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# Review on Computer Aided Detection Systems of Breast Cancer

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***Abstract--****Breast cancer is life threatening disease for women.According to World Health Organisation breast cancer is second leading cause of death in the world.Many lives can be saved by early detection of breast cancer.Most widely used breast cancer screening technique is mammography. Mammography is used for detection and clinical evaluation of breast cancer. Computer aided detection techniques(CAD) are used to assist doctors and radiologists for analysing mammograms.CAD techniques plays very important role in early detection of breast cancer.In this paper total forty five papers are referred to present overview of signs of breast cancer,screening technique and survey of algorithms for detection of Micro-calcifications,masses and architectural distortion.*

***Key words—****Architectural distortion detection,CAD(Computer aided detection),Mammography,Mass, Microcalcifications.*

## I. INTRODUCTION

Biomedical engineering plays important role in healthcare technology. Healthcare technology brought revolution in variety of domains of medical field such as pathology, various screenings like X-ray,MRI,CT scan and surgical procedures[1].Outcomes of these health care systems are quick treatment, early diagnosis and quality life. Biomedical engineering dramatically turned the style of diagnostic methods opted by physicians in last half century. Wide varieties of tools are made available for improving diagnosis and disease treatments. These tools include medical imaging,computer-aided detection and medical instruments [2].CAD systems are being used extensively by radiologists as it reduces the human errors due to low contrast of medical images. Particularly, computer-aided detection is playing major role in detection and prevention of life threatening diseases like breast cancer, lung cancer, skin cancer and many more. Here we will focus on breast cancer which is second leading cause of death [3].Deaths due to breast cancer can be decreased by early detection. High risk patients are identified based on various factors like age,gender, past occurrences in family and density[4].Mammography is widely used for breast screening and diagnostic procedures worldwide for the early detection of breast cancer. [5].Masses,Microcalcifications,architectural distortion and bilateral asymmetry are signs of breast cancer in mammograms[6].Usually benign masses are with definite shape like round or oval with regular boundaries, and low density. Masses are difficult to detect due to their density variation and shape.Micro calcifications are deposits of calcium which are very small in size and bright as compared to normal tissues. Their average diameter is of 0.3mm.Generally Clustered Microcalcifications are malignant[7].Architectural distortion is nothing but distorted normal architecture of breast. Bilateral asymmetry is nothing but asymmetry between left and right breast parenchyma.Asymmetric small sized bright spots and contrast in both breasts is bilateral asymmetry. Radiologists may miss any abnormality due to human error.

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Therefore to reduce errors, researchers proposed computer aided detection techniques for detection of these abnormalities. As a result of this false positive cases are reduced and hence unnecessary biopsies can be avoided.

## II. MAMMOGRAPHY

X-ray film screen mammography is one of the most recommended and widely used imaging methods for diagnosis of breast diseases. Mammography machine is as shown in Figure1(a). It consists of X-ray tubes, detector, anti scatter grids and compression device. There are two types of mammography. Screening mammography is performed in asymptotic women for early detection of breast cancer.Diagnostic mammography performed after screening mammography if there is any abnormality or symptoms of cancer[8].

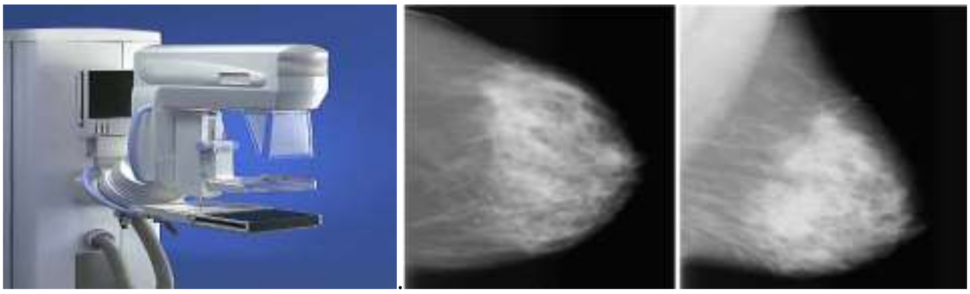

Figure 1. (a) Mammography Machine (b)Cranio-caudal(CC) and Mediolateraloblique(MLO) views

Mammography senses and displays changes or abnormalities in the breast at least two years before a physician can feel them. According to literature survey chances of cancer increases after age of forty[9](BIRADS,WHO). Mammography is recommended on regular basis by physicians after age of forty.Cranio-caudal(CC) and Mediolateraloblique(MLO) are two standard views per breast as shown in Figure 1.(b).

## III. CAD(Computer aided detection )

CAD systems are used extensively as a second opinion to radiologists. Preprocessing, ROI selection, feature extraction, selection of training and testing data and classification as benign or malignant are the fundamental steps of CAD system. Textural features, statistical features like mean, standard deviation, variance and features like area,shape,boundary etc. are selected depending on abnormality[10].Support vector machine, relevance vector machine, back propagation neural network and decision tree classifier and many more are used for classification of different abnormalities.

Some commercial CAD systems are available listed below

1.Second Look (iCAD Inc., OH, USA) [11]
2.Cyclopus CAD (CyclopusCAD Ltd, Palermo, Italy) [11]
3.MammoReader CAD system, made by ISSI, Inc. - FDA approved[12]
4.Imagechecker CAD system, made by R2 Technology - FDA approved[12]
5.CAD MammoReader software, made by ICAD, Inc. - FDA approved[13]
6.Mammex Tr made by Scanis, Inc.[13]

Evaluation parameters using CAD are accuracy,sensitivity and specificity [14]

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

### 3.1 Microcalcification detection

Microcalcifications are detected as early sign of breast cancer 30 to 50% in mammography test. Survival rate can be increased by detecting microcalcifications in early stage significantly.Microcalcifications are not uniform in shape and size therefore detection of individual is challenging task.Generalized block diagram for microcalcification and mass detection is as shown in Figure2.

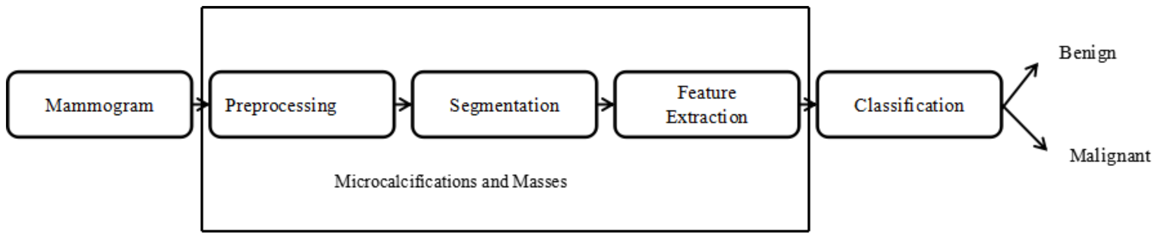


**Figure 2.** Generalized block diagram for microcalcification and mass detection

Robin and Hee used two stage method in which biorthogonal spline wavelet is used for detecting microcalcification further image is enhanced and achieved 82% detection of true clusters at a rate of 0.7 false positive per image[15].There are various algorithms for image enhancements like RUM, ANCE, contrast-limited adaptive histogram equalization (CLAHE), and direct image contrast enhancement (DICE). Karen proposed new algorithm Non linear unsharp masking NLUM using SDME measure and achieved better enhancement[16]. Further adaptive enhancement and denoising algorithm using wavelet transform is used by Mencattini for image enhancement[17].Malignant microcalcifications are usually with rough border. Therefore Tiago compared Harr, Symmlets, Daubechies and Coiflets wavelets for classification as benign or malignant calcifications based on smoothness of border.Symmlets wavelet performed well among other types of wavelets[18][19].New two stage RVM classifier is compared with RVM and SVM. Two stage RVM is fast by maintaining same sensitivity i.e. approximately 90% per one FP per each image. Execution time for RVM is decreased to 30s from 250s of SVM and for two stage RVM it is reduced to 7.26s only[20].Further 46 benign and 54 malignant cases from DDSM are analyzed for tissue surrounding texture analysis. Preprocessing is carried out by contrast enhancement and segmentation using region growing method.ST-ROI(surrounding tissue regions of interest) are defined after preprocessing. Gray-level texture features and wavelet coefficient texture features are extracted. A probabilistic neural network classifier is used for classification and achieved area under ROC curve (Az) equal to 0.989[21].Noise equalization is carried out for detection of microcalcification clusters in direct digital X-ray images. Truncated distribution method is used for estimation of quantum noise as a function of gray levels.Kristin et al. compared performance with film screen noise equalization method developed by Veldkamp and achieved better results[22].Seventy five abnormal cases are used from DDSM and MIAS database and suitable dose of noise is added to these images first and then SR noise-based detection algorithms is used for microcalcification detection[23].Performance of new semi supervised algorithm CO-trained Random FOREST (Co-Forest) is compared with co training, self training algorithms, random forest and random tree. The average FP rate is decreased by 5.8% the average FN rate of the learned hypothesis decreased by 20.0% by using Co-Forest algorithm[24].High sensitivity CAD algorithm is divided in two parts. In part one separation of microcalcification regions and other unwanted region is carried out with wavelet layers and Renyi's information theory. In part two microcalcification clusters are recognized with the help of total 49 descriptors such as inertia, shape, compactness etc. With the combination of PCA and Back-propagation Neural Network classifiers TP rate of 97.12% and FP rate 7.89% is achieved[25].Liyang[26] used a data set collected by the Department of Radiology at the University of Chicago. This data set consisted of 697 mammograms from 386 clinical cases, among them 75 were malignant, and the rest (311) were benign. Following eight features are selected 1) the number of MCs in the cluster2) the mean effective volume (thickness) of individual MCs 3) the area of the cluster 4) the circularity of the cluster 5) the relative standard deviation of the effective thickness 6) the relative standard deviation of the effective volume 7) the mean area of MCs and 8) the second highest MC-shape-irregularity measure. support vector machine (SVM), kernel Fisher discriminant (KFD), relevance vector machine (RVM), and committee machines (ensemble averaging and AdaBoost) five machine learning classification algorithms are developed for detection of clusterd microcalcification.SVM performed well among all classifiers by obtaining ROC Az=0.85.Total 300 mammograms from Digitized DDSM and MIAS datasets are used for microcalcification cluster classification. Very good area under ROC curve Az = 0.96 is obtained by using following steps for topological modelling:1.Connectivity between microcalcification cluster is estimated.2. Based on the spatial connectivity relationship between microcalcifications graph at each scale is generated. Topological features are extracted from graphs.4. KNN classifier is used for classification of benign and malignant microcalcification cluster[27].

### 3.2 Mass detection

Mass detection is challenging task due to variation in shape, boundary and breast density.Low contrast of masses with surrounding tissue is also one of the difficulty in their detection.Various algorithms are invented by researchers for mass detection.

**Table.1** Methods for the detection and classification of Masses

| Authors | Dataset | Method | Results |
|---|---|---|---|
| Petrick with | University of | DWCE- density-weighted contrast enhancement | 96% TP rate |
| et al[28] | Michigan | LDA or BPN classifier | 4.5 FP |

| | | | |
|---|---|---|---|
| I.Christoyianni et al[29] | MIAS | Radial Basis Function Neural Network classifier | 86.8% TP rate |
| Naga R. Mudigonda[30] | MIAS | GLCMand boundary sharpness<br>posterior probability classifier<br>Jack and knife classifier | Accuracy:83%,Az:0.94<br>Accuracy:77.4%Az:0.84 |
| Peter et al.[31] | DDSM | variable Hidden Neuron Ensemble Technique | Accuracy :98% |
| Shen T.[32] et al[2013] | DDSM | GLCM Optical density features Gabor<br>Linear Discriminant Analysis | Sensitivity:97.3%,4.9FP<br>$A_z$:0.981 |
| Xiaoming[33] Liu et al.[2014] | DDSM | (SVM-RFE)SVM based recursive feature elimination with a normalized mutual information feature | $A_z$:0.9615 |
| Shen T.et al.[2014] [34] | DDSM | GLCM+Optical density features<br>ODCM+Optical density features<br>LDA | $A_z$:0.981<br>$A_z$:0.976 |
| M. Jiang[35] et al.[2015] | DDSM | (SIFT) scale-invariant feature transform features vocabulary tree and(CBIR) content-based image retrieval | Accuracy:86.9% |
| Ghongade [36] et al.[2017] | MIAS | (FCBF)Fast Correlation Based Feature Selection<br>RF classifier | Accuracy:97.32% |

### 3.3Architectural distortion

Third most common cause of breast cancer is Architectural distortion. The term architectural distortion is used, when the normal architecture is distorted with no definite mass visible. This includes thin straight lines or spiculations radiating from a point, and focal retraction, distortion or straightening at the edges of the parenchyma(BIRADS). Appearance of architectural distortion and overlapping breast tissues is same therefore detection of the same becomes critical.Generalized block diagram for architectural distortion detection is as shown in Fig.2.

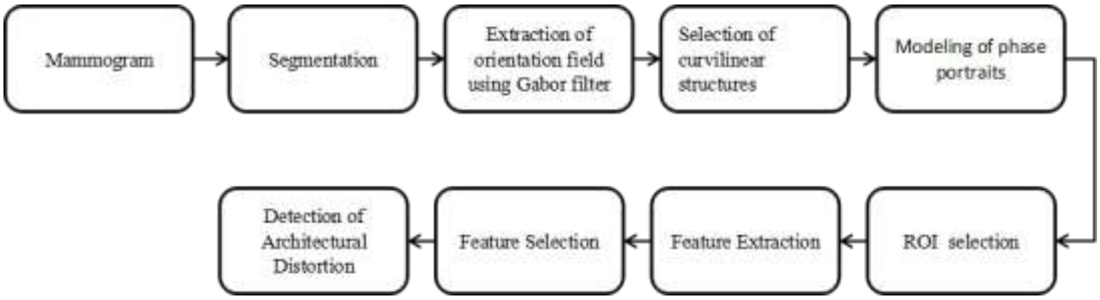


**Figure 2.** Generalized block diagram for architectural distortion detection

**Table 2**. Methods for the detection and classification of Architectural distortion

| Authors | Dataset | Method | Results |
|---|---|---|---|
| Sujoy Kumar and dipti[37] | MIAS , DDSM | Probabilistic modelling using oriented filter bank and textural descriptors and Gaussian mixture model (GMM) | Sensitivity:89.2% Specificity:86.7% Accuracy:88.3% |
| Magdalena et al.[38] | DDSM | Differential directions method (DD)&Ardist method | DD:Sensitivity:86% Specificity:89% Ardist:Sensitivity:68% |
| Fabio and Rangaraj[39] | MIAS | Phase portrait modelling using Gabor filters | Sensitivity:84% Sensitivity:95% |
| Mitsutaka et al.[40] | National Cancer Center Hospital East (Chiba,Japan) | Likelihood speculation is calculated and convergence index is calculated with weighing for enhancement of distortion | Sensitivity: 80.0% |

| | | | |
|---|---|---|---|
| Orawan etal.[41] | MIAS | Fuzzy Co-occurrence Matrix,PCA,SVM | Sensitivity:93% Specificity:91% |
| Xiaoming Liu et al.[42] | DDSM | subclass based multitask learning technique (SMTL) ,sparse representation based classification (SRC) | Accuracy:91.79% Sensitivity:92.14% Specificity:91.43% |
| Rami et al.[43] | DDSM | Region proposal convolution neural nets domain specific R-CNN (DS-RCNN) followed by SVM | Sensitivity 80.8 % Specificity: |

Many researchers worked on Prior mammograms for detection of architectural distortion. The “prior mammogram.” is a mammogram acquired prior to the detection of cancer during screening program.The “detection mammogram,” is a mammogram on which detection of cancer is dignosed. When cancer is detected outside the screening programme in between the interval of scheduled screenings called as “interval cancer”.Prior mammograms helps in the early detection of architectural distortion.Rangraj achieved sensitivity of 79% at 8.4 FP/image by using Gabor filter,phase portrait and texture features for architectural distortion detection with 14 prior mammograms.Further Rangraj et al.used 106 prior mammograms and sensitivity is improved to 80% at 7.6 FP/image detection Haralick’s texturefeatures are extracted in this study along with other features.[44][45].Free-response receiver operating characteristics indicated sensitivities of 0.80 and 0.90 at 5.8 and 8.1 false positives per image, respectively, with the Bayesian classifier and the leave-one-image-out method[46].Further Rangayyan improved sensitivity of 0.80 at 3.7 FPs per patient[47].

## IV.CONCLUSION

To improve survival rate mammography must be done regularly after the age of forty as per the recommendation of doctors. Microcalcifications,masses and architectural distortion are the signs of breast cancer,which may be missed due to dense breast tissues and due to human errors.CAD techniques overcomes these issues and helps in early detection of breast cancer.In past 22-23 years preprocessing algorithms,segmentation techniques and classifiers are used to improve evaluation parameters like accuracy and sensitivity which are discussed in this paper

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