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A review of Computer-aided Diagnosis of Mass and Microcalcification in Breast Cancer

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Abstract:CAD system act as second observation for the radiologist. The summary of recent development in CAD strategies are described in this paper. The various breast image modalities helpful in detecting lesion by using CAD system that helpful in detecting abnormality.Abnormalities detection, abnormalities classificationisreviewed. For the abnormalities detection, micro-calcification detection and mass detectionbased mostly detection are presented in this paper. For the abnormalities classification, micro-calcification classification and mass classification also reviewed in detailed in this paper.

Keywords: Breast cancer**,** Mass,Microcalcification(MC),Computer-aided detection(CAD).

I. INTRODUCTION

Breast cancer is known to be as a deadly tumorwhich are malignant in nature among ladies after cervical cancer.According to Statistics report, the number of new breast cancer for the women worldwide is about 1.67 million in 2012. This high morbidity accounts for about 25% in all cancers [1]. If breast cancer can be early detected, it is one of the most treatable malignancies [2]. From 1990s, the mortality of breast cancer has an obvious decrease in developed countries, such as in Europe and America [3,4]. It has been revealed from the report of GLOBOCON that, every two women diagnosed for breast cancer, loses her life due to this abnormality [5]. This report also reveals that an early diagnosis of may help to decrease the mortality rate. Similarly the annual report of WHO shows that approximately 1,55,863 cases were identified in 2015 in India [6].The data from Population Based Cancer Registry (PBCR) that 25 % -32% women affected by abnormality in metro cities in India.[7] The breast cancer continuous increasing and around one lac new case are detected. It is big alarm, therefore lack of unawareness is major cause [8]. The situation for our native state i.e. Punjab is also not good where cities like Chandigarh and SAS Nagar recorded more than twice higher than rural areas registered cases of breast cancer in 2013[9]. There is immediately need to control breast cancer to improve survival rate.

II.Breast Image Modalities

Breast imaging modalities are used for detecting lesions which mainly comprise of the morphological judgment of visible structures in the breast [10].

Different imaging modalities are under different theories and show different characteristics in breast cancer detection. Mammography is one of the widely used modalityfor breast cancer screening [11]. The breast needs to be compressed during mammography. In screening mammography, two breasts are imaged, and both different views are taken for each breast. The two divergent views are cranio-caudal (CC) and mediolateral-oblique (MLO). An example for the four view mammograms is shown in Fig1. The CC view is taken from a top view. Only few mammograms show the pectoral muscle. The MLO view is taken from an oblique view. The pectoral muscle is pictured obliquely and stretches right down to the extent of the nipple or ore down. The shape of the muscle ought to be curve or bulge outward.

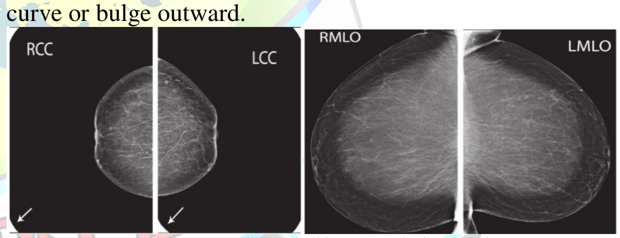

Fig1: Four Mammogram a)RCC b)LCC c)RMLO d) LMLO

The image processing technique and pattern recognition theory are used by Computer-aided detection (CAD) systems to explore abnormalities in mammograms, which might offer an objective view to the radiologist [12]. The abnormalities that are noticeable in mammograms include microcalcifications (MCs), masses, architectural distortion, and asymmetry. In the past a few years many related methods for abnormalities detection and classification are studied. Paper provides a detailed overview of some CAD methods. The aim of this paper is outline as follows.

III.Microcalcification(MC)

The micro-calcifications and hence tumor masses are covered up inside serious bosom tissues particularly in more youthful ladies, making each both the identification of diseases and identification extra progressed [13].Microcalcificationsare small calcium deport found inside the breast.[14]. The calcification can be seemed of varied range and shape. Size, a form of morphology, distribution, and number are its characteristic. It is a bunch of white dots on the mammogram. It can appear in to be in either isolation or in clusters [15]. Breast

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calcification is commonly shown in womenof age more than 40.

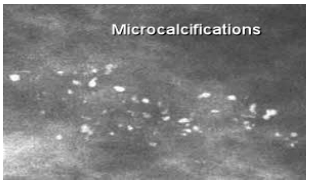

Fig2: Microcalcification

Extensive researches are conducted for MCs detection. Nakayama et al. [16] first decomposed the mammogram by filter bank. Then regions of interest (ROIs) were culled from the eight quintessential characteristics were extracted for each ROI. Finally, the Bayes discriminant function was used for identifying MC ROIs from traditional ROIs.Halkiotis et al. [17] combined mathematical morphology and artificial neural network (ANN) for MC detection. Bhattacharya et al. [18] put forward a technique supported on wavelet transform, top-hat transformation and fuzzy c-means clustering to detect MC. A multi-stage detection system was specified in Pal et al. [19]. First a back-propagation neural network was accustomed understand to realize the candidate calcified regions. Then the network output was clean victimization connected part analysis and an algorithm for eliminating thin lengthened structures. Finally, a live of native density was used for a final classification. Oh et al. [20] first segmented the breast region using grey level co-occurrence matrix (GLCM). Then, foveal technique was exploited to extract candidate of MC. Finally, false positive (FP) MCs were removed using a set of 8 features. Peng et al. [21] employed stochastic resonance (SR) noise to detect MCs. Mohanalin et al. [22] presented a detection method using a type II fuzzy index. Tested on 247 mammograms, the author reported a true positive (TP) rate is 96.55% with 0.4 FPs per image. Oliver et al. [23] detected the MCs supported extracting native options for characterizing the morphology of the MCs. The developed approach mechanically learns and selects the foremost salient features. Then a boosted classifier was wont to observe individual MCs. Zhang et al. [24] first enhanced the MCs using well-designed filter. Then the subspace learning algorithm was used for feature selection. Finally a twin support vector machine (TWSVM) was developed for classification. Recently, Zhang et al. [25] presented a methodology ingrained in a morphological image processing and wavelet transform. Zhang et al. [26] gave a technique using mathematical morphology and SVM. The author reported a detection rate of 94.85% at 0.53 FPs/I.V.Marga B. Romingeret.al.[27] used BIRAD policy for classification of mammogram.

IV.Masses

Mass is the region occupied by associate degree begin from scrape which is viewed similarly to two distinct angles in an exceeding mammogram [28]. A mass is like a lump or a tumor. It is irregular in shape like round, oval, circular and irregular. Mass is of high density or modesty of equipping dense in compassion to the nearer by tissue. Masses are areas that look abnormal, furthermore as cysts (non-cancerous) and non-cancerous solid tumor (such as fibroadenomas). Cysts are easy fluid-filled sacs or are going to be half solid called solid masses. Normal cysts are not cancer and no need to test with the diagnostic test. If a mass isn't an easy cyst then a diagnostic test is also to needed to create bound isn't cancer [29]. The masses can be classified as malignant and benign when seen at one edge, the mass is asserted to be a partner uneven thickness. Mass is further classed as under:

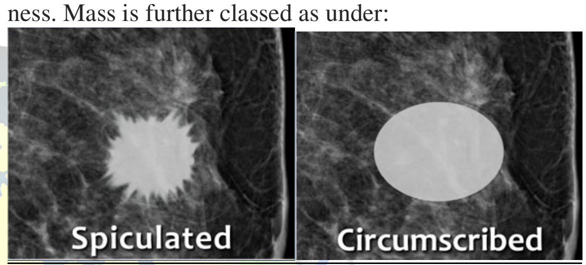

Fig3:Spiculated and Circumscribed Mass

a) Spiculated Mass

This type of mass may be like breast cancer that's displayed as the shedding of moment particles from a focal delicate tissue

b) Circumscribed Mass

It describes a benign condition that includes a very much determined limit. Its Characteristics resemble a limit, number, and thickness zone unit to be analyzed with heaps of consideration.

V.Detectionof masses in mammogram

The method for mass detection has three steps. First, the doubtful regions are detected. Then characteristics of the shape and texture of the region are extracted. Finally, FP regions are removed based on the extracted features.

Petrosian et al. [30] used the texture features computed from GLCM to differentiate between mass and non-mass regions. Tested on a small database, a difference in the training and testing results was found.Campanini et al. [31] employed wavelet decomposition and SVM to detect masses in mammograms. The multi-resolution over-complete wavelet representation was first performed to the image. Then three expert systems were obtained under different SVM classifier. The result was achieved by majority voting among the three systems. The author reported a detection rate of 80% with 1.1 FPs/I. Cascio et al. [32] first used an edge-based algorithm to segment the boundary of a ROI. Then geometrical features and shape features were extracted. Finally, a neural network was trained for recognizing true mass. The author reported a

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detection rate of 82% with 2.8 FPs/I under 3762 mammograms. Pereira et al. [33] used sixteen texture features to represent a ROI. Then nonparametric KNN classifier was trained to discriminant normal ROIs from abnormal ROIs. Guo et al. [34] compared five fractal dimension (FD) estimation methods in describing mass ROIs and normal ROIs. The author reported that FD of mass ROI was datavery much decreased than that of normal ROIs for all methods stated by author Ke et al. [35] first employed bilateral analysis to detect mass candidate. Then FD and two-dimensional entropy were extracted from the ROI. Finally a SVM classifier was trained. Tested on 106 mammograms, the author reported a detection rate of 85.11% at 1.44 FPs/I. Giordano et al. [36] employed a 2D Haar wavelet transform and region-based segmentation for mass detection. Gargouri et al. [37] proposed a new local pattern model named gray level and local difference (GLLD) to represent a ROI. Using 1000 ROIs from Digital Database for Screening Mammography (DDSM) database, the author reported the range under the ROC curve is 0.95.Tai et al. [38] put forward a system using native and discrete texture features for mammographic mass detection.

VI.CAD for mass detection

For interpreting the mammogram, a radiologist normally compares four mammograms of a case. When a suspicious region is found in LCC view, the corresponding regions in theleft mediolateral oblique view(LMLO) and*Renal Cell* Carcinoma(RCC) are checked. If the region in LMLO is also suspicious, the likelihood of this region being abnormal is increased. If the region inRCC is normal tissue, the likelihood of this region being abnormal is also increased. Combing different projection views of the same breast called ipsilateral analysis. Combing the same projection view of the left breast and the right breast is called bilateral analysis. Methods combining information from multiple mammographic views simulate the radiologist interpreting, which may improve the CAD performance using single view. Many abnormal detection methods using multiple views were also studied.

Sun et al. [39] obtainable an ipsilateral multi-view CAD scheme for mass detection. Concurrent analysis was first developed for CC-MLO matching. Then a supervised ANN was employed as a classifier. Van Engeland et al. [40] built a cascaded multiple-classifier system for mass detection. First the pixel level features were extracted and classified. Then the suspicious pixel was located and segmented. Region level features were extracted and input to another classifier. Finally, regions in different views were linked and two-view features were extracted. The final output is the third classifier with two-view features as input. The outcomes showed that the lesion-based detection performance was improved compared with the single view CAD. However, case-based sensitivity did not improve. An FP reduction method based on bilateral analysis was presented [41]. GLCM-based texture options and morphological options were extracted from the suspicious ROI and its corresponding ROI on the contralateral mammogram. Then bilateral options were computed. Linear discriminant analysis (LDA) classifier was trained for unilateral features and the bilateral features, correspondingly. The result was the third classifier with unilateral-LDA and bilateral-LDA as inputs. Velikova et al. [42] employed a Bayesian network to model the relationship between the CC view and the MLO view. Li et al. [43] developed a CC-MLO MC detection system based on spatial matching and feature matching. Samulski et al. [44] presented a multi-view CAD system in order to optimize the case-based detection performance. After the suspicious ROIs in each view were found. Geometry-based matching, features in single view and the malignancy score for the ROI were employed to extract the similarity feature. Then a correspondence classifier was trained using the similarity feature. The final result was the combination of two two-view classifiers. The author reported a substantial increase of case-based detection performance. Ericeira et al. [45] first sensed asymmetric ROIs in one mammogram based on with two sided observation. Then the asymmetric ROIs were classified as normal or mass based on variogram. Li et al. [46] used the bilateral similarity analysis to reduce the FPs. The tested on a set of three hundred thirty two mammograms, the methods show a 34% FP reduction compared with the single-view CAD, with the detection sensitivity at 85%.

The methods combine two mammograms to improve the detection performance. Wei et al. [47] presented a four-view CAD system. The CAD system consists of single-view detection, two-view analysis and bilateral analysis. The author reported the performance of the four-view CAD system is higher than the additional three systems.

VII Abnormality Classification in MCs

Singh et al. [48] first segmented the ROI by contour and morphological operations. Then shape, texture and statistical features were extracted. Finally, a SVM classifier was trained to classify MC clusters as either benign or malignant. Verma et al. [49] used 14 features to represent the ROI. Then a neural-genetic algorithm was proposed for feature selection. Wei et al. [50] presented a MC classification scheme assisted by content-based mammogram retrieval. Chen et al. [51] first analyzed the connectivity and topology of the MCs. Then graph theoretical features were extracted. Recently, Raghavendra et al. [52] employed Gabor wavelet and locality sensitive discriminant analysis (LSDA) to classify normal, benign and malignant abnormalities.Benign and malignant MCs are shown in Fig 4 .

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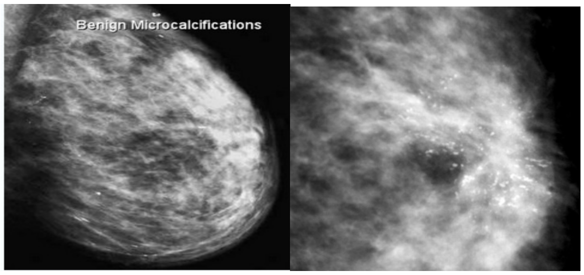

Fig4: Benign and Malignant Microcalcification

Mass classification in mammogram

The extracted features, mass classification can be separated into shape feature-based method and texture feature-based method. A precise mass contour segmentation is a pre-processing for shape-based classification. However, the texture-based classifications are more robust to the mass contour segmentation.

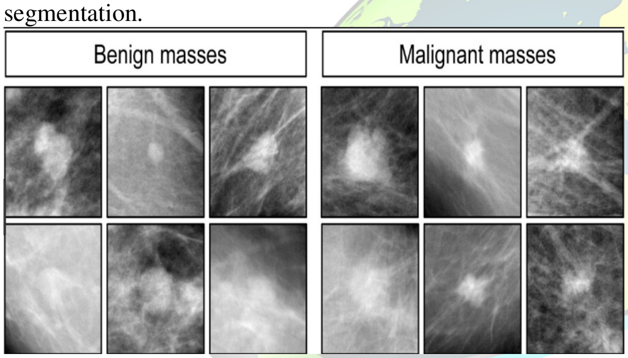

Fig 5: Benign and Malignant masses

a) Shape-based classification: The shape based classification of Benign masses are typically round or oval and possess well-defined edges. Malignant masses are generallySpiculated and possess ill-defined edges. Benign masses and malignant masses are shown in Fig 5 Rangayyan et al. [53] suggested an edge acutance feature to describe the gray transition of the contour pixels. Then masses were classified as benign or malignant combining the acutance, compactness and the Fourier descriptor. In Rangayyan and Nguyen [54] four approaches to compute the FD were given. This method was tested to a dataset of 111 breast masses. For FD, the area under the ROC curve is 0.89. For computing shape-based features, the mass contours should be known. In these three methods, manually segmentation was employed to get the mass contours. Liu et al. [55] gave an automated mass segmentation method. Then several shape-based features were compared for mass classification. 292 images from the DDSM database were passed down for experiments. The method achieved an accuracy of 86.6% with mutual information-based feature selection and SVM classifier.

b) Texture-based classification: After shape based classification in texture based classification in mass .Mudigonda et al. [56] extracted options from the GLCM to implement the mass classification. The GLCM features were extracted from each the full mass region and the ribbon breadth across the mass contour. A complete of fifty-four images were accustomed take a look at the result. The author reportable the higher result's obtained victimization GCLM-based features calculated from the ribbon. There are alternative texture features includes independent component analysis (ICA) [57], wavelet transform coefficient [58], Curvelet transform coefficient [59], Contourlet transform coefficient [60] and Krawtchouk moment [61]. Texture descriptors show respectable performance in many classification tasks. Thus, local ternary pattern (LTP), local phase quantization (LPQ) [62] and text on [63] were employed to classify a mass as malignant or benign.

Recently, a mixture of shape features and texture features were tested. Mu et al. [64] evaluated a set of twenty-two features including 8 shape features and 14 texture features. Using selected combinations of these 22 features, the classification performance was improved. Rouhi et al. [65] extracted intensity, texture, and shape features from a segmented tumor. Then the GA methodology was accustomed choose options and ANN was used for classification.

VIII Conclusion

CAD is served as a second read within the initial detection of breast cancer. An oversize quantity of effort has been completed in this field. This paper given an outline of the recent development in CAD strategies.For abnormalities detection, MC can get decent detection performance. However, the detection performance for mass is not satisfying. In previous studies, masses are detected using single view information.For multi-view-based detection, many problems are not well solved. Existing multi-view CAD normally employ two mammograms, ipsilateral mammograms or bilateral mammograms. Using four mammograms to detect simulates the radiologist's interpretation. Thus, develop the four-view based CAD method is demanding. Abnormalities detection, abnormalities classification are briefly reviewed. Single-view based detection is that the foundation of multi-view-based detection and has been studied deeply. Multi-view based mostly detection simulates the radiologist's interpretation. More research for classification require deep learning in this field.

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