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Review Article

Detection of Breast Cancer from Digital Mammogram images using Medical Image Processing: A Review

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Abstract

Breast cancer is the most common cancer that causes deaths for women worldwide over past the 50 years. Early detection is the most effective way to manage the breast cancer. Currently Digital Mammography technique is used for early detection of breast cancer. The result of mammographic image varies with image quality and knowledge of radiologist. Many papers have documented many advanced techniques of Computer Aided Diagnosis using mammogram for detection of breast cancer. This review provides a summary about various recent trends and developments in the field of Computer Aided Diagnosis of breast cancer detection using digital mammograms. This survey focus on the some CAD techniques that was recently developed for detection of breast cancer including detection of masses, detection of architectural distortion, detection of calcification or microcalcification and bilateral asymmetry detection.

Keywords: Architectural distortion; Bilateral asymmetry; Computer Aided Diagnosis; Digital mammography; Mass screening; Microcalcifications.

Introduction

Breast cancer is type of cancer that affects the cells of the breast. Early detection of breast cancer and proving proper treatment is the most effective way to reduce mortality rate [1]. Currently Digital mammography is the most used technique for early detection of abnormalities in the breast [1, 2] (Fig. 1). Although mammogram is the most successful tool for the early detection of Breast cancer, during examination the noncancerous region can be misinterpreted as cancer and in other instance cancer may be not detected. Due to misinterpretation of radiologists rate of False Positive test results and False Negative test results are increased. The radiologist fails to detect about 10 to 30 percentage of breast cancer [2].

Recently, Computer Aided Detection/ Diagnosis (CAD) system have been developed to improve the capability of radiologist in interpretation of mammographic image [3]. CAD system uses various approaches for the detection of abnormalities of mammogram image. Various abnormalities that lead to breast cancer are calcification, bilateral asymmetry, masses and architectural distortion [4]. Efficiency and accuracy of detecting the breast cancer in mammogram image can be improved by using these CAD based techniques [5].This paper gives an overview of CAD systems and related techniques that was currently developed for the detection of breast cancer using mammogram.

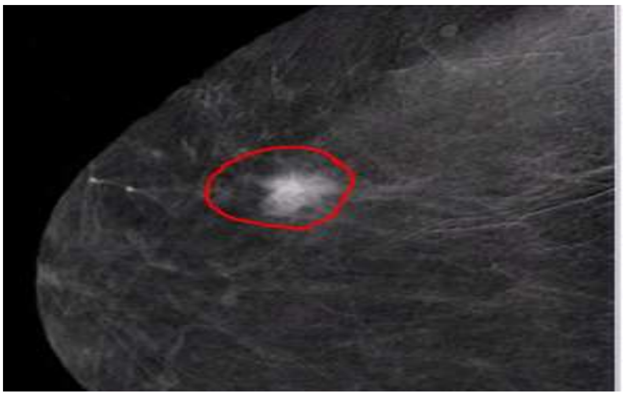

Fig. 1. Digital Mammographic image marking breast cancer

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The rest of this paper includes, Section 2 introduces basic concepts in breast cancer diagnosis using digital mammography. It also discusses about the advantages of using CAD based system over double reading of mammogram images. Section 3 details some key techniques used in CAD systems for breast cancer, for detection of abnormalities in breast. Abnormalities such as bilateral asymmetry, calcifications, masses and architectural distortion are detected by using various techniques. Section 4 covers evaluation of CAD based system with its results. Section V is the conclusion the paper.

Detection of breast cancer using Mammography

Mammography is a specific type of breast imaging that uses low-dose X-ray to examine the breast. It is currently the most effective method for detection of breast cancer [6]. The output of mammography is a high-quality image at a low radiation dose. Currently, digital mammography is used which takes an electronic image of the breast and stores it directly on a computer [7]. Digital mammography has improved image contrast, with lower X-ray dose, enhanced image quality and lower noise [8].

There are two types of examinations that can be performed using mammography:1) screening mammography and 2) diagnostic mammography. Screening mammography is carried out to find out whether there is breast cancer or not, whereas Diagnostic mammography is performed as a follow up examination after an abnormal screening mammography [9].Screening mammography generally consists of four views, the Cranio Caudal (CC) view which includes Left CC (LCC) and Right CC (RCC) views and two Medio Lateral oblique (MLO) views such as Left MLO and Right MLO [9].

One of the major difficulties with mammography is, it generally have low contrast image [10]. This makes it very difficult for radiologists to interpret the results which result in high rate of false positives and false negative test results. Because of the false positive test results women may undergo further clinical evaluation or breast biopsy without even having breast cancer [11,12]. Several solutions have been proposed to increase the accuracy, specificity, and sensitivity of mammography images. Double reading of mammogram image is recommended to reduce the percentage of missed cancers [13, 14]. However, it is a time consuming process and cost associated with double reading are also high. Because of these reasons CAD system is introduced instead of double reading. By using the CAD system workload of the radiologists could be reduce and is also proven that CAD systems can improve the detection rate of cancer in its early stages [14].

Techniques for CAD system

Survey has shown that CAD represents a useful tool for the detection of breast cancer [16-18]; however, other research [15] has shown that CAD may make readings less accurate. In this survey, there are many techniques for the detection of calcifications, masses, architectural distortion, and bilateral asymmetry, as well as for image enhancement. This survey focuses on various techniques and methods that have been reported recently in the literature.

Methods for detection of microcalcification (MC) clusters

Microcalcifications are tiny deposits of calcium that appear as small bright spots in mammograms. MCs clusters can be an important sign of breast cancer (see Fig.1). These MCs are detected about 30-50% of cases by mammographic screenings [19]. Calcifications detected on a mammogram are an important indicator for malignant breast disease. The presence of MCs is detected by enhancing the image which includes filtering approaches [20].Another problem is that, sometimes the image have low contrast to the background and MCs can be misinterpreted as noise in the background [21].

For instance, the difference image approach can be viewed as a band pass filter, which can be sensitive to noise. To alleviate this, morphological operators were applied to reduce false positives in a post processing step. More recently, [22] investigated a Markov random field (MRF) based approach for MC detection [23] also compared different approaches based on Gaussian mixture models. Using of MRF models for segmentation is much better than some other statistical methods due to its expertise to characterize the spatial intensity distribution of an image.

In certain, wavelet transforms are widely analyzed for MC detection. In some instance, undecimated biorthognal wavelet transforms in used for the detection of MCs which were represented by circular Gaussian shapes [24]. Multiplexed wavelets were explored with mammograms treated as oscillatory signals [25]. Combination of filter bank decomposition with a Bayes classifier is used to detect MCs [26]. Combination of wavelet transforms with hidden Markov trees in a maximum likelihood framework for MC detection [27]. Methods based on evolutionary genetic algorithms were proposed [28,29], these algorithms were used to search optimal bright spots that could be classified as MCs. A more recent development in machine learning algorithm is support vector machines (SVMs). Conceptually, SVM utilizes an implicit nonlinear kernel mapping to a higher dimensional space. SVMs were recently reported to achieve high accuracy in MC detection in the literature [30]. It is demonstrated that the computational efficiency could be improved by maintaining the best prediction power using Relevance vector machine (RVM) [31].

Detection of masses in mammogram

A mass is defined as a space-occupying lesion seen in more than one projection [32]. Masses have different density, different margins and different shape. A mass is usually characterized by its shape and margin [33]. A mass with an irregular shape has a higher chance for malignant, the different shapes and margins of masses (Fig. 2). Most of the mass detection algorithms have two stages, First stage is detection of suspicious regions on the mammogram and second stage is classification of suspicious regions as mass or normal tissue [34]. The algorithms for the first stage in mass detection are generally pixel-based or region-based [34].

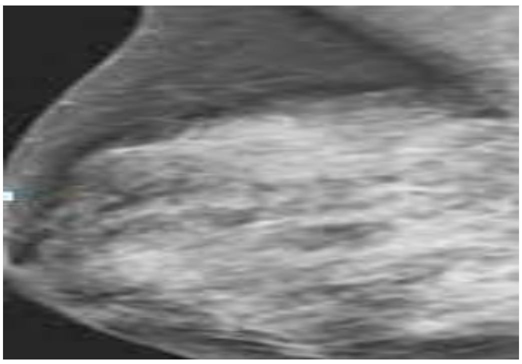

Fig. 2. Different shapes and margins of masses

In the pixel-based approaches, features extraction for each pixel is done and then it is classified as normal or suspicious [21]. Pixel-based approach is used in which texture features and local oriented edge characteristics are extracted from regions of interest. The authors reported 100% sensitivity and specificity of 82% [35]. Other research is based on a multi resolution scheme to detect spiculated lesions. The image is decomposed into a multi resolution characterization and four features were extracted. The authors reported 84.2% true positive test result is obtained at less than 1 false positive per image, and 100% true positive test result is detection at 2.2 false positives per image [36].

Another SVM-based featureless approach is introduced for mass detection, Instead of extracting the features of ROIs; authors used multiresolution over complete wavelet representation. The authors reported that the algorithm achieved nearly 80% true positive detection at false positive rate 1.1 per image for mammograms containing malignant tumors [37]. Recently, multiple-concentric-layers-based algorithm is proposed to detect masses in mammograms. The authors reported the sensitivity of 92% at 5.4 false positive per image [38].

The second approach used for mass detection is region-based approach, which is the first stage if mass detection [21]. In the region-based approach, first region of interests is segmented and then features are extracted from each region. Many region-based approaches have been proposed. A convolution neural network was employed as the classifier to distinguish between the mass and normal breast tissue. The authors reported that the area under the ROC curve was 0.87, which corresponded to a true positive fraction of 90% at a false positive fraction of 31% [39]. Methods using both gradient-based and texture-based features are used to differentiate benign masses from malignant tumors. After combining the gradient-based and texture-based features classification of breast masses is done using the Mahalanobis distance. Stepwise linear discriminant analysis (LDA) with Simplex optimization was implemented. The trained LDA classifier with the most useful feature set was employed to differentiate masses from normal tissues. The authors reported sensitivity of 90% at 1.82 false positive per image [40].

A completely automated CAD system for mass detection is proposed. Here mammographic images are diagnosed by radiologists, 80% sensitivity of mass detection was found at 4.23 false positives per image [41]. An SVM were employed as a classifier to detect the temporal changes in mammographic masses [42]. Template matching method based on mutual information is proposed [43]. First Tumor-like template was used for template matching and then similarity between doubtful area and the template was measured in order to detect masses present [44]. A support-vector-based fuzzy neural network classifier was proposed for the classification of masses [45]. An automated breast mass detection system using the Watson filter model was studied [46].

Detection of architectural distortion in mammograms

Architectural distortion is a mammographic descriptive term in breast imaging which is distorted with no definite mass visible. Architectural distortion is the third most common mammographic sign of invisible breast cancer but, it is often missed during screening [33,47]. In Architectural distortion about 12-45% of breast cancers are misinterpreted in screening mammography [48,49].To detect architectural distortion Gabor filters and phase portrait maps is applied to characterize texture patterns in mammograms [50,51]. This method is tested and resulting sensitivity rates of 84% at 4.5 false positives per image [51].

Architectural distortion is investigated using the Hausdorff fractal dimension and an SVM classifier to distinguish ROIs exhibiting architectural distortion [52]. A classification accuracy of 72.5% was obtained [53]. Mathematical morphology is used to detect architectural distortion; a sensitivity rate of 94% with 2.3 false positives per image is acquired [54]. An automatic method is developed to detect areas of architectural distortion with spiculations by means of a concentration index of linear structures; a sensitivity of 68% at 3.4 false positives per image was produced [55].

Detection of bilateral asymmetry in mammograms

Asymmetry between the left and right image of mammograms is an important sign of breast cancer (Fig. 3) [56]. A few studies have been presented on digital image processing techniques about bilateral asymmetry, in which some type of alignment of the left and right breast images is applied before performing the analysis. A directional feature to quantify oriented patterns is proposed. However, alignment procedures encounter problems such as the natural asymmetry of the breasts, the lack of corresponding points to perform matching, and distortions inherent to mammographic imaging [57]. Another technique is proposed for the detection of bilateral asymmetry which includes a semi-automated texture based approach for the segmentation of the glandular tissue and measures of shape. An accuracy of 86.7% was reported by using this technique [58].

Fig. 3. Mammogram image showing asymmetry breast

In another report, the detection of bilateral asymmetry is done based on measures of shape, topology, and distribution of brightness in the fibro glandular disk. The method was tested on 104 mammogram pairs and a classification accuracy of 74% was obtained [59]. Method for the analysis of asymmetry in mammograms is developed using directional filtering and with Gabor wavelets [60].The fibro glandular disk is segmented and the resulting image is decomposed using a bank of Gabor filters at 12 orientations and four scales. The Gabor filters differentiate the directional distribution of the fibro glandular tissue [61]. Extending the method of [60] and including morphological measures to quantify differences in fibro glandular-tissue-covered areas, which relate to size and shape. In addition to that, the directional data were aligned with reference to the edge of the pectoral muscle. Sensitivity of 82.6 % and specificity of 86.4% were acquired for the detection of bilateral asymmetry.

Evaluations of CAD system techniques

The system is evaluated by measuring the accuracy, specificity and sensitivity. This is measured by knowing the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values.

$$\text{Accuracy}=\frac{TP+TN}{TN+FP+FN+FP} \quad (1)$$

$$\text{TNR}=\frac{TP}{FN+TP} \quad (2)$$

$$\text{FPR}=\frac{FP}{TN+FP} \quad (3)$$

By using these formulas the rate of False Positive, rate of True Negative and Accuracy of the detection rate of mammogram images are detected for the particular methods. Table 1 discusses about the pros and cons of results reported in various research papers.

Table 1. Evaluation of Existing system

S. No.	Proposed method	Pros	Cons	Result	Ref. No.
1	k-nearest neighbor and fuzzy mean	Accuracy is improved about 70% to 82%.	Very complex data space.	Change of intensity is used as a discriminating.	[62]
2	Multi- Wavelet and hard threshold	The proposed method has produced best PSNR values.	Affected area may be removed by noise removal.	Good result for dense mammogram by noise cancellation.	[63]
3	Vector quantization	It is the method of clustering and texture analysis.	Absence of over and under segmentation.	It is 90% accurate.	[64]
4	Level set a method uses the Gaussian filter	Reduces the usual workflow time.	CAD based system is used in order to get better test results.	This will leads to more accurate diagnosis.	[65]
5	Fuzzy Enhanced Mammogram Segmentation (FEMS)	It is very fast, accurate and can be more useful for the diagnosis of abnormal tumors or masses.	FEM1 out performs than FEM2.	The processing time is 6.25 times less.	[66]
6	Unsharp masking and crispening	It is computationally cheaper and produces better results.	The execution time is lower when compared to Euclidian distance.	It is better capable of enhancing the abnormalities in details.	[67]
7	Fractal based detection	The result displays the abnormal region exactly and produced better result.	Still no unique method was developed to segment the entire suspicious regions.	The hybrid techniques produce good accuracy, sensitivity and specificity.	[68]
8	Wavelet based segmentation	It can detect the suspicious tumor region exactly.	Unsuccessful in case of benign.	Abnormal region are extracted completely.	[69]
9	Segmentation using wavelet	It utilize the Orientation and frequency selectivity.	It is only for malignant tissues.	Showed the ability of wavelet in MC detection.	[70]
10	Wavelet analysis and genetic algm	It overcomes the limitation of analyzing only CC and MLO views.	SD value of AOM for the proposed method was 79.2 ± 8%.	Produce 95% sensitivity.	[71]

11	Back propagation, Quasi newton, levennberg Marquardt algm	It was trained with normal statistical cleaning process to identify noises.	--	The highest accuracy of 99.28% is achieved. It has 99.28% sensitivity	[72]
12	Feed forward, Back propagation.	Faster classifier model, It reduces the diagnose time.	Only eliminate records with missing values.	It has 92% sensitivity.	[73]
13	Segmentation with GLCM and watershed method	Division of image is done on the basis of discontinuities.	Validation is necessary in case of larger histological slides.	It produce 90% accuracy	[74]
14	PSO and FCM	Detection of micro calcifications is done.	--	It produce 88.50 % sensitivity	[75]
15	Neuro-fuzzy	The proposed method produced better result when compared to other system.	The threshold limit is set as 190pixels. Image having more than 190 pixels are considered as candidate pixels.	It produce 95% accuracy and98% specificity.	[76]
16	PSO based Wavelet transformation	Wavelet transformation is applied to enhancement image,	Uses the application of PSO to identify the masses of mammograms.	94.99% of detection rate is obtained by the method.	[75]
17	Textural features, ANN	It reduces the dimensionality of the data.	Complex process when compared to other method.	It has 85.65% sensitivity.	[77]
18	Particle Swarm Optimized Wavelet Neural Network (PSOWNN)	Produce better of accuracy than SONN and DEOWNN.	The classifier trying to improve the classification rate by focusing on initial neural-network.	It has 93.67% accuracy 92.105% Specificity, 94.17 % sensitivity.	[78]
19	Textural features PCA	Reduction of False Positive test results is obtained	It is a Lengthy process.	It produces 86% sensitivity.	[78]
20	Morphological operation and wavelet transform	It has 92.9% of true MC cluster per image.	0.08% false MC cluster per image.	It has a sensitivity rate of 92.9%.	[80]
21	Maximum likelihood active contour model using level set	The results are compared with active contour and showed better performance.	It is estimated using gamma distribution.	It has 86.85% sensitivity	[81]
22	CNN, ANN and GA	It is used to segment the masses from input image.	It uses two methods for segmentation.	It has accuracy 96.47%,specificity 95.94% and 96.87% Sensitivity.	[82]

23	Wavelet and GLCM MIAS	Accurate when compared to other method.	14 features of the image are extracted.	It has 94.2% accuracy, 98.8% specificity and 97.4% sensitivity.	[82]
24	Iterative modified watershed algorithm, GLCM and SVM	Speckle Noise Removal and EM algorithm is used for enhancing the image.	--	It has 98% accuracy, 100% specificity and 97.5% sensitivity.	[83]
25	Intensity and FCM based segmentation	The suspicious area is determined by threshold than 140 to100 pixels per images.	An intensity based method to identify the mammogram is normal or abnormal.	It has 91.66% accuracy, 85% specificity and 95% Sensitivity	[84]
26	EABCO and Bilateral Subtraction	The EABCO was used to detect the border.	--	It produces 96.40 % accuracy.	[85]
27	Back propagation neural network (BNN) classifier	Each node represents a variable, and merges the extracted features.	It consumes more time when compared to other methods.	94% sensitivity is obtained.	[86]
28	NN (Neural Network)	Spike noise is completely removed through morphology.	Has multi- stage neural network.	It has 76.32% accuracy, 89.66% specificity and 53.33% sensitivity	[87]
29	LDA (Linear Discriminant Analysis)	Has improvement when combining classifier.	Final accuracy rate obtained in the experiments are relatively low.	It has 76.32% accuracy 77.78% specificity and 75.86% sensitivity	[88]
30	GLCM based feature extraction and SVM classifier	Rate of getting false positive and false negative test results are reduced	Takes more time because of the usage of many algorithms	Rate of misinterpretation has been reduced	[89]
31	Hybrid SVM-KNN for classification	It classify breast tissues in normal/ abnormal classes and further abnormal class into benign/malignant	Usage of artificial intelligence so, have to train more image	Classification accuracy of 100 % for DDSM and 94% for MIAS database	[90]

Conclusions

CAD is an important tool for early detection of breast cancer. Compared to double reading, CAD reduces the workload of radiologists and also reduces the rate of misinterpretation. However, the performance of CAD systems has to improve in order to meet the requirements of the routine clinical applications fully. This paper provided an overview of the recent advances in CAD systems and related techniques. This described some basic concepts related to breast cancer detection and diagnosis, and reviewed many key CAD techniques for breast cancer: detection of calcifications, masses, architectural distortion, and bilateral asymmetry. This can be seen from Table I with results from various CAD based techniques. Here, the best results obtained are around 99.28%, which is not sufficient enough for implementation in clinical trials. CAD-based readings can provide an improved diagnostic accuracy for radiologists. The main goal of CAD must be to increase diagnostic accuracy with advanced mathematical and computational techniques.

Conflicts of interest

Authors declare no conflict of interest.

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