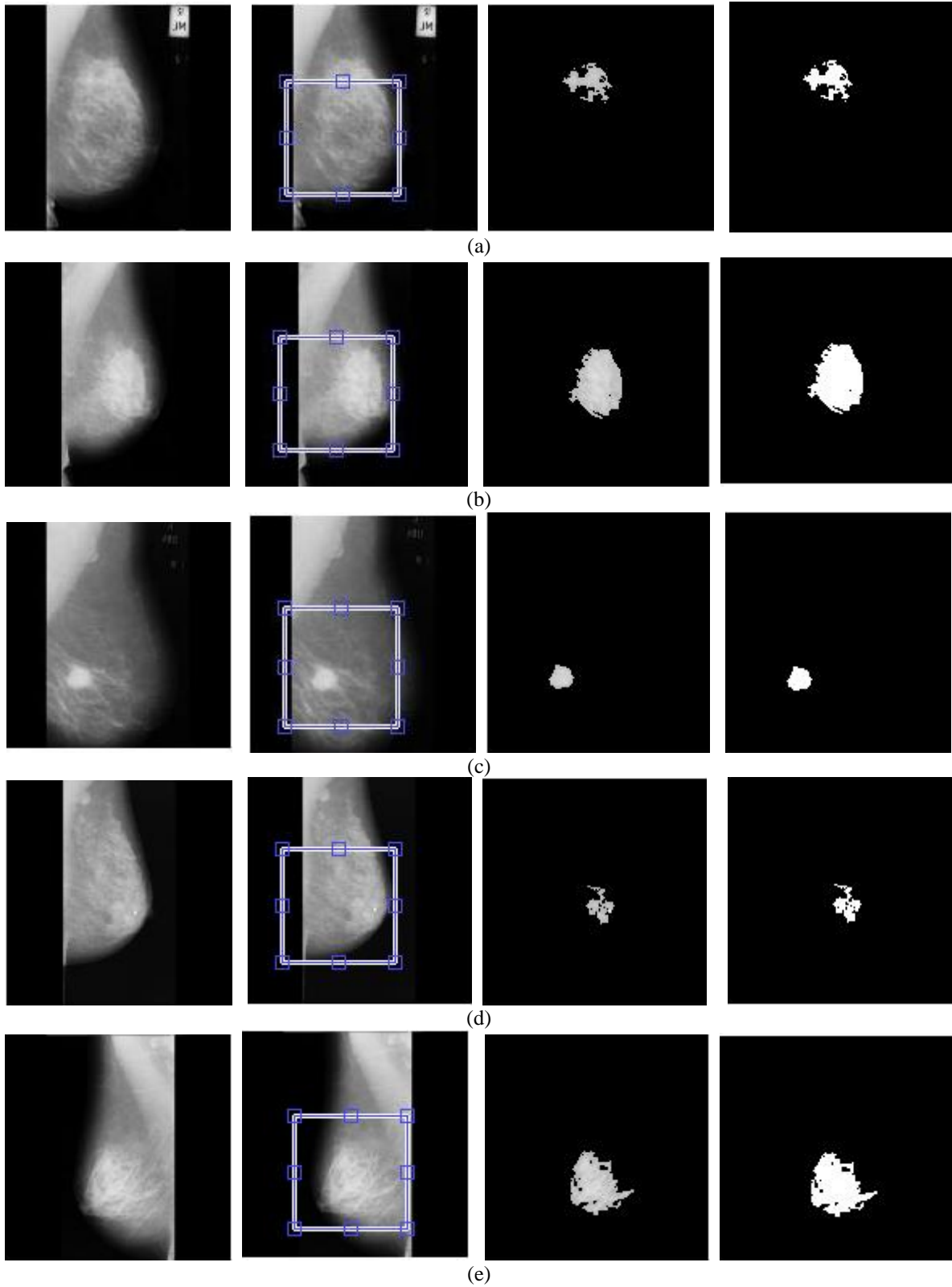
Figure 3 : Represents the process of extraction of Region of Interest (ROI) . Figure 3(a), 3(b), 3(e) represents the extraction process in case of non-cancerous images. Figure 3(c), 3(d) represents the segmentation process in case of cancerous images.
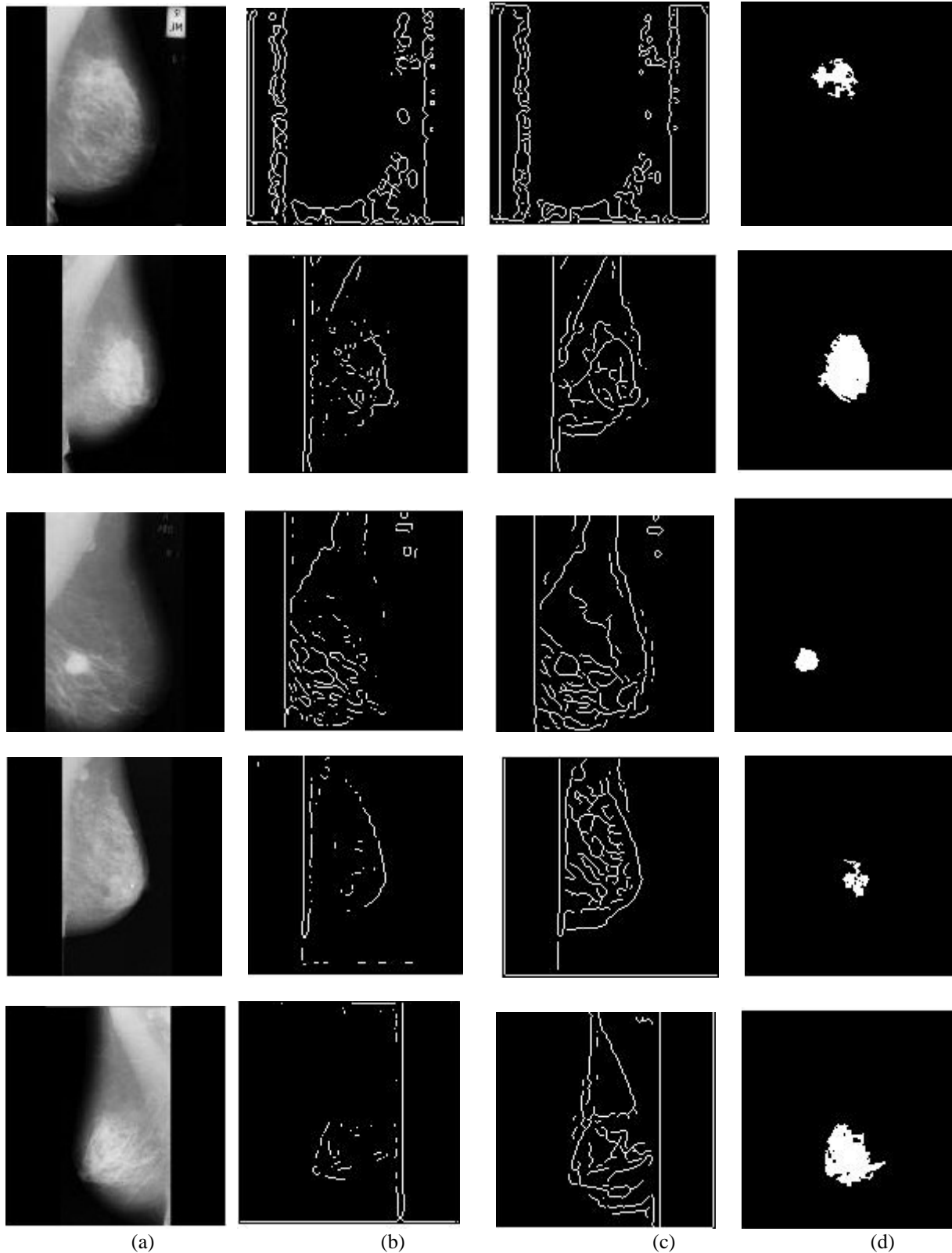
Fig. 4 represents the comparison of the proposed algorithm with various state of art techniques for segmentation. 4(a) represents the original image, 4(b) represents the Laplacian of Gaussian segmentation , 4(c) represents the canny edge detection, 4(d) represents the segmentation with the proposed algorithm.

index considers the affluence of species and taxonomical relationship between them. Therefore, the value expresses the mean taxonomical distance between any two people picked from the sample randomly.

$$\Delta = \frac{\sum\sum_{i<j} w_{ij} x_i x_j}{[n(n-1)/2]} \qquad (1)$$

Where $x_i (i = 0,..........,s)$ is the ith species abundance, $x_j (j = 0,..........,s)$ is the jth species abundance, s represents the totality of species, n is the total number of individuals and w_{ij} is taxonomic classification distance between species i and j.

The taxonomic distinctness index (Δ^*) represents mean taxonomical distance between two people that belong to different species [12]. This index is outlined by

$$\Delta^* = \frac{\sum \sum_{i<j} w_{ij} x_i x_j}{\sum \sum_{i<j} x_i x_j} \qquad (2)$$

where $x_i (i = 0,............,s)$ is the abundance of the ith species, $x_j (j = 0,...........,s)$ is the abundance of the jth , s represents the number of species and w_{ij} is that the distance from species i to species j within the taxonomical classification.

The other features used along with the above two features are used in the classification of the image as cancerous or non-cancerous. Contrast defines the difference in luminance by means of which an object is distinguishable. It is computed by finding the difference between the object of interest and other objects in the image. Correlation is a simple operation but finds it application as a feature when we are to use it for distinguishing pixels forming cancerous and non-cancerous areas. It is shift invariant and linear operator which means we can perform the same operation at every pixel. Homogeneity feature is used to depict that pixels in the region of interest are related to each other or not. It can be computed by means of Grey Level Co-occurrence Matrix. Next feature that is used is Entropy. Given a source of random events from the discrete set of possible values with associated set of possible values, the average information per source is modelled as Entropy. Last but not the least, two features mean intensity and standard deviation were used for classification of mammogram images. For above algorithm, the values of the features used in the algorithm are computed below as shown in Table 1.

IV. RESULTS AND DISCUSSION

This part elaborates and discusses the results accomplished by the employed approach in the paper for classifying the various mammograms as cancerous and noncancerous. The experiment was performed by using the methodology (pre-processing, region of interest extraction, feature extraction, classification and validation of results.) The work includes the results on mammographic pictures for

MIAS databases. In total 220 image set was used for the database. The accuracy of 98.314 was achieved by using different combination of testing and training images. Table 2 display the effectiveness of the method used for classification with rest of the methods. Our method gives accuracy of 98.314% which when compared with the other methods employed in MIAS databases is nearly 2% increase in accuracy. Only in our method used on MIAS database, we have computed Sensitivity and Specificity which is 98.62% and 98.39% respectively.

The classification results using Support Vector machine are shown in the Fig. 5. In the Fig. 5(a) , the images on the bottom axis shows mass images and the images on upper axis represent the non-mass images. In the first image, the total number of images are 30 , from which 9 images are classified as mass images and 21 images are classified as non-mass images. In fig. 5(b), the total number of testing images are 10 , from which the Support Vector Machine classify the four images as mass images and the six images as non-mass images.

In the Experimental setup, the various combination of testing and training image combination was used. The combinations used equal number of images from MIAS database which include Fatty, Glandular and Dense mammograms in equal proportions. The experimental set up was run five times and from those combinations, the values of Mean Accuracy, Standard Deviation, Mean Sensitivity and Mean Specificity were computed. In the testing and training combination, the parameters were computed and tabulated in form of Table 2.

V. CONCLUSION

The use of the texture features combination used in the proposed work lead to improved results in classification of images into non-masses and masses. The segmentation result based on external and internal masking produced better segmentation results in comparison with the contemporary techniques. The taxonomic indexes used in the proposed algorithm are not dependent on the sample effort and hence doesn't compromise the approach. Lastly, the method presented can be used in collaboration with CADx/CAD tools for classifying the suspect region as non-masses and masses for the detection and recovery of breast cancer.

Table 1: Computation of various features used in algorithm.

Image No.	Contrast	Correlation	Energy	Homogeneity	Entropy	Mean Intensity	SD	Taxonomic Distinctness	TD
1	0.16542	0.80698	0.96011	0.9939	0.19996	3.173	20.873	641.55	0.806
2	0.16372	0.94208	0.89939	0.9917	0.54092	9.6948	33.7939	1873.82	0.942
3	0.043692	0.91008	0.98295	0.99796	0.10306	1.5398	16.0241	287.27	0.91
4	0.10881	0.75986	0.11358	0.99624	0.11358	1.6779	16.0053	336.97	0.759
5	0.2171	0.90856	0.90995	0.98928	0.47496	8.2568	31.3765	1614.62	0.908

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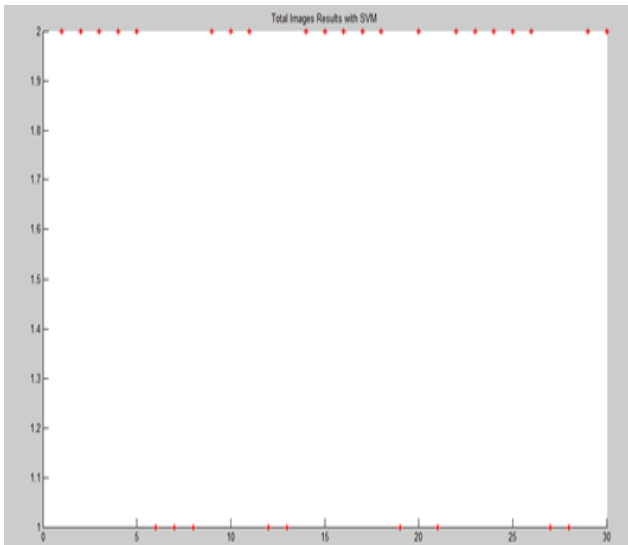

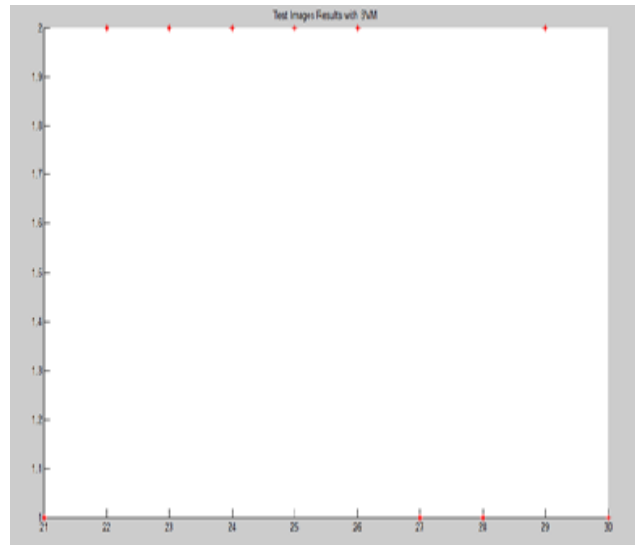**Fig. 5(a) Classification result with the testing image as 30**

Fig. 5(b) Classification result with testing image as 10

Table 2 : Experiment with the Mean Accuracy (MA), Mean Senstivity (MS), Mean Specificity(MSp) and Standard Deviation (SD) with respect to training and testing images.

Training/Testing Combination	Parameters			
	MA	SD	MS	MSP
Training/Test -> (90/10)	98.05	0.11	98.93	98.47
Training/Test -> (80/20)	98.45	0.12	98.74	98.18
Training/Test -> (70/30)	98.40	0.19	98.04	98.80
Training/Test -> (60/40)	98.40	0.16	98.66	98.43
Training/Test -> (50/50)	98.27	0.13	98.73	98.11

Table 3 : Comparison of proposed algorithm with other algorithms.

Techniques Used	Comparison				
	Database	Sample	Accuracy	Sensitivity	Specificity
Support Vector Based Fuzzy Neural Network, Genetic Algorithm	MIAS	90	96.6		
Contourlet Transform, non-subsampled Contorulet Transform, SVM	MIAS	250	95.61		
Wavelet transform by local seed growing, SVM ,Spherical Wavelet Transform	MIAS	60	96		
Diversity trees and texture features, feature extraction and SVM	MIAS	210	98.314	98.62	98.39

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