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A Comparative Study on the Methods Used for the Detection of Breast Cancer

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Abstract—Among women in the world, the death caused by the Breast cancer has become the leading role. At an initial stage, the tumor in the breast is hard to detect. Manual attempt have proven to be time consuming and inefficient in many cases. Hence there is a need for efficient methods that diagnoses the cancerous cell without human involvement with high accuracy. Mammography is a special case of CT scan which adopts X-ray method with high resolution film. so that it can detect well the tumors in the breast. This paper describes the comparative study of the various data mining methods on the detection of the breast cancer by using image processing techniques.

***Keywords**-Breast Cancer; Image Processing; Segmentation; Pre-Processing; Mammogram; Machine Learning.*

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I. Introduction

The main cause of cancer death in women is due to Breast cancers. Early detection and diagnosis can be done through digital mammography which prevents the death rate increase all around the world. Early diagnosis prevents the unwanted growth of malignant cells which saves the life of the patients. The abnormalities in the breast are of various types such as masses, micro calcifications, speculated lesions and architectural distortions. These abnormalities occur in two types called begin and malignant. The beginning is non-cancerous abnormalities whereas the malignant abnormalities are reported as cancers by the radiologist. The breast masses normally occurs in the dense regions with different shapes, which includes shapes such as circumscribed, stellate, lobulated. They are difficult to detect because of the poor contrast, different sizes, shapes and the similarity to other breast muscles, blood vessels, fibrous tissues and breast parenchymal. The micro calcification occurs in clusters and they are tiny granules of calcium deposits which usually occur in the size range 0.1 mm to 0.7 mm with irregular shapes.

The extraction of abnormalities from the digital mammograms is the main goal of image segmentation techniques. The segmentation methods consist of the breast regions segmentation and Regions of interest (ROI) segmentation. Segmenting the breast region, suppresses the background of the image and separates the breast regions for eliminating the surrounding areas which include the muscles, blood vessels, fibrous tissues and breast parenchymal. Segmentation of the regions of interest (ROI) is done by extracting the suspicious candidates which are targets of cancers by partitioning the image into non-overlapping regions of interest (ROI). Segmentation is done on single view mammograms and multi view mammograms. The single view mammogram segmentation consists of the supervised and unsupervised methods which includes region. The multi view mammogram segmentation works on the images of the left and right breasts, multiple views of the same breast and similar views taken at different time intervals. The entire segmentation process also includes the regions with false positives which are eliminated in the classification stages.

II. Breast Cancer Detection

Early detection has been the rallying cry of breast cancer from the outset of the response to the disease. While exact causes of breast cancer are not known, evidence suggests that a combination of inherited and environmental causes must be present for it to develop. Efforts to prevent breast cancer are hampered by the disease's complexity and the limits of our current scientific knowledge. Many established risk factors for breast cancer, including being a woman, aging, breast density, family history, genetics or a prior breast cancer diagnosis which cannot be modified. On the upside, evidence demonstrates that the risk of developing breast cancer can be reduced by maintaining a healthy body weight, being physically active, eating well and limiting alcohol consumption. However, because personal risk reduction is still no guarantee, early detection has been the ballast of hope and action for breast cancer. Until we are able to effectively prevent breast cancer, early detection will remain our leading strategy for reducing mortality and illness due to the disease. Early detection means using an approach that aims to diagnose breast

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cancer earlier than might otherwise occur. Breast cancer screening sometimes referred to as secondary prevention, is the routine testing of individuals without symptoms that aims to detect breast cancer at its earliest stages, so effective treatment can be offered. Since breast cancer screening began in Canada in the late 1980s, it is attributed with helping reduce breast cancer mortality by an estimated 25 - 30 percent.

III. Related Works On The Detection Of Breast Cancer By Using Different Methods

The following depicts the different Image Processing and Data Mining methods for the detection of breast cancer.

The authors ChiranjiLalChowdhary, D. P. Acharjya in the paper [1], utilizes the Intuitionistic Fuzzy Set, Rough Set, Indiscernibility Relation, Restricted Equivalence Function methods for the detection of the breast cancer. In that paper, the hybrid scheme starts with image segmentation using intuitionistic fuzzy set to extract the zone of interest and then to enhance the edges surrounding it. The experimental analysis shows the overall accuracy of 98.3% and it is higher than the accuracy achieved by hybridizing fuzzy rough set model.

In the paper [2], the authors Monica, Singh Sanjay Kumar, AgrawalPrateek, MadaanVishu, used the following methods Haar Wavelet Transform, Binarization, Segmentation, Artificial Neural Network. It is observed that the breast images are analyzed after decomposition. However, the image become smaller and crucial information may be lost by virtue of image decomposition and when region of interest is applied only on the specific segment of image as above said, some information get lost. Further, the high pass decomposed image using wavelet transform over enhance the intensity variation that may be falsely detected and cancer characteristics leading to erroneous analysis. These limitations could be overcome by denoising the given input image using the wavelet transform and analysis made on inverse transformed image. The texture features should also be considered while analyzing an image for cancer detection. A back propagation neural network is trained using the mammogram images in different categories and tested using the sample as well as unknown images 13 feature neurons are used for N/W training and testing as well. The N/W is trained for normal images as well as abnormal cases. The classification accuracy has been observed to the tune of 89%.

D. Selvathi and A. AarthyPoornila in the paper [3] used Unsupervised Deep Learning method. The proposed system uses an unsupervised, deep learning based technique which uses Mammogram in the detection of breast cancer. The labeled data serves as the training set and the un-labeled images are classified with deep-learning nets. The deep network consists of stacked auto encoder and soft max classifier. The auto encoder has four hidden layers and a novel sparsityregularizer which incorporates both population sparsity and lifetime sparsity. The model is easy to apply and generalizes to many other scoring problems. The proposed model has achieved an accuracy of up to 98.5% in classifying dense mammogram images.

M. Kanchana and P. Varalakshmi in the paper [4] used Discrete Wavelet Transform, Probabilistic Neural Network. In this paper initially, the mammography images are segmented using wavelet based threshold method. The proposed system provides valuable information to the radiologists and is helpful in detecting abnormalities faster than the traditional methods. The proposed Computer Aided Diagnosis (CAD) system is tested using Mammography Image Analysis Society (MIAS) database and achieves an accuracy of 92.3%.

In this paper [5], the following methods are used by the authors, Wavelet decomposition, multi-scale region-growing, curvature scale space, adaptive mathematical morphology. In this paper, automatic quantitative image analysis technique of BCH images is proposed. For the nuclei segmentation, top bottom hat transform is applied to enhance image quality. Wavelet decomposition and multi-scale region growing (WDMR) are combined to obtain regions of interest (ROIs) there by realizing precise location. A double-strategy splitting model (DSSM) containing adaptive mathematical morphology and Curvature Scale Space (CSS) corner detection method is applied to split over lapped cells for better accuracy and robustness. For the classification of cell nuclei, 4 shape-based features and 138 textural features based on color spaces are extracted. Optimal feature set is obtained by support vector machine (SVM) with chain-like agent genetic algorithm (CAGA). The proposed method was tested on 68 BCH images containing more than 3600cells. Experimental results show that the mean segmentation sensitivity was 91.53% (74.05%) and specificity was 91.64% (74.07%). The classification performance of normal and malignant cell images can achieve 96.19% (70.31%) for accuracy, 99.05% (70.27%) for sensitivity and 93.33% (70.81%) for specificity.

The authors Harry Strange in the paper [6], used Manifold Learning method. In this paper, the author said that there is a strong correlation between relative mammographic breast density and the risk of developing breast cancer. As such, accurately modeling the percentage of a mammogram that is dense is a pivotal step in density based risk classification. In this work, a novel method based on manifold learning is used to segment high-risk mammograms into density regions. As such, finer details are present in the segmentations and more accurate measures of breast density are produced. A set of high risk (BI-RADS IV) full field digital mammograms with density annotations obtained from radiologists are used to test the validity of the proposed approach. By exploiting the manifold structure of the input space, segmentations with average accuracy of 87% when compared with radiologists' segmentations can be obtained.

This is an increase of over 12% compared with segmentation in the high-dimensional space.

In the paper [7], the authors used ICA mixture model. In this work, we are proposing to use the technique called Enhanced ICA Mixture Model (EICAMM) for automatic segmentation of breast masses, aiming to comparing it to other segmentation methods known for segmentation of medical images such as Watershed, Self-Organizing Map (SOM), K-means and Fuzzy C-means techniques. The segmentation rates achieved in this paper 48.25% of pre-processes images and 51.75% for images without pre-processing.

The authors in the paper [8], used the k–means thresholding. Breast skin–air interface and pectoral muscle segmentation are usually first steps in all CAD applications on scanned as well as digital mammograms. Breast skin–air interface segmentation is much more difficult task when performed on scanned mammograms than on digital mammograms. In case of pectoral muscle segmentation, segmentation difficulty of analog and digital mammograms is usually similar. In this paper the authors present adaptive contrast enhancement method for breast skin–air interface detection which combines usage of adaptive histogram equalization method on small region of interest which contains actual edge and edge detection operators. Pectoral muscle detection method uses combination of contrast enhancement using adaptive histogram equalization and polynomial curvature estimation on selected region of interest. This method makes segmentation of very low contrast pectoral muscle areas possible because of estimation used to segment areas which have lower contrast difference than detection threshold. The successful segmentation rate is 89.69%.

In this paper [9], the authors used Morphological operations. The objective of this study is to examine an algorithm of automated breast profile segmentation for mammographic images. The main contribution of proposed algorithm is applying the combined of thresholding technique and morphological preprocessing to segregate background region from the breast profile and remove radiopaque artifacts and labels. To show the validity of our segmentation system, it is extensively tested using over all mammographic images from the MIAS database. The MIAS database comprises 322 images with high intensity rectangular labels. Bright scanning artifactswere found to be present in majority of the database images. All square high intensity labels, apart from three were removed at a rate of 99.06%. The qualitative assessment of experimental results indicates that the method can accurately segment the breast region in a large range of digitized mammograms, covering all density classes.

The authors in the paper [10], Gradient based method is used. Accurate segmentation of the breast from digital mammograms is an important pre-processing step for computerized breast cancer detection. In this study, we propose a fully automated segmentation method. Noise on the acquired mammogram is reduced by median filtering; multidirectional scanning is then applied to the resultant image using a moving window 15 1 in size. The border pixels are detected using the intensity value and maximum gradient value of the window. The breast boundary is identified from the detected pixels filtered using an averaging filter. The segmentation accuracy on a dataset of 84 mammograms from the MIAS database is 99%.

TABLE 1.Study on the different Techniques for detection of Breast Cancer

Author Name	Title	Methods	Qualitative Analysis of the paper
Chira njiLalCho wdhary, D. P. Acharjya [1]	A Hybrid Scheme for Breast Cancer Detection using Intuitionistic Fuzzy Rough Set Technique	Intuitionis tic Fuzzy Set, Rough Set, Indiscernibilit y Relation, Restricted Equivalence Function.	The classification accuracy obtained by the methods used in this paper is 98.3%
Monic a, Singh Sanjay Kumar, AgrawalPr ateek, MadaanVi shu [2]	Breast Cancer Diagnosis using Digital Image Segmentation Techniques	Haar Wavelet Transform, Binarization, Segmentation, Artificial Neural Network	The classification accuracy has been observed to the tune of 89% in this paper by using the given methods.
D. Selvathi and A. AarthyPoo rnila [3]	Breast Cancer Detection In Mammogram Images Using Deep Learning Technique	Unsupervi sed Deep Learning	The proposed model has achieved an accuracy of up to 98.5% in classifying dense mammogram images.
M. Kanchana and P. Varalaksh mi [4]	Breast Cancer Diagnosis Using Wavelet Based Threshold Method	Discrete Wavelet Transform, Probabilistic Neural Network.	In this paper, the proposed Computer Aided Diagnosis (CAD) system is tested using Mammography Image Analysis Society (MIAS) database and achieves an accuracy of 92.3%.
Pin Wang, Xianlling Hu, Yongming Li, Qianqian Liu and Xinjian Zhu [5]	Automatic cell nuclei segmentation and classification of breast cancer histopathology images	Wavelet decomposition , multi-scale region-growing, curvature scale space, adaptive mathematical morphology	In this paper, an experimental results show that the mean segmentation sensitivity was 91.53% (74.05%) and specificity was 91.64% (74.07%). The classification performance of normal and malignant cell images can achieve 96.19% (70.31%) for accuracy, 99.05% (70.27%) for sensitivity and 93.33% (70.81%) for specificity.
Harry Strange	Manifold Learning for	Manifold Learning	In this paper, by exploiting the manifold

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et.al [6]	Density Segmentation in High Risk Mammograms		structure of the input space, segmentations with average accuracy of 87% when compared with radiologists' segmentations can be obtained.
Patricia B et.al [7]	Automatic segmentation of breast masses using enhanced ICA mixture model	Independent Component Analysis mixture model	The segmentation rate achieved in this paper 48.25% of pre-processes images and 51.75% for images without pre-processing
Mario Mustr, MislavGrgic [8]	Robust automatic breast and pectoral muscle segmentation from scanned mammograms	k–means thresholding	This method makes segmentation of very low contrast pectoral muscle areas possible because of estimation used to segment areas which have lower contrast difference than detection threshold. The successful segmentation rate is 89.69%.
LuqmanMahood Mina, Nor Ashidhi Mat Isa [9]	A Fully Automated Breast Separation For Mammographic Images	Morphological operations	In this paper, the segmentation accuracy is achieved as 99.06% by using Morphological operations
Pelin Kus, IrfanKaragoz [10]	Fully automated gradient based breast boundary detection for digitized X-ray mammograms	Gradient based method	The segmentation accuracy on a dataset of 84 mammograms from the MIAS database is 99%

IV. Comparative Study On The Performance Analysis On The Related Works Done On The Breast Cancer Detection

In this section, the performance analysis is compared with the various papers for the detection of breast cancer.

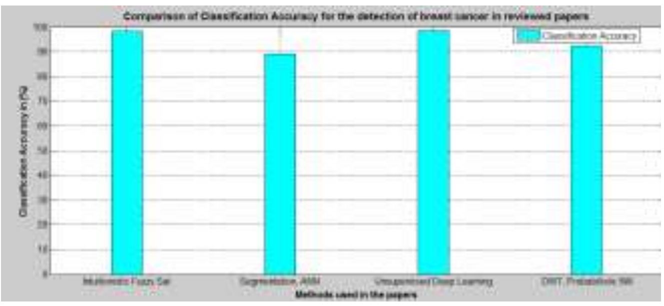

Figure 1. Performance analysis on the Accuracy of various reviewed paper.

From the above figure 1, the methods like Intuitionistic Fuzzy set and Unsupervised Deep Learning methods gives the maximum accuracy than the papers used segmentation, Artificial Neural Network, Discrete Wavelet Transform and Probabilistic Neural Network.

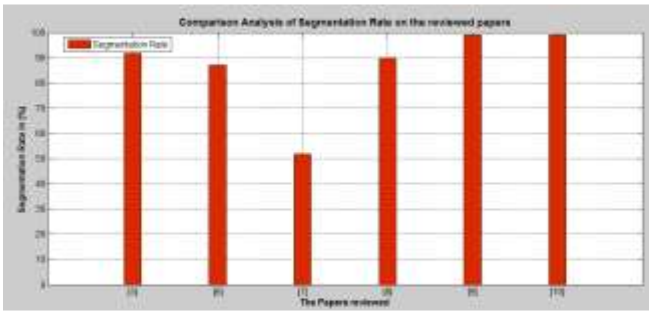

Figure 2.Performance analysis on the Segmentation Rate of various reviewed paper

From the above figure 2, the x-axis represents the papers reviewed and the y-axis depicts the segmentation rate in %. The papers which use the morphological operations, Gradient based method gives the better segmentation rate than the other methods used in the papers.

V. Conclusion

This paper presented a survey and the comparative analysis on the classical approaches of the image processing techniques used in Digital Mammography. The techniques described in papers include all the segmentation detection algorithms for both single view and multi view mammograms and these techniques suitable for breast region segmentation and ROI segmentation.

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