IOSR Journal of Engineering (IOSR JEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
PP 42-47

Literature Review on Detection of Breast Cancer by Mammogram Interpretation Using CAD System

Grace John M[1], Amresh Kumar[2]
[1]*Assistant Professor, VimalJyothy Engineering College, Chemperi, Kerala, INDIA, [1]gracejohn@vjec.ac.in*
[2]*Assistant Professor, G.H. Raisoni College of Engineering, Nagpur, Maharashtra, INDIA,*

Abstract: *Breast cancer is one of the major causes of non-accidental death in women. Early diagnosis of the disease allows physician to administer suitable treatment, and can improve the patient's survival rate. Traditional diagnosis involves trained physicians to visually examine the medical images of breast for any signs of tumor development in the region. However due to the large scale of the medical image data, this manual diagnosis is often laborious and can be highly subjective due to inter-observer variability. Inspired by the advanced computing technology which is capable of performing complex image processing and machine learning, researches had been carried out in the past few decades to develop computer aided diagnosis (CAD) systems to assist clinicians detecting breast cancer. This paper reviews CAD techniques adopted in mammogram image analysis and interpretation for breast cancer detection. The review focused on recent breast cancer detection techniques introduced by researchers with variety of methods. This work can be utilize to study existing efficient techniques and help to develop more versatile CAD system for the detection of breast cancer.*
Keywords: *CAD (Computer Aided Diagnosis) system, Classification, Feature extraction & selection, Mammogram, Preprocessing, Segmentation.*

I. Introduction

Breast cancer is the most frequently diagnosed cancer in women worldwide and the leading cause of cancer death among females. Breast cancer accounts for 23% of the total cancer cases and 14% of the cancer death in both developed and developing countries. It is estimated that more than 1.6 million new cases of breast cancer occurred among women worldwide in 2010. In 2011, nearly 1.7 million people were told to have breast cancer. Breast cancer originates from breast tissues, most commonly from the inner lining of milk ducts or the lobules that supply the ducts with milk, breast cancer occurs in humans and other mammals. The overwhelming majority of human cases occur in women.

Since the cause is still remains question, early detection of breast cancer increases the survival rate and increases the treatment options. Mammography is currently the most effective tool for the early detection of breast cancer. Mammography, also called mastography is the process of using low-energy X-rays, usually around 30 kVp to examine the human breast, which is used as a diagnostic and screening tool. An x- ray (radiograph) is a noninvasive medical test that helps physicians diagnose and treat medical conditions. Imaging with x- rays involves exposing a part of the body to a small dose of ionizing radiation to produce pictures of the inside of the body. X-rays are the oldest and most frequently used form of medical imaging. Mammography can be used to check for breast cancer in women who have no signs or symptoms of the disease. It can also be used if you have a lump or other sign of breast cancer. The goal of mammography is the early detection of breast cancer, typically through detection of characteristic masses and micro calcifications. Digital mammography, also called full-field digital mammography (FFDM), is a mammography system in which the x-ray film is replaced by electronics that convert x-rays into mammographic pictures of the breast. These images of the breast are transferred to acomputerforreviewbytheradiologistandforlongtermstorage.The patient'sexperience during a digital mammogram is similar to having a conventional film mammogram. The mammogram confirms whether the changes are benign (noncancerous) and no treatment is needed, or whether the changes indicate breast cancer and further tests and treatment will be required.

Radiologists visually search specific abnormalities present in the mammogram images. Some of the important signs of breast cancer that radiologists look for are clusters of micro calcifications,masses, and architectural distortions. However, the analysis of mammograms by radiologists results in high rates of false positive cases. This is possibly due to several reasons. Detection of suspicious abnormalities is a repetitive and fatiguing task since there will be a huge database resulting after a screening test. For every thousand cases analyzed by a radiologist, only 3 to

4 are cancerous and thus an abnormality may be overlooked. As a result, radiologists fail to detect 10-30% of cancers. Approximately two-thirds of these false- negative results are due to missed lesions that are evident retrospectively. Due to the considerable amount of overlap in the appearance of malignant and benign abnormalities, mammography has a positive predictive value (PPV) of less than 35% , where the PPV is defined as the percentage of lesions subjected to biopsy that were found to be cancer. Thus, a high proportion of biopsies are performed on benign lesions. Avoiding benign biopsies would spare women anxiety, discomfort, and expense. Dense breast tissue can look white or light gray on a mammogram. Dense tissues obscuring the cancer and the fact that the appearance of cancer on mammograms has a large overlap with the appearance of normal tissues. This can make mammograms harder to interpret in younger women, who tend to have denserbreasts.

To overcome these problems regarding with the interpretation and thus diagnosis of the breast cancer,human start to depend machines for better result. Generally,computers are employed to process and effectively evaluate biomedical images for more accurate diagnosis. Humans are prone to mistakes and their analysis is normally subjective and qualitative.Objective and quantitative biomedical image analys is made possible with the use of computers results in a more accurate diagnostic assessment by the physician. CAD system is designed and developed to alert a radiologist to abnormal areas of a mammogram.TypicallytheCADtoolprocessesadigitizedversionof a mammogram and marks it with „prompts" to highlight mammographic features that the reader should examine. The designgoalforCADistoaidthereaderstonoticefeaturesina mammogram that might indicate cancer but that they may otherwisemiss.

II. Literature Review

Chun-Chu Jen and Shyr-Shen Yu (2014)[1] used mean filter for the image denoising. The study first investigates image pre- processing techniques for obtaining more accurate breast segmentation prior to mass detection, including global equalization transformation, denoising, binarization, breast orientation determination and the pectoral muscle suppression. After per- forming gray level quantization on the breast images segmented, the presented feature difference matrices could be created by five features, such as mean, standard deviation of the total pixel intensities, the number of different layer heights in which the pixel intensities are equivalent on a layer of the same height, the mean gradient and the total gradient extracted from a suspicious ROI, subsequently, principal component analysis (PCA) is applied to aid the determination of feature weights. The mean filter is used to eliminate short- tailed noise such as uniform and Gaussian-type noise from the image. ADC classifier is a two-stage classifier for automatic detection of abnormal mammograms based on the features extracted from the ROI. In the first stage, PCA technique is used to compute eigen values for the first defined abnormal and normal feature difference matrices, the initial feature weights would be obtained. After that, the ADC calculates respective centroid coordinates for the two feature difference matrices using the proposed feature weight adjustment algorithm and then generates two rows of normalization denominators for further calculation. In the second stage, by measuring two different Euclidean distances between the tested image that is adjusted by multiplying respective weight factors then divided by the normalization denominators and the corresponding centroid coordinates, the ADC can automatically detect if an abnormality exists in a tested image for the entire mammographic dataset. The experimental results show that applying the algorithm of ADC accompanied with the feature weight adjustments to detect abnormal mammograms has yielded prominent sensitivities of 88% and 86% on the two respective datasets. Comparing other automated mass detection systems, this study proposes a new method for fully developing a high-performance, CAD system that can automatically detect abnormal mammograms in screeningprograms, especially when an entire database is tested.

J. Dheeba et al (2014)[2] introduced a classification approach for the detection of breast abnormalities in digital mammograms using Particle Swarm Optimized Wavelet Neural Network (PSOWNN). Global thresholding techniques and intensity histogram methods were used in the preprocessing stage. The proposed abnormality detection algorithm is based on extracting Laws Texture Energy Measures from the mammograms and classifying the suspicious regions by applying a pattern classifier. The method was applied to real clinical database of 216 mammograms collected from mammogram screening centers. The detection performance of the CAD system was analyzed using Receiver Operating Characteristic (ROC) curve. This curve indicates the trade-offs between sensitivity and specificity that is available from a diagnostic system, and thus describes the inherent discrimination capacity of the proposed system. The result showed that the area under the ROC curve oftheproposedalgorithmis0.96853withasensitivity94.167% of and specificity of92.105%.

S.D. Tzikopoulosetal. (2010) [3] proposed a fully automated segmentation and classification scheme for mammograms, based on breast density estimation and detection of asymmetry. In the preprocessing stage thresholding and median filtering were employed. In the segmentation stage, interface combining algorithm for breast boundary detection, straight line estimation and validation for pectoral muscle detection and thre sholding for nipple detection are used. SVM classifier is used for the classification of mammogram image which detect breastasymmetry.

R. Llobetaetal (2014)[4] presented a semi-automated and a fully automated tools to assess breast density from full-field digitized mammograms. The semi automated tool is based on a supervise dinteractive thres holding procedure for segmenting dense from fatty tissue. The fully automated method presented combines a classification scheme based on local features and thresholding operations that improve the performance of the classifier. Histogram Stretching are used for contrast & brightness correction and thresholding is used for segmentation of semi automated system. The segmentation obtained is used as a method of supervised pixel labeling, which is used to train a fully auto-mated classifier. Classifiction stage of fully automated system used KNN classifier.

In the paper by Rahimeh Rouhietal.(2014)[5] ,twoautomated methods to diagnose mass types of benign and malignant in mammograms are proposed. In the first method, segmentation is done using an automated region growing whose threshold is obtained by a trained artificial neural network (ANN) and in second method, segmentation is per for medbya cellular neural network (CNN) whose parameters are determined by agenetic algorithm (GA). Local area histogram equalization and then the median filtering is applied to suppress noise. In the histogram equalization stage, the intensity of image pixels is stretched to extend the contrast. Median filteringisan on linear operation often used in image processing to reduce ‘salt and pepper’ and speckle noise. Intensity, textural, and shapefeatures are extracted from segmented tumors. GA is used to select appropriate features from the set of extracted features. In the next stage, ANNs are used to classify the mammograms as benign or malignant. The obtained sensitivity, specificity, and accuracy rates are 96.87%, 95.94%, and 96.47%, respectively.

A good primer to ‘Image denoising based on wavelet transforms need wavelets and smoothing functions’, is introduced by J. Scharcanski and C. R. Jung (2006)[6]. At each resolution, coefficients associated with noise are modelled by Gaussian random variables; coefficients associated with edges are modelled by Generalized Laplacian random variables, and a shrinkage function is assembled based on posterior probabilities. The shrinkage functions at consecutive scales are combined, and then applied to the wavelets coefficients. The image de- noising process is adaptive which does not require further parameter adjustments, and the selection of a gain factor pro- vides the desired detailenhancement.

Shen-Chuan Tai et al. (2014)[7] presents an automatic CAD sys- tem that uses local and discrete texture features for mammographic mass detection. The Otsu thresholding method applied to the image to find the breast region and then gamma expansion enhances the pectoral muscle. The proposed system used two types of morphological filters, the opening filter which smooths bright object contours and removes small dark spots and closing filter which smooths the dark object con- tours and removes small bright spots. Thesuch template matching method is applied to the filtered breast region to identify suspicious mass regions. Two feature extraction approaches were introduced, by combining co-occurrence matrix texture features and optical density features. One is a combination of GLCM (Gray-Level Co-occurrence Matrix) features and optical density features, describes both the gray-level characteristics of local textures and photometric discrete textures based on the global optical density. The other method com- bines ODCM (Optical Density Co-occurrence Matrix) features with optical density features which characterizes local textures in an optical density image instead of the gray-levelimage.

Vibha Bora Bafna et al. (2015)[8] adopted pattern basedradon transformtodetecttheorientationofmammograms.Thepro- posed orthogonal radon transform detects the orientation of chest wall and pectoral muscle, and is capable of correcting vertical as well as upside down orientation present in the mammogram. After the application of the method, mammogramisorientedwithchestwallinleftandpectoralmusclein uppercornertoincreasetheaccuracyofpostprocessingsteps in CAD. Median filtering and global thresholding were employed in the preprocessing stage. The algorithm was tested on240imagesinwhich100imagesfromminiMIAS,100computed radiography images and 40 full field digital mammogramimages.For98.75%ofpositioninvariantcases,orientation was detected and corrected. Due to its robustness, simplicity and fast speed, the method may be used for automatically detecting and correcting orientation of mammogramsin CAD analysis.

Jawad Nagi et al. (2010)[9] proposed an automated technique for segmentation of ROI in digital mammogram images. The presence of pectoral muscle in mammograms biases detection procedures, which recommends removing the pectoral muscle during mammogram pre-processing. The proposed algorithm uses morphological preprocessing and seeded region growing (SRG) algorithm for remove digitization noises, suppress radiopaque artifacts, separate background region from the breast profile region, and remove the pectoral muscle, for accentuating the breast profile region. They adopted two-dimensional (2D) Median Filtering approach in a 3-by-3 neighborhood connection for the noise removal and thresholding method for artifact suppression and background separation. To demonstrate the capability of proposed approach, digital mammograms from two separate sources are tested using Ground Truth (GT) images for evaluation of performance characteristics. Experimental results obtained indicate that the breast regions extracted accurately correspond to the respective GT images.

Hitiksha shah (2015)[10] presented a CAD system for automatic classification of breast masses in digital mammograms. The digital mammogram is pre-processed by 2D-median filter, connected component labelling method, and morphological functions for breast extraction. Wavelet transform is used for enhancement of mammogram and triangular mask is used for pectoral muscle suppression. Morphological functions such as opening, closing, erosion, dilation and reconstruction are used for the segmentation of mammogram to extract ROI. From ROI, intensity histogram based texture features are extracted. Extracted features are classified by neural network which is applied for two levels. In the first level, neural network classify the segmented ROI into normal (without tumor) and abnormal (with tumor) ROI. Second level neural network classify abnormal ROI into malignant and benign masses.

Zaheeruddin,Z.A.JafferyandLaxmanSingh(2012)[11]proposed a method for detection and shape feature extraction of breast tumor in mammograms. In this work, the noise and uneven illumination are removed using a weiner filter, then, applied thehistogramequalizationmethodtoenhancetheimagecontrastthatscalesthegraylevel ofeachvoxelbyp redefinedfactor. Segmentation of breast tumor in mammograms presents many challenges related to selection of optimal threshold in various segmentation techniques. In the proposed paper, a mean based region growing segmentation (MRGS) is presented that automatically finds the seed pixel and optimal thresholdvalueandthusmakesthesegmentationprocess very fastandaccurate.Basicregiongrowingmethodisknowntobe themosteffectivetoolforperformingthequantitativeanalysis of anatomical structures in medical images. But, it does not lead to the accurate detection of an object, when directly appliedonrawinputimagescontainingthenoiseandpoorcontrast. So, the proposed algorithm could be applied on the mammographic images effectively, when the noise and other local irregularities are removed from the input images. The experimental results were compared with the findings of ex-pert radiologist and marker controlled watershed segmentation approach. A set of 3 mammogram images was used to demonstrate the effectiveness of the segmentationmethods.Numerical validation of the results was also provided.

AbdelaliElmoufidietal.(2016)[12]introducedamethodtogenerate and select the features of suspicious lesions in mammograms and classifying them by using support vector machine, in order to build a CADx system to discriminate between malignant and benign parenchyma. The proposed method is divided into two major blocks such as extraction and selection of technical features for each region of interest, and classification of ROIs extracted to benign or malignant parenchyma. Eighteen features, such as mean value, standard deviation, entropy, skewness, kurtosis, uniformity, sum entropy, sum average, difference variance, difference entropy, inverse difference moments, area, perimeter, convexity, compactness, aspect ratio, area to background percentage and perimeter ratio were selectedandextractedfortheclassification.SVMclassifierwas used to diagnose breast cancer. The method has been verified with the well-known Mammographic Image Analysis Society (MIAS) database and they have used the Receiver Operating Characteristics (ROC) to measure the performance of the method. The experimental results produced a classification accuracyof96.36%,with96.77%sensitivityand95.83%specificity in the training phase and achieved an overall classification accuracyof94.29%,with94.11%sensitivityand94.44%specificity in the testingphase.

Luqman Mahmood Mina and Nor Ashidi Mat Isa (2015)[13] presented a fully automated breast separation for mammographic images. The main contribution of this 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 this segmentation system, it isextensively tested using over all mammographic images from the MIAS database. The MIAS database comprises 322 images with high intensity rectangular labels. Bright scanning artifacts were 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 densityclasses.

Moh'dRasoulA.Al-Hadidietal.(2012)[14]proposedamethodfor solving mammography problems of breast cancer detection using artificial neural networks and image processing techniques. They presented a complementary technique ofbreast cancerdiagnosisthatcoversfivestagesofbreastcancerdetectionbasedonmammography,whichsolvesmanyoftheproblems. Many methods and techniques were successfully mergedinordertoobtainausefulresultforhumanuse,which includescalingoftheimage,removingsmallobjects,smoothing, extracting features, ROI extraction and many image processing techniques. Besides, neural networks are used to trainthesystemtodetectcanceraccordingtothedataset.This combinationofmultipletechniquescansolveproblemsofthe breastcancerdetectionwithahighdegreeofaccuracy.Adaptivehistogramequalizationisusedtoimprove contrastinthe mammogram images. Morphological closing wasperformed in order to smooth out the edges and to make sure that no irregularities occur at the edge of the image.

Pelin Kus and Irfan Karagoz (2012)[15] presented a fully auto- mated gradient based breast boundary detection for digitized x-ray mammograms. Median filtering method is used for the noise removal of the acquired mammogram. Then multidirectional scanning is applied to the resultant image using a moving window of size 15 X 1. By using the intensity value and maximum gradient value of the window, the border pixels are detected. The breast boundary is identified from the detected pixels filtered using an averaging filters. The results obtained by using the gradient based border estimation method introduced are close to the boundary drawn by the expert radiologist. No user guidance is required and all steps are carried out automatically. Selecting the starting point or obtaining initial borders, which are the main disadvantages of the other methods, are not encountered in the presented method. Moreover, the method is not as complicated as other methods and it does not include iterative calculations. Future studies will focus on detecting objects inside the breast region. The method performs well in three directions but for further mass detection application needs vectorial applications of this algorithm must be consider. The segmentation accuracy on a dataset of 84mammograms from the MIAS data baseis99%.

M. Radhaand Dr. S. Adaekalavan (2016)[16] proposed frequency domains moothing sharpening technique to enhance mammogram images. The presented technique had the advantages of enhance and sharpening process thataims to highlight sudden changes in the imageintensity, it isusually appliedtore move random noise from digital images. This method also eliminates the drawbacks of each of the two sharpening and smoothing techniques resulting from their individual application in image processing field. Gaussian filter was used tore- move noises presentedin the mammogram, and segmentation is doneusing thres holding technique. K-meansalgorithm was used to detect the breast cancer in the early stage. The selection of parameters is almost invariant of the type of back- ground issues and severity of the abnormality, giving significantly improved results even for denser mammographic images. The simulated results show that the high potential to advantageously enhance the image contrast hencegiving extra aid to radiologists to detect and classify mammograms of breast cancer.

III. Conclusion

In this survey of mammogram image based CAD system for breast cancer detection, we had studied the major methods for detecting the breast cancer. The study includes existing effective computer methods introduced by various researchers in this area for the past ten years. This work will be a mile stone for all the researchers working in the medicalimage processing field. In future we are developing a fully automated CAD system for the early detection of breast cancer stages by comparing these existingtechniques.

Acknowledgment

We submit the work in divine feet of **God** Almighty for blessing us with his wisdom for surpassing every difficulty faced during this work. We wish to thank everyone who supported to fulfill the worksuccessfully.

References

[1]. Chun-Chu Jen and Shyr-Shen Yu, ‚Automatic detection of abnormal mammogramsinmammographicimages', ExpertSystemswithApplications,vol.42,pp.3048–3055,2015.

[2]. J.Dheeba, N.Albert Singh and S.Tamil Selvi, ‚Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach', Journal of Biomedical Informatics, http://dx.doi.org/10.1016/j.jbi.2014.01.010 ,2014.

[3]. S.D. Tzikopoulos, M.E. Mavroforakis, H.V. Georgiou, N.Dimitropoulos and S.Theodoridis, ‚A fully automated scheme for mammographic segmentation and classification based on breast density and asymmetry', computer methods and programs in biomedicine , Elsevier,vol. 102 ,pp. 47–63,2010.

[4]. R. Llobeta, M.Pollánb, J. Antóna , .J. M Garcíad , M.Casalsd, I. Martínezd , F.R Peralesd , B.P Gómeza , D.S Trejod and J.CCortés,

[5]. ‚Semi-automated and fully automated mammographic density measurement and breast cancer risk prediction', Computer methods and programs in biomedicine, vol. 116,pp. 105–115, 2014.

[6]. Rahimeh Rouhi ,Mehdi Jafari, Shohreh Kasaei and Peiman Keshavarzian, ‚Benign and malignant breast tumors classification based on region growing and CNN segmentation', Expert Systems with Applications , Elsevier,vol. 42 ,pp. 990–1002,2014.

[7]. J. Scharcanski and C. R. Jung, ‚Denoising and enhancing digital mammographic images for visual screening', Computerized Medical Imag.Graphics,vol.30,no.4,pp.243–254,2006.

[8]. Shen-Chuan Tai, Zih-Siou Chen and Wei-Ting Tsai, ‚An Automatic Mass Detection System in Mammograms Based on Complex Texture Features',IEEEjournalofbiomedicalandhealthinformatics,vol.18,no. 2, pp. 2168-2194,2014.

[9]. Vibha Bora Bafna, Ashwin Kothari and Avinash Keskar, ‚A Heuristic Approach for Automated Mammogram Orientation in Computer Aided Diagnosis', 7th International Conference on Emerging Trends in Engineering & Technology, IEEE,vol.34,pp.56-61,2015.

[10]. Jawad Nagi, Sameem Abdul Kareem1, Farrukh Nagi and Syed Khaleel Ahmed, ‚Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms', IEEE EMBS Conference on Bio- medical Engineering & Science(IECBES2010),pp.87–92,2010.

[11]. Hitiksha shah, ‚Automatic Classification of Breast Masses for Diagnosis of Breast Cancer in Digital Mammograms using Neural Net- work',InternationalJournalofScienceTechnology&Engineering,1,11, pp. 47 –52,2015.

[12]. Zaheeruddin , Z. A. Jaffery and Laxman Singh, ‚Detection and Shape Feature Extraction of Breast Tumor in Mammograms", Proceedings of theWorldCongressonEngineering,vol.II,pp.978-988,2012.

[13]. Abdelali Elmoufidi, Khalid El Fahssi, Said Jai-andaloussi, Abderra- him Sekkaki , Gwenole Quellec, Mathieu Lamard and GuyCazuguel,

[14]. ‚Automatic Diagnosis and Classification of Abnormalities in Digital X-rayMammograms', WSEAS Transactions On Biology And Biomedi- cine,2016.

[15]. Luqman Mahmood Mina and Nor Ashidi Mat Isa, ‚A Fully Automated Breast Separation For Mammographic Images', 2015 International Conference on BioSignal Analysis, Processing and Systems (IC- BAPS),IEEE, vol. 4, pp. 37-41,2015.

[16]. Moh'dRasoulA.Al-Hadidi,MohammedY.Al-GawagzehandBayan Alsaaidah, ‚Solving mammography problems of breast cancer detection using artificial neural networks and image processing techniques ,vol. 5, pp. 2520-2528,2012.

[17]. Pelin Kus and Irfan Karagoz, ‚Fully automated gradient based breast boundary detection for digitized x-ray mammograms', Computers in BiologyandMedicine,Elsevier,vol.42,pp.75–82,2012