A REVIEW ON COMPUTER AIDED DIAGNOSIS OF BREAST CANCER USING IMAGE PROCESSING AND PATTERN RECOGNITION TECHNIQUES

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Abstract - Breast cancer has been the main cause for high mortality rate in women. To improve the survival rate, regular screening and early diagnosis of breast cancer is essential. Mammography imaging reveals the presence of calcifications if present. These calcifications can be classified as benign and malignant, out of which malignant ones need serious attention. Manual investigation of these images is time consuming and error-prone. Computer based approaches are sought for this purpose. Image processing and pattern recognition based techniques have been widely adopted in this regard. This work reviews the existing approaches owing to image processing and pattern recognition towards breast tumour identification. The approaches are divided into filtering based, morphology based, multi-scale based, model based and pattern recognition based approaches to facilitate a clear understanding. The work suggests that opportunities still exists in various aspects to improve the detection accuracy of breast cancer.

Keywords - Breast cancer; Mammogram; Image Processing; Pattern Recognition; Morphology; Filtering; Multi-scale.

I. INTRODUCTION

The prevailing rate of cancer has dramatically increased in the recent times. Awareness programs are being campaigned to create alertness among the public regarding this disease. The treatment for cancer has proved to be fruitful only when detected during early stages. Cancer involves abnormal growth of cells, which could spread from one location to another, characterizing high mortality rate [1]. Cancerous cells can be formed at any part of the human body causing various types of cancer such as breast cancer, lung cancer, blood cancer, renal cancer, bone cancer, brain tumor etc. The mass of cells formed is referred as tumor. The tumors can be malignant or benign [2]. The benign tumors do not invade to other places and hence is not serious. The malignant tumors, on the other hand, require immediate attention. In women, the possibility of getting affected by breast cancer and ovarian cancer is very high, when compared to other types of cancer. Breast cancer [3] is a condition, where the cancerous tumor cells (tissue mass) are formed from the breast cells, with high mortality. Early identification of this disease requires regular screening of the patient. The

screening presents the mammographic images [4] of the breast tissue, providing insight to the presence or absence of tumor cells. A sample of the mammographic image with tumor is shown in Fig.1.

Manual investigation of these images is time consuming, error-prone and subject to inter-variability among the experts. Hence computational solutions are sought for this purpose. Image processing [5] and pattern recognition [6] techniques have been widely used to detect and diagnose breast cancer at its initial stage. The image processing techniques perform necessary procedures to identify the region of interest and then decide if it is benign or malignant. In order to use pattern recognition techniques, initially, the image is processed to expose the region of interest clearly, and then features of these regions are extracted. Followed by this, a learning model is built to predict if the tissue is cancerous or not. An extensive literature in this regard is available.



Fig. 1. Sample of Mammogram image showing cancerous breast tissue

This paper presents a review on the state-of-art image processing and pattern recognition techniques applied for the detection of breast cancer from mammographic images.

The paper is structured as follows: Section 2 presents a generic framework involving image processing and pattern recognition techniques for breast cancer identification. Section 3 reviews the image processing and pattern recognition based techniques involved in breast cancer diagnosis. Section 4 concludes the paper.

II. A GENERIC FRAMEWORK OF IMAGE PROCESSING AND PATTERN RECOGNITION TECHNIQUES FOR BREAST CANCER DETECTION

Image processing and pattern recognition techniques have been extensively used for medical image analysis [7, 8]. Generic framework for detection of breast cancer through image processing and pattern recognition techniques is portrayed in Fig 2. With regard to medical image analysis and identifying abnormality in the images, certain generic steps can be followed. The process either involves image processing and pattern recognition techniques, or it involves only image processing techniques. In the view of image processing, the processes involved are image acquisition, image pre-processing, image transformation and image segmentation.

Image acquisition is related to acquiring the medical image of interest. Different kinds of imaging techniques are available to expose various body parts and its abnormalities. With respect to breast cancer, mammogram, ultrasound and Magnetic Resonance Imaging can be performed to image the breast for detection of abnormality. In this work, mammogram images are focused.

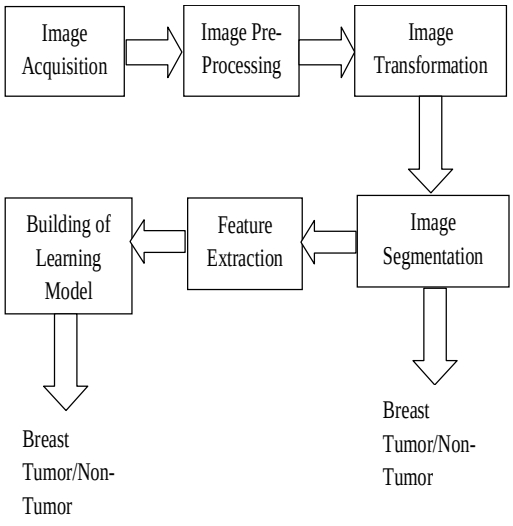


Fig. 2. Generic Framework for Breast Cancer Detection through Image Processing and Pattern Recognition Techniques

After the acquisition of images, the mammogram images are pre-processed to eliminate or diminish the noise that may be present in the image. Filtering techniques can be utilized for this purpose. It also involves elimination of unwanted structures such as background. Further, to improve the quality of the image through elevation of contrast, contrast enhancement techniques are adopted. Certain specific and novel pre-processing techniques have also been proposed in the literature for this purpose.

The pre-processed image is further considered for processing. In certain cases, image transformation techniques are applied to transform the image to a different domain such that the region of interest (tumor in this case) is exposed more clearly. Wavelet transformation, Curvelet transformation, Fourier transform etc., are commonly used for this purpose. The process of image segmentation is then performed on the obtained transformed image or the pre-processed image or both to delineate the region of interest. The most commonly used segmentation technique is thresholding, where the region of interest is depicted with white pixels and the other regions with black pixels. Once the region is segmented, morphological operations are executed to remove some false regions and to clean the image. Pertaining to execution of image processing techniques alone, the process of detection ends here and the detected region of interest is diagnosed as the tumor.

In the case of incorporating pattern recognition techniques also, further steps have to be performed. To implement pattern recognition techniques, expressive features are extracted from the segmented region, pre-processed images, transformed images or all of them. Then, significant features are selected from the extracted features with respect to distinguishability. The selected features are then fed into machine learning procedures such as classification and clustering to generate a learning model that predicts if the image contains tumor or not. Classification techniques demand training data with ground truth for building the learning model while clustering techniques do not require ground truth.

The pattern recognition procedures can be adopted at pixel level, component level or image level. In the case of pixel level, the feature set represents the pixel values from various transformed domains whereas in the context of component level, the properties of the detected regions of interest such as its area, perimeter, mean etc., forms the feature set while in image level, aggregated features of the entire image form the feature vector. In pixel level analysis, the prediction refers to whether the pixel is a tumor pixel

or background pixel; in component analysis, the prediction refers to whether the component is a tumor or false region whereas in image level the prediction denotes if the image is normal or diseased.

The obtained detection results depict four conditions namely true positive, true negative, false positive and false negative. True positive denotes a tumor being detected as tumor while true negative refers to non-tumor being correctly detected as non-tumor. False positive and false negative signifies a wrong detection; false positive refers to a negative condition being predicted as positive and false negative represents a positive condition being denoted as negative. With these values, metrics such as accuracy, sensitivity, specificity, true positive rate etc., can be estimated. Accuracy is defined as the ratio of sum of true predictions (true positive and true negative) to the total number of predictions. Sensitivity is measured as the ratio of true positives to the total number of positive samples. Sensitivity is computed as the ratio of true negative to total negative samples. True positive rate is defined as the ratio of true positive to total positives detected.

Having presented an overview of a generic framework for breast cancer detection using image processing and pattern recognition techniques, the next section reviews the state-of-art techniques towards breast cancer detection.

III. REVIEW ON BREAST CANCER DETECTION

Breast cancer is characterized by high mortality rate in women. To improve the survival rate, early detection of the disease is essential. Computational techniques are sought in this regard. Various image processing and pattern recognition techniques have been extensively used in this regard. The existing works are segregated into filtering based, morphology based, model based; multi-scale based and pattern recognition techniques to facilitate a clear view.

3.1. Filtering Based Approaches

Various filter such as average filter, wavelet filter etc., have been adopted to diagnose breast cancer. A few works relate to this are projected here. In 1997, a method based on Difference of Gaussian and Derivative features was proposed [9]. The methodology comprised of Difference of Gaussian based filter to highlight the candidate segments, reduction of non-malignant regions, extraction of size, shape, contrast and Laws texture features, derivative based feature selection and multilayer Perceptron neural network classification. The system demonstrated a sensitivity of 92% when tested on a database with 272 images.

In 1998, the capacity of wavelet transform in detecting calcifications was studied [10]. The image was decomposed into sub-bands and the high frequency sub-band revealed the calcifications to an extent. It was recommended that further exploration of wavelet transformation towards breast cancer detection could yield better results.

In 2013, a methodology based on wavelet transformation, feature extraction, selection and classification was put forth [11]. Initially, the images were transformed to wavelet domain to reduce the noise in the image and then the regions of interest were extracted. Then, 20 Gray Level Co-occurrence Matrix features were extracted from each region of interest and were fed as input to various classifiers to compare the performance of breast cancer mass prediction. The approach was tested on 322 images of mini-MIAS dataset.

In 2015, an approach based on Quality threshold and classification was advocated [12]. Initially, a low pass filter was used to reduce noise and improve contrast. Then, wavelet transform with a linear function was adopted. Subsequently, a quality threshold is utilized for segmentation of the candidate mass regions. Followed by this, texture features, shape features, correlogram function were computed and fed as input to support vector machine to classify the segments as tumor or not. Accuracy of 83.53%, sensitivity of 93=2.31% and specificity of 82.20% was achieved through this process.

From the study, it is realized that filtering techniques can be used to pre-process the image and make it suitable for further processing. Choice of correct parameters for the filters greatly affects the performance. Transformation to other domains namely wavelet and curvelet can be still explored to achieve better results for the task in hand. The next sub-section presents on the existing approaches to detect breast cancer through morphological operations.

3.2. Morphology Based Approaches

Morphological methods have also been extensively adopted to identify breast cancer. The works pertaining to these kinds of operations are presented here. In 1987, a technique based on difference image and Monte Carlo method of clustering was put forth [13]. Primarily, a difference image obtained from subtracting signal suppressed image from signal enhance image eliminated the structured background. Then, features related to physical properties of the micro-calcifications were extracted followed by Monte Carlo method of generating simulated clusters of micro-calcifications. The approach achieved a true positive cluster rate of 80% at a false positive detection rate of one cluster per image.

In 1998, micro-calcification detection based on fuzzy logic was suggested [14]. Initially, the calcifications were enhanced based on intensity and non-uniformity. Then, irrelevant breast structures were eliminated through a curve detector. Then, the calcifications were identified through iterative thresholding. Reconstruction of shape of the micro-calcification and removal of isolated pixels were performed through morphological operations. The approach applied a fuzzified range of a mammogram image to locate the candidate regions and to impose the fuzzified image on original image to provide fidelity. Free response ROC was computed to validate the performance of the approach.

In 2005, a two stage approach based on morphological operations and classification was put forth [15]. The first stage incorporated morphological and region growing operations to delineate segments that could contain tumors. Then shape, intensity variations, and spread pattern characteristics of these segments were estimated and fed as input to the classification process to distinguish the segments into normal, benign and malignant. Mammogram images of MIAS database were used for evaluation of this approach and a total accuracy of 82.90% was obtained.

In 2007, a procedure to detect clustered micro-calcifications through mathematical morphology and artificial neural networks was developed [16]. Morphology techniques extracted the segments even if the background was not uniform. Morphological filters were applied to eliminate noise and regional maxima that did not correspond to calcification. Then, features were elicited from these extracted segments and provided to multilayer perceptron and neural networks based on radial basis functions. The multi-layer perceptron yielded higher results reporting a true positive rate of 94.70% and 0.27 false positives per image.

In 2009, a two step methodology involving morphological operations and Fuzzy C-Means clustering was put forth [17]. During the first step, the regions of interest were segmented through application of morphological operations. Then, the segments were subjected to Fuzzy C Means clustering for intensity based segmentation. The results showed justifiable performance.

In 2010, a methodology based on morphological operations and region growing was advocated [18]. The proposed method involved mathematical morphology based pre-processing and seeded region growing for noise reduction, suppression of radio-opaque artifacts, separation of breast profile region from background and removal of pectoral muscles.

In 2015, another approach that employed scale-specific blob detection technique was advocated [19]. Initially, kurtosis and skewness were computed through a sliding window to eliminate normal images from further processing. For the abnormal ones, energy of the pixel is computed at two different scales and ratio-energy measure is estimated. The original image was also operated by tophat morphological operation. The intersection of both the images revealed micro-calcification and macro-calcifications. The approach was tested on 64 images of DDSM database yielding an accuracy, sensitivity and specificity of 93%, 91% and 97%.

From the investigation, it is clear that morphological operations provide an excellent tool for pre-processing and post-processing the candidate regions to reconstruct the shape of the region and eliminate regions that have inappropriate shape and geometric properties when compared to original regions. The structural element utilized for morphological operations greatly contribute for the process. Improvements and novel ideas towards design of structural elements can yield better results for breast cancer identification.

3.3. Model Based Approaches

Model based methods and domain based methods to diagnose breast cancer is concisely presented here.

In 1991, an approach based on symmetric property of the left and right breasts was proposed [20]. Initially the mammograms were aligned to compensate the differences that could arise due to variation in size and shape between the two breasts. Subsequently, various asymmetry based measures were estimated between the corresponding positions of the two breasts. This approach resulted in an increased sensitivity when tested on a set of mammogram images.

In 2005, a two stage procedure was put forward to identify breast tumor [21]. The first stage incorporated closed form mathematical model to calculate the location and shape of candidate micro-calcifications. During the second stage, spatial, spectral and texture features were extracted from each candidate segment. Sequential forward search algorithm was then executed to select the significant features. Then General Regression Neural Network and Support Vector Machine were used to classify the data. SVM outperformed the other by achieving 98% of accuracy.

In 2015, a methodology based on rough set theory and classification was suggested [22]. Initially, chain codes were used to delineate the regions of interest. Then, rough set methods were adopted to enhance

the regions of interest. Then, the mass region was segmented from the region of interest through an improved vector field convolution snake. Subsequently 32 features were extracted from the mass region and its neighborhood. Various classification methods such as Random Forest, SVM, and Genetic Algorithm based SVM, Particle Swarm Optimization SVM and decision tree were utilized. Two datasets namely DDSM and MIAS were used for evaluation achieving an accuracy of 97.73% and MCC of 0.8652.

Model based approaches are quite complex to implement mad require extensive research on setting of its parameters. Snake contours can be still explored to detect the contour of tumorous regions. The next sub-section deals with multi-scale approaches in identifying breast tumor.

3.4. Multi Scale Based Approaches

The multi-scale operators help in detecting regions of interest of various sizes and orientations. The works related to multi-resolution analysis is also presented here.

In 1990, a two stage methodology was developed with regard to detecting breast cancer [23]. The methodology comprised of two steps. Initially, multi-resolution image processing was performed through fuzzy pyramid linking such that the pixel groups with high possibility of being tumor were identified. Subsequently, the identified pixel groups were presented to a classifier such that firstly, simple properties were used for classification of these pixel groups into tumor and non-tumor. However, if it could not be classified, then complex features were adopted to distinguish tumor and non-tumor.

In 2009, Curvelet transform was advocated for identification of breast cancer [24]. Initially, the image was decomposed in curvelet basis. Then, the biggest co-efficient were extracted as features. Euclidean distance between them was used to build the supervised classification model. A classification accuracy of 98.59% was achieved indicating that curvelet transform had a high potential in identifying breast cancer.

In 2010, Breast Cancer classification through Gabor features was proposed [25]. The methodology was composed of three stages. Firstly, image pre-processing was performed involving down sampling, quantization, denoising through non-linear diffusion and enhancement. Then, segmentation was done through circular Gaussian filter in frequency domain. After that adaptive thresholding based on histogram analysis was applied to delineate the candidate segments. Gabor filter banks with five banks on four directions were formulated and edge histogram descriptors were elicited. Fuzzy C-Means clustering and K-Nearest Neighbor classification was then performed on these features to eliminate false candidate regions. When tested on DDSM database, the approach yielded true positive rate of 90% at false positives per image of 1.21 and true positive rate of 93% at false positives per image of 1.19.

In 2011, Gabor wavelet based classification of breast cancer from mammogram images was recommended [26]. Primarily, the images were filtered using Gabor Wavelet and then directional features along various orientations and frequencies. Then Principal Component Analysis was adopted to reduce the dimensionality of the features. Then, the extracted features were provided as input to the SVM classifier. It was observed that Gabor Wavelet features revealed better distinguishability than the features from original image.

In 2013, image level breast cancer classification through features obtained from wavelet transformed images was put forward [27]. Initially wavelet transform was performed at different size scales. Then, statistical features were extracted from each transformed image and significant features were given as input to Naïve Bayes classifier. DDSM and MIAS databases were used for evaluation reporting a sensitivity and specificity of 100% and 79% respectively.

In 2015, breast cancer categorization based on wavelet and contourlet features was advocated [28]. Initially, the image was transformed into wavelet and contourlet domains. Then the feature vector was formulated through features from these transformed images. The extracted features were fed into Support Vector Machine for classification of the mass.

From the existing works, it has been observed that multi-scale analysis have always been able to perform better in segmentation. It can capture the candidate regions in various scales and orientations. For these approaches also, choice of scale and orientation are very significant in performing the required operation. The features extracted from the multi-scale analysis are more expressive in distinguishing the malignant tumor from benign ones. The following sub-section presents on the pattern recognition based approaches.

3.5. Pattern Recognition Based Approaches

Patter recognition based approaches have been extensively utilized in medical image analysis [29]. Supervised and unsupervised techniques are the commonly adopted pattern recognition techniques [30]. Supervised approaches have been widely used

to detect tumor pixels or regions in view of breast cancer identification. These approaches demand training data with ground truth to build the learning model. Most widely used unsupervised approaches are clustering, that do not demand ground truth for building its learning model. A few works implementing supervised and unsupervised approaches for breast cancer detection are concisely presented here.

In 2005, image level and component level analysis was performed [31]. The image level classification of mammogram images was implemented through wavelet based analysis. The component level analysis was done on the region of interest through fuzzy-neural technique. The proposed approach was validated on MIAS database.

In 2006, an approach based on ROI selection and neural network classification was proposed to detect micro-calcifications [32]. Initially ROI hunter algorithm was implemented to delineate the region of interest. Then geometric and shape based parameters were elicited and given as input to neural networks with momentum. The algorithm was assessed on 3762 images acquired from different hospitals yielding an AuC of 0.882 and 2.8 false positives per image at a sensitivity of 82%.

In 2007, a hybrid scheme that combined the fuzzy and rough set concepts was introduced [33]. Initially, the images were subjected to fuzzy image processing for contrast improvement, extraction of regions of interest and enhancing the edges around the regions of interest. Then, Gray Level Co-Occurrence Matrix features were extracted from these regions of interest. Rough set method was implemented to generate all reducts that include minimal rules and attributes. Then these rules were presented to a classifier to facilitate classification. The results reported an overall accuracy of more than 98% with miniinal rules.

In 2012, a method based on feature selection and ensemble techniques was developed [34]. Primarily, forward search and backward search techniques were analyzed to select the significant features that contributed to breast cancer mass classification. Then, ensemble of Decision Tree, Support Vector Machine – Sequential Minimal Optimization was used for classification reporting better results than when done by individual classifiers.

In 2013, a classification approach biased on trainable segmentation, feature reduction and classification was proposed [35]. Initially, trainable segmentation with decision tree learner as base was performed. Large set of features were extracted, which were reduced through genetic search optimization. The selected features were then classified through AdaBoost ensembled K-Nearest Neighbor classification.

In 2014, Particle Swarm Optimized Wavelet Neural Network was put forth to classify breast cancer from mammogram images [36]. Law texture energy measures were extracted from the suspicious regions of the image and fed into the proposed pattern classifier. The approach was tested on real 218 mammogram images and reported an AuC of 0.9685 with a sensitivity and specificity of 94.17% and 92.11% respectively.

Again in 2014, a fuzzy K-Nearest Neighbor Equality classification was proposed to classify the mass into benign and malignant [37]. Haralick and run length texture features were extracted and fed as input to Fuzzy Nearest Neighbor Equality classification procedure achieving an accuracy, sensitivity and specificity of 96.52%, 94.46% and 96.81% respectively.

In 2017, a technique involving noise reduction, feature extraction and classification was put forth [38]. Primarily the impulse noise present in the image was reduced by Weiner filter. Then K-Means clustering is performed to delineate the candidate malignant tissues. Subsequently, twenty Gray Level Co-occurrence Matrix features were extracted from the candidate segments and were provided to classification through K-Nearest Neighbor and Support Vector Machine. The methodology was assessed using mini MIAS database.

From the investigation, it is realized that pattern recognition based approaches form a vital role in breast cancer detection. Even with other approaches such as filter based approaches, morphology based approaches, multi-scale based approaches and model based approaches, pattern recognition techniques were adopted to identify the tumor regions from the identified candidate regions, thus reducing the false positives. The performance of pattern recognition techniques are greatly based on the expressiveness of the feature vector fed as input to it. Hence, extraction of expressive and distinguishing features remains a challenge. Exploitation of various classification procedures was minimal. Still many classification and clustering techniques could be exploited and enhanced to yield better accuracy rate in detection of breast cancer.

Having presented the review on computerized methods to detect breast cancer with main emphasis on image processing and pattern recognition techniques, this work concludes that there still exists

many challenges in implementing a computer aided system that could help the radiologists to detect breast cancer automatically in real time. Exploration and exploitation with regard to filtering techniques, morphological operations, model formulation, multi-scale analysis and pattern recognition techniques is essential to develop an efficient real time breast cancer diagnosis system.

CONCLUSIONS

Breast cancer has been identified as the second leading cause for mortality in women. Women above 40 years of age are advised to regularly screen their breasts to ensure that they are out of danger. Treatments for breast cancer, if present are fruitful only when they are detected early. Mammography imaging of the breast reveals the presence of abnormal tissues if present. Not all calcifications identified are cancerous, only malignant tumors need immediate attention. Image processing and pattern recognition based approaches have been widely used to detect the cancer automatically. This work presented a review on these techniques for breast cancer detection. The approaches were categorized into filtering, morphology, multi-scale, model and pattern recognition based approaches. The filtering techniques comprised of techniques such as wavelet, curvelet, low pass filtering etc., to pre-process and enhance the image to elicit efficient features for building learning model to predict tumor. Morphology based techniques involved application of morphological operations such as dilation, erosion, opening, closing, tophat etc., to delineate the candidate mass regions, reconstruct their shape and eliminate false regions. Multi-scale approaches utilized Gabor wavelets, Gabor filters etc., at various scales and orientations to capture the exact boundary of the calcifications. Model based approaches incorporated a model to segment the regions of interest. Pattern recognition based approaches focused on the selection of expressive features, application of various feature selection procedures, building of learning model through classifiers such as SVM, Neural Networks, and Multi-Layer Perceptron etc. The review concludes that there still exist many challenges that need to be addressed to attain a computer aided system for automated breast cancer detection.

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