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Latest Advances in Diagnosis of Breast Cancer Using Image Processing Techniques in Digital Mammographic Images

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***Abstract*—Breast cancer is one of the most common types of cancer in women. As no primary prevention is available, early detection of breast cancer is important to reduce the death rate among women. At present, mammography is considered the most reliable, cheap and highly sensitive technique for detection of breast cancer [1]. The aim of the paper is to provide an overview regarding the latest advances in the diagnosis of breast cancer using image processing techniques. The paper also presents detailed description regarding the basic concepts related to breast cancer.**

***Keywords*— microcalcifications, bilateral asymmetry, masses, architectural distortion.**

I. Introduction

Breast cancer is one of the major causes of death in women. The statistics shows that one in eight women develop breast cancer in their life time [2]. Recent development in medical field and involvement of information technology in this field has led to a decrease in death rate by 30% among women affected by breast cancer. Various techniques that are used for breast analysis are: mammograms, MRI, FNAC, PET (Positron Emission Tomography). So far, the most economical and effective breast image analysis method has been mammography as it is cheap, simple and portable.

American College of Radiology Breast Imaging Reporting and Data System (BIRADS) is becoming a standard on the assessment of mammographic images. A radiologist assessing the mammograms will look for the following types of changes.

1. Micro calcifications
2. Masses
3. Bilateral Asymmetry
4. Architectural Distortion

II. Relevance Of The Work

In many countries, it is mandatory for asymptomatic women to undergo regular mammographic screening. Hence, today it is one of the most common areas for radiological malpractice suits in the United States [3]. Radiologists analyze mammograms in batches of hundred and more in one sitting. Only 0.5 % of these mammograms will have breast cancer. Hence, chances are that radiologists may miss some mammograms with indications of malignancy and they will be diagnosed as normal because it is often difficult to be ever so vigilant. About 5 to 30 % women with mammograms indicating malignancy are diagnosed normal. Here, CAD (Computer Aided Diagnosis) can play a vital role in providing the radiologists with a second opinion and thus reducing the chances of a cancer being missed. The remaining part of the paper is organized as follows:

Section III deals with recent advances in CAD systems and newly developed algorithms for detection of masses, calcifications, architectural distortion and bilateral asymmetry. Section IV deals with conclusion and scope for future work.

III. Review of Key Techniques for CAD Systems.

Several techniques for the detection of breast cancer has been put forth so far. In this section, a review of important techniques for the detection of masses, calcification, architectural distortion and bilateral asymmetry in mammograms is given.

A. Detection of microcalcifications in mammograms

Microcalcifications are tiny granule like calcium deposits. Clusters of microcalcifications are important signs of detection of breast cancer. Typically, at least,

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three micro calcifications per square centimeter are required to be considered a cluster [4]. Calcifications are neither benign nor malignant but are the results of epithelial cells that have undergone benign or malignant transformation. The size and shape of calcification can vary greatly from 10 µm to several millimeters in diameter and from spherical to elongated. The density of the calcification can also vary depending on the amount of fluid present in the concretion. Benign calcifications [5] include the following types;

1. Skin calcifications
2. Vascular Calcifications
3. Coarse calcifications
4. Large rod like calcifications
5. Lucent Centered Calcifications.
6 Milk of Calcium
7 Egg shell Calcifications.
8 Dystrophic Calcifications.
9 Suture Calcifications.

Benign Classifications are larger, more rounded, smaller in number, less densely packed and homogenous in size and shape.

The characteristics of malignant calcifications are :

1. Small in size
2. Densely packed
3. Numerous in number
4. Varying size and orientation

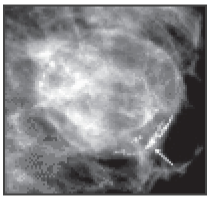

Fig 1a). Egg shell calcification.

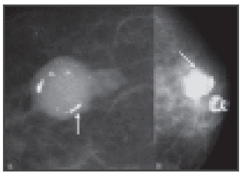

Fig 1 b). Coarse and popcorn calcification.

Fig 1. Benign Microcalcifications.

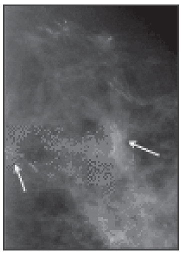

Fig 2. Malignant microcalcifications

Nakayama et al [6] developed a computerized scheme for detecting microcalcifications in mammograms based on the idea of Hessian matrix for classifying nodular structures and linear structures. The computerized scheme used Bayes discriminant function with 8 features for distinguishing among 3 types of ROI, yielded a sensitivity of 100% and a false positive rate of 0.98 % per mammogram.

Deeba et al [7] proposed swarm optimized neural netwok for classification of microcalcifications. The proposed classifier is evaluated based on the MIAS database where 51 malignant, 63 benign and 208 normal images are utilized. The approach was also tested on 216 real time clinical images having abnormalities. With the proposed methodology, the area under the ROC curve (A(z)) reached 0.9761 for MIAS database and 0.9138 for real clinical images.

Dhawan et al [8] proposed a feedforward backpropagation neural network to classify mammographic microcalcifications using the image structure features. Four networks were trained for different combinations of training and test cases, and number of nodes in hidden layers. False Positive (FP) and True Positive (TP) rates for microcalcification classification were computed to compare the performance of the trained networks. The results of the neural network based classification were compared with those obtained using multivariate Baye's classifiers, and the k-nearest neighbor classifier. The neural network yielded 74% accuracy.

Bankmann et al [9] used Bayesian classifier for classification of microcalcifications with 100% accuracy.

Kramer et al [10] used K-Mean algorithm for characterizing malignant tissues from benign ones. He reported with a success rate of 100 %.

In 2003, Cheng et al [11] gave detailed survey of different approaches used in automated detection and classification of microcalcifications.

Liyang et al [12] proposed several machine learning methods for automated classification for clustered micro classifications. The kernel based methods Support Vector Machine(SVM), Kernel Fisher Discriminant (KFD) analysis, RBM yielded the best performance compared to the approach based on Neural Networks.

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B. Detection of masses in mammograms

A mass with or without calcification is another important change seen on a mammogram. Masses may be cysts(non- cancerous, fluid- filled sacs), solid tumors (fibroadenomas) but sometimes sign of cancer. The size, shape and margins of the mass may help the radiologist to determine if the cancer is present. Benign mass is smoothly marginated and are round or oval in shape. The masses with distorted margin which gets more speculated as time passes is the malignant one. The early diagnosis improves the life quality and survival rates. The algorithms are composed of two stages:

1. Detection of suspicious regions on the mammograms
2. Classification of suspicious region as normal , benign or malignant

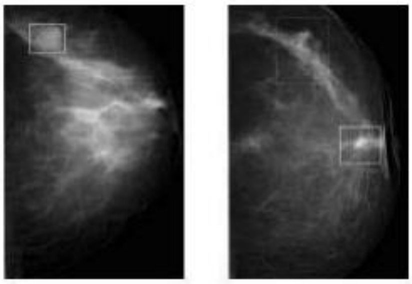


Figure 2. A Sample Mammographic Image

a) Benign Breast Mass **b)** Malign Breast Mass

Pelin el al [13] proposed Support Vector Machine (SVM) to classify masses. Here feature extraction was done by wavelet coefficient. It involved 66 digitized mammographic images. It showed 84.8 % accuracy by using SVM with RBF kernel.

Lubomir et al [14] proposed a new type hybrid classifier based on adaptive resonance theory and LDA (linear discriminant classifier) which divided the masses into two classes.A class containing malignant masses and another containing a mix of benign and malignant masses. The masses from the second class were given as input to LDA which separated the malignant ones from benign masses. This hybrid classifier was also compared to the LDA classifier and back propagation neural network. The accuracy of hybrid classifier was 81 %, whereas that of LDA was 78 % and BPN 80%.

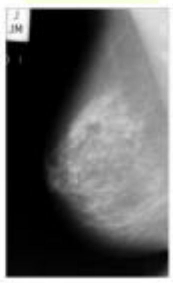
Sampat [15] made an attempt to analyze the various methods for identification and classification of masses and micro calcifications.

Cheng et al [16] discussed various approaches for automated detection and classification of masses in mammograms.

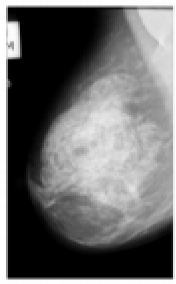
Varma et al [17] used extreme Machine Learning (ELM) with wavelet features , GLSDM and Gabor Filter based features for classification of masses and reported 94 % accuracy. Three different activation functions namely unipolar , bipolar, and Gaussian were used. Maximum efficiency is reported for bipolar activation function.

C. Detection of Architectural Distortion in mammograms

The normal architecture of the breast is distorted with no definite mass visible. It includes focal retraction at the edge of the parenchyma and speculation radiating from a point. 12-45% of architectural distortions go unnoticed in screening mammograms because it is subtle and has a changeable presentation [19] [20]. Architectural distortion is the third general sign of non palpable cancer. [21] .



Normal Breast image



Breast image with Architectural distortion.

Sujoy et al [22] proposed a model with two layer architecture for recognizing architectural distortion. This model constructed an efficient set of distinctive textures for recognizing architectural distortion in digital mammograms. In the first layer, the mammograms were analyzed by a multiscale oriented filter bank to form texture descriptor of vectorized filter responses and the set of textural primitives (or textons) is represented by a mixture of Gaussians which builds up the second layer of the proposed model. The observed textural descriptor in the first layer is assumed to be a stochastic realization of

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one (hard mapping) or more (soft mapping) textural primitive(s) from the second layer. The results obtained on two publicly available datasets, namely Mammographic Image Analysis Society (MIAS) and Digital Database for Screening Mammography (DDSM), showed the efficiency the anticipated approach.

Rangaraj et al [23] proposed a method to detect signs of premature breast cancer from mammograms. Here the authors checked for architectural distortions based on a method using Gabor filters, fractal analysis and Haralicks texture features. Analysis of the performance of the methods with free-response receiver operating characteristics indicated a sensitivity of 0.80 at 7.6 false positives per image. The methods have good potential in detecting architectural distortion in mammograms of interval cancer cases.

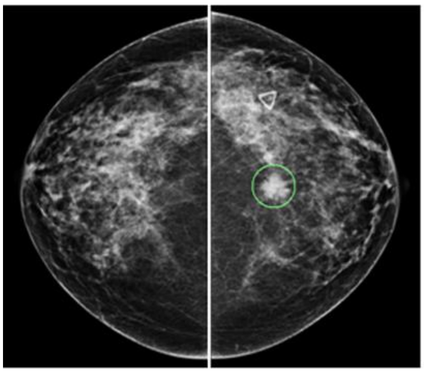
Mastubara et al [24] used fractal dimensions to differentiate between normal and architectural distortion patterns in mammographic ROIs. The area under ROC curve achieved was 0.89.

Ichikawa [25] used mathematical morphology and a concentration index to detect architectural distortion. Sensitivity rates of 94% with false positives per image and 84% with 2.4 false positive per image were reported.

D. Detection of Bilateral Asymmetry in Mammograms

Asymmetry between the right and the left mammograms of a specified subject is one of the main signs used by the radiologists to diagnose breast cancer [26]. According to BIRADS[27] asymmetry indicates the occurrence of greater density in one breast not including distinct mass, tiny asymmetric dense region, parenchyma distortions.

There are only a small number of publications on the detection of bilateral asymmetry [28] [29].



Breast image with Bilateral Asymmetry

Jelena et al [31] proposed an algorithm for bilateral asymmetry that uses B-spline interpolation for breast alignment. Alignment of the right and left breast is important step in computer-aided detection algorithm in order to allow comparison of corresponding points in right and left breast. Differential analysis of breasts is based on simple subtraction technique. The results were highlighted with colour in each image and presented on a computer monitor thereby indicating the regions that need to have a second look by the radiologist and be further investigated.

Ferrari et al [30] proposed a method for the analysis of left right bilateral asymmetry which is based on Gabor Wavelets used for the detection of linear directional components by means of multi resolution representation. Accuracy rate of 74.4 % was achieved.

Miller and Astley [32] detected bilateral asymmetry using semi automated texture based methods and measures of shape topology and brightness in the fibro glandular discs, The approach on an average classified 80% of the breast area correctly.

IV. Conclusion and Future work

There is no doubt that CAD is a vital system in facilitating the early detection of cancer. The performance of the present day CAD systems need improvement. But the advances in technology will definitely help to develop their performance in future.

Presently, several CAD systems that support micro calcification detection have been used in the clinics. There have been mixed reviews regarding these systems, some showing performance improvement and others no improvement at all.

Masses are hard to discover than micro calcifications because they may be hidden or may behave like normal breast parenchyma. Also, detection of architectural distortion and detection of bilateral asymmetry are important research topics as not much research has been done on them.

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