INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
(Volume2, Issue4)
Available online at: www.Ijariit.com

Review of Different Approaches in Mammography

Prabhjot Kaur[1], Amardeep Kaur[2]
[1]*Punjabi University Regional Centre for IT and Management, Mohali, Punjab*
[1]*kaurprabhjot173@gmail.com*
[2]*Punjabi University Regional Centre for IT and Management, Mohali, Punjab*
[2]*amardeep_tiet@yahoo.com*

Abstract- Breast cancer screening remains a subject of intense and, at times, passionate debate. Mammography has long been the mainstay of breast cancer detection and is the only screening test proven to reduce mortality. Although it remains the gold standard of breast cancer screening, there is increasing awareness of subpopulations of women for whom mammography has reduced sensitivity. Mammography has also undergone increased scrutiny for false positives and excessive biopsies, which increase radiation dose, cost and patient anxiety. In response to these challenges, new technologies for breast cancer screening have been developed, including; low dose mammography[1]

Keywords- Breast cancer, mammography

I. INTRODUCTION

Breast cancer is the most frequent form of cancer in women and is also the leading cause of mortality in women each year. The World Health Organization estimated that 521,907 women worldwide died in 2012 due to breast cancer. Studies have indicated that early detection and treatment improve the survival chances of the patients. In order to detect it in its early stage, many countries have established screening programs. Among all the diagnostic methods currently available for detection of breast cancer, mammography is regarded as the only reliable and practical method capable of detecting breast cancer in its early stage [2]

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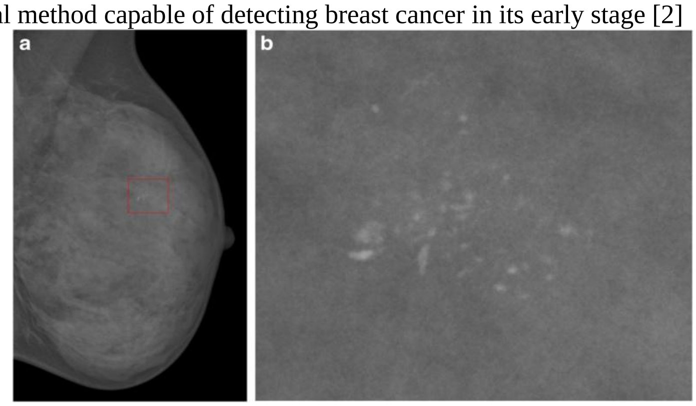

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Fig. 1 Mammogram with a microcalcification cluster. a) Original image. b) Enlarged view of the microcalcification part of a outlined with a red rectangle[2]

The screening programs generate large volumes of
Mammograms to be analyzed. However, due to the complexity of the breast structure, low disease prevalence (approximately 0.5%), and radiologist fatigue, abnormalities are often ignored. It is reported that about 10–25% abnormal cases shown in mammography have been wrongly ignored by radiologists. Double reading can improve the detection rate, but it is too expensive and time consuming. Thus, computer-aided cancer detection
technologies have been investigated. The adoption of a computer-aided detection (CAD) system could reduce the experts' workload and can improve the early cancer detection rate [2]

II. Literature Review

Over the years, a lot of work has been done for the detection of microcalcification. In order to understand the topic properly many papers from various journals are reviewed. So, a brief review of all the techniques developed for the detection of microcalcification has been discussed below:

Al-Najdawi et al. have investigated combining several image enhancement algorithms to improve the performance of breast-region segmentation. The masses that show in mammogram images are further analyze and classified into 4 categories that consist of: benign, probable benign and possible malignant, probable malignant and possible benign, and malignant. The main contribution of this work is to reveal the optimal combination of different enhancement techniques and to segment breast region in order to get better visual interpretation, analysis, and classification of mammogram masses to help radiologists in making correct decisions. The experimental dataset consists of more than 1300 mammogram images from both the King Hussein Cancer Center and Jordan Hospital. Results achieved cancer classification accuracy values of 90.7%. Moreover, the results shows a sensitivity of 96.2% and a specificity of 94.4% for mass classifying algorithm [3].

Antony et al. proposed a new approach to determine the classification of mammographic image using k-means clustering algorithm which can use different features of the image like shape, intensity values and density features and region features to compute the feature vector. They computed the mean values of intensity values of the pixels in the region extracted to compute the intensity mean value. The density measure is also computed in the similar fashion. The region metric is computed with the extracted region values and it has seven different features hidden. k-means clustering is used based on the computed feature vectors to identify the class of the input image. The proposed system reduces the space and time complexity and produces good results. It has produced classification accuracy up to 99% which is more than other methodologies in this era [4].

Abbas et al. proposed a study in which they are using two principal morphological operations: dilation and erosion. To detect breast cancer, the proposed system will help the doctors to improve the diagnosis of the disease. The best result was obtained with the (disk) structure element of disk with (15*15) mask and the worst result is the (line) structure element of disk with the (3*3) mask. The results that have been obtained by applying Mean Square Error and Peak Signal to Noise Ratio are the good indicator of image quality because they are easy to generate and seemingly unbiased. The dataset of mammogram image were taken from Baghdad madina Al-tab andazadi hospital Kirkuk [5].

Liu et al. integrated the possibilistic fuzzy c-means (PFCM) clustering algorithm and weighted support vector machine (WSVM) for the detection of microcalcification clusters in full-field digital mammograms (FFDM). For each image, suspicious microcalcification regions are extracted with region growing and active contour segmentation. Then geometry and texture features are extracted for each suspicious microcalcification, a mutual information-based supervised criterion is used to select important features, and PFCM is applied to the cluster samples into two clusters. Weights of the samples are calculated based on the possibilities and typicality values from the PFCM, and the ground truth labels. A weighted nonlinear support vector machine (SVM) is trained. During the test process, when an unknown image is presented, segmentation step is used for locating suspicious regions, selected features are extracted, and the suspicious microcalcification regions are classified as containing microcalcification. Finally, the microcalcification regions are analyzed with spatial information to locate microcalcification clusters. The proposed method is evaluated using a MIAS dataset and compared with the standard unweighted support vector machine (SVM) classifier. The detection performance is evaluated by the response receiver operating (ROC) curves and the free-response receiver operating characteristic (FROC) curves. The proposed method obtained an area under ROC curve of 0.8676, while the standard support vector machine (SVM) obtained an area of 0.8268 for microcalcification detection. For microcalcification cluster detection, the proposed method obtained a high sensitivity of 92% by a false-positive rate of 2.3 clusters image, and it is better than standard support vector machine (SVM)with 4.7 false-positive clusters image at the same sensitivity [2].

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Pratiwi et al. proposed a study in which there are three main processes, which are pre-processing, feature extraction, and classifier. In this study two classifiers are used that are Back-Propagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN). Before the dataset get into the classifier, it will be pre-processed first. Then, the features of each mammogram extracted using Gray-level-Co-occurrence Matrix (GLCM) to get the features vector containing the texture information of mammogram. For the evaluation and development of the proposed system, the two different classifiers (BPNN, RBFNN) are trained multiple times in order to achieve best accuracy. This paper report and attempt on using the Radial Basis Function Neural Network (RBFNN) for the mammograms classification based on the Gray-level Co-occurrence Matrix (GLCM) texture based features. Normal and abnormal breast images are used as the standard input taken from Mammographic Image Analysis Society (MIAS) database. The computational experiments show that RBFNN is better than BPNN in performing breast cancer classification [6].

Xie et al. presented a novel automatic detection processing in terms of mammographic images for microcalcification clusters detection. Studies has been made to resolve the problem by establishing an automatic detection procedure of an input mammographic image. With the help of this process we can easily reduce the complexity for mammographic image analysis. In order to overcome the problem of low contrast mammograms a new algorithm based on blob detection was proposed. Preliminary evaluation of the proposed method performs on MIAS database instead of synthetic images. Comparison was done with Cohen's kappa coefficients and some other experiments and it was observed that we can obtain better microcalcification clusters detection outcome in terms of accuracy, sensitivity and specificity with this technique [7].

Sharma et al. proposed an experiment using CAD system to classify malignant and nonmalignant mammogram patches. Suitable methods were used for preprocessing, which helped to removes the artifacts, unwanted components, and extracts the breast region from its background along with extraction of abnormal regions from mammograms. To avoid the processing of full mammogram, methods to extract the fix-sized ROI patches are also proposed. The Zernike moments are based on texture feature extraction technique and it is used to recognize the pattern of malignancy or non malignancy in the mammogram patches. The variations in the outcome are observed by the experimenting with the low-order and high-order Zernike moments. Experiments are performed with the other well known texture descriptors gray level co-occurrence matrix (GLCM) and discrete cosine transform and (DCT), and it is observed that the proposed CAD system works well with Zernike moments. It has been observed that SVM with RBF kernel attains the highest sensitivity and specificity values at lower orders of Zernike moments. CAD system has improved the accuracy of diagnosis and promises to perform a second reader role [8].

CONCLUSION

Breast cancer is the main cause of death among women. Early detection and diagnosis through regular screening and timely treatment can prevent cancer. This paper presents a review of different techniques and classifier used in mammographic images. Some of techniques used in this review paper are CLAHE, median , Gaussian filtering, Histogram equalization method, fuzzy c-means (PFCM) clustering algorithm, Gray-level Co-occurrence Matrix (GLCM) texture based features, Chan-Vese Model, Hough Transform, blob detection and Zernike moments. Regarding mammogram classification mainly Radial Basis Function Neural Network and Back-Propagation Neural Network, weighted support vector machine (WSVM) and Support Vector Machines are used as classifier. By using histogram equalization method and k-means clustering algorithm it produces classification accuracy 99% which is best and reduces time and space complexity.

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