PERFORMANCE ANALYSIS IN COMPUTER AIDED DETECTION OF BREAST CANCER BY MAMMOGRAPHY

***R.Bhanumathi**

****G.R.Suresh**

ABSTRACT

Breast cancer is one of the frequent and leading causes of mortality among woman, especially in developed countries. Early detection and treatment of breast cancer are the most effective method for detecting breast cancer at the early stage. Computer-aided-detection (CAD) system can plays a vital-role in the early detection of breast cancer and can reduce the death rate among women with breast cancer. This paper aims to provide an overview of recent advances in the development of CAD systems and related techniques. Primarily we begin with a detailed introduction of some basic concepts related to breast cancer detection, then focus on the key CAD techniques developed recently for breast cancer, including comparative analysis on detection of masses, calcification, architectural distortion, and bilateral asymmetry in mammograms.

Keywords: Breast cancer, Microcalcification, Computer- aided detection, Mammography.

*** Department of Computer Science, Apollo Engineering College, Chennai, India**

**** Department of Electronics and Communication Engineering, Easwari Engineering College, Chennai, India**

1. INTRODUCTION

In recent years breast cancer was found to be the most recurrent form of cancer in women. The use of mammography as a screening tool for the detection of early breast cancer in otherwise healthy women without symptoms continues to be debated. Critic point out that a large number of women need to be screened to locate cancer, two-thirds of the decrease in cancer deaths is due to mammography screening. There is evidence which shows that early diagnosis and treatment of breast cancer can significantly increase the chance of survival for patients [1]–[4]. The earlier the cancer is detected, better the chances that a proper treatment can be arranged. At present, there are no effective ways to prevent breast cancer, because its origin remains unidentified. However, efficient identification of breast cancer in its early stages can give a woman a better chance of full improvement. Therefore, early detection of breast cancer can play an important role in reducing the associated morbidity and death rates.

Computer-aided detection is a system which is specifically planned to spot the abnormalities in mammograms such as calcification, masses, architectural distortion and bilateral asymmetry and aid the radiologist in detecting apprehensive areas on the mammograms. For research scientists, there are more than a few interesting research topics in cancer detection and diagnosis system, such as high-efficiency, high-accuracy lesion detection algorithms, including the detection of masses, calcification, architectural distortion, and bilateral asymmetry in mammograms.

This paper deals with the basic concepts related to breast cancer detection and focuses on CAD techniques that are developed recently for breast cancer. As a result, comparison of comparative analysis of masses, calcification, architectural distortion, bilateral asymmetry in mammograms is done.

This paper is organized as follows. Section II, presents the related works undergone in CAD systems for breast cancer, including many newly developed algorithms for detection of masses, calcification, architectural distortion and bilateral asymmetry in mammograms. Section III, describes the experimental results and section IV concludes the paper.

2. RELATED WORKS

Even though many techniques have been put forth so far, the growth of new algorithms for Computer-aided-detection of breast cancer is still an active research field, mainly in regard to the detection of slight abnormalities in mammograms [20]. In this section, different techniques for the detection of masses, calcification, architectural distortion, bilateral asymmetry in mammograms is reviewed.

2.1. Microcalcification MC Clusters in Mammograms

By analyzing a mammogram, pathologists could detect the presence of microcalcification in ones breast. Microcalcifications are tiny granule-like deposits of calcium as shown in Fig (1). The occurrence of clustered microcalcification in X-ray mammograms is an important display for the detection of breast cancer, particularly for individual microcalcification with diameters of about 0.7 mm and with an average diameter of 0.3mm [5]. Radiologists describe a cluster of microcalcification as the occurrence of three or more visible microcalcification within a square centimetre region of the mammogram [5]. The detection of clustered microcalcification in mammograms has been of great interest to many researchers [6]–[15]. MC detection methods could be broadly separated into four categories: 1) basic image enhancement methods; 2) stochastic modeling methods; 3) multiscale decomposition methods; and 4) machine learning methods.

Wavelet transform is basically a filtering technique that represents images hierarchically on the basis of scale or resolution. Nakayama et al [18] proposed a computerized scheme for detecting early-stage microcalcification clusters in mammograms. It developed a novel filter bank based on enhancement of NC, enhancement of NLC, sub images can be used to reconstruct the original image. It was shown to have potential to detect microcalcification clusters with a clinically acceptable sensitivity and low false positives.

Liyang et al. [19] investigated the use of SVM, KFD, RVM, and committee machines for classification of clustered MCs in digital mammograms. These different classifier models were trained using supervised learning to classify whether a cluster of microcalcification is benign or malignant, based on quantitative image features extracted from the microcalcification.

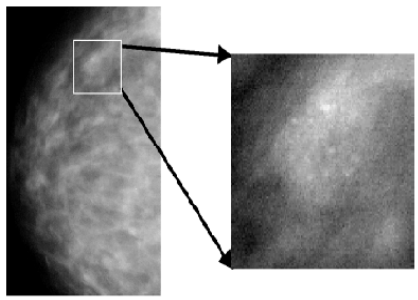

Fig. 1. Left: a CC view mammogram; right: expanded view showing clustered MCs. MCs is small granule-like deposits of calcium, and appear as bright spots in a mammogram

2.2. Masses in Mammograms

A mass is defined as a space-occupying lesion seen in more than one projection [21]. A mass is regularly characterized by its shape and margin [20], [22]. In general, a mass with a normal shape has a higher probability of being benign, whereas a mass with an unequal shape has a advanced probability of being malignant as shown in Fig (2). In the pixel-based approaches, features are extracted for each pixel and classified as suspicious or normal [20]. The subsequent approach for mass detection is region-based [20]. In the region-based approach, ROIs are segmented, and then, features are extracted from each region, which are then used to classify the regions as suspicious or not suspicious.

Lubomir et al.[23] proposed a hybrid unsupervised and a supervised model to improve classification performance. The classes were separated into two type, individual containing only malignant masses and the supplementary containing a mix of malignant and benign masses. The masses from the malignant classes are classified by ART2 and the masses from the varied classes were input to a supervised linear discriminate classifier (LDA).

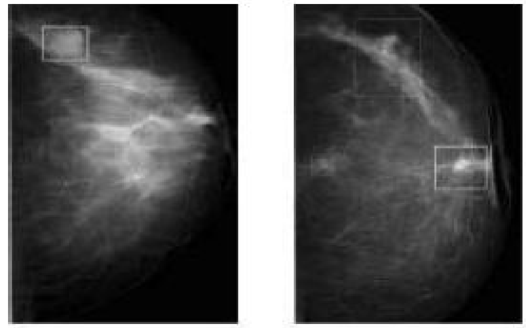

Fig. 2. A Sample Mammographic Image from Our Data Set

2.3. Architectural Distortion in Mammograms

The normal architecture (of the breast) is distorted with no definite mass visible. This includes speculations radiating from a point and focal retraction at the edge of the parenchyma. Architectural distortion also is an associated finding as shown in Fig (3). Architectural distortion is the third most general mammographic sign of nonpalpable breast cancer [25], [26] [27], [28]. But due to its subtlety and changeable presentation, it is often missed during screening.

Sujoy et al. [29] proposed the problem of categorizing a mammographic region-of-interest (ROI) as a two class classification problem as AD or non-AD [29]. The two-layer architecture first collects low-level rotation-invariant textural features at different scales and then learns latent textural primitives from the collected features by GMM.

Rangaraj et al. [30] proposed methods for the detection of architectural distortion in prior mammographic images of interval-cancer cases. The methods are based upon the analysis of spicularity and angular dispersion caused by architectural distortion. Novel measures of spicularity and angular dispersion are proposed for the characterization and detection of architectural distortion using the mammographic image, Gabor magnitude response and Gabor angle response and coherence.

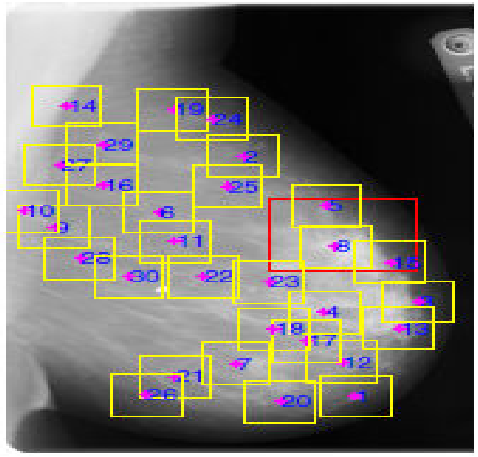

Fig. 3. A prior mammogram of an interval-cancer case with architectural distortion

2.4. Bilateral Asymmetry in Mammograms

Asymmetry between the left and right mammograms of a specified subject is a main sign used by radiologists to diagnose breast cancer [30]. The BI-RADS [21], [25], [31], [32]. Description of asymmetry indicates the occurrence of a greater density of breast tissue not including a distinct mass, in one breast as compare to the corresponding area in the other breast. Examination of asymmetry can give clues about the early signs of breast cancer, such as increasing densities, parenchymal distortion, and tiny asymmetric dense regions as shown in Fig (4).

Ferrari et al. [33] proposed a new scheme based upon a bank of self-similar Gabor functions and the Karhunen–Loève (KL) transform to analyze directional components of images [19]. The method is applied to detect global signs of asymmetry in the fibro-glandular discs of the left and right mammograms of a given subject. Jelena et al. [34] proposed a method for bilateral asymmetry detection in which the left and right breasts were aligned using the B-spline interpolation. After the breast alignment the differential analysis was performed. The difference between the breasts was calculated using simple subtraction technique.

Fig. 4. Bilateral Asymmetry

3. Experimental results and Discussion

3.1. Comparative analysis based on sensitivity

Table 1 displays the Performance of Sensitivity of all the four types of CAD systems namely microcalcification, masses, architectural distortion and bilateral asymmetry. The sensitivity works best in case of both microcalcification and masses and poor in case of architectural distortion and bilateral asymmetry. In fig 5 shows the graphical representation of sensitivity performance in types of CAD system.

Table 1. Performance of Sensitivity in different CAD system

Types of CAD Systems	Sensitivity
Microcalcification	93.7
Masses	94.7
Architectural distortion	84.2
Bilateral Asymmetry	81.8

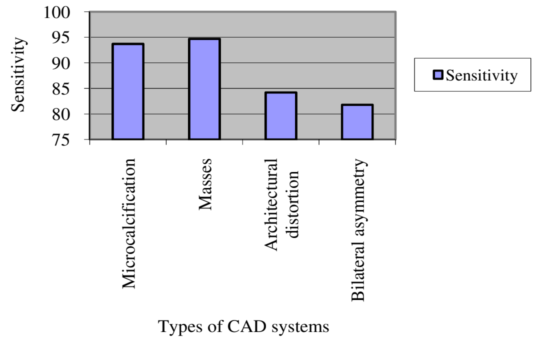

Fig 5: Performance of Sensitivity in different CAD System

3.2. Comparative analysis based on sensitivity

In table II shows the Specificity works best in case of architectural distortion and poor in case of microcalcification, masses and bilateral asymmetry. However the corresponding specificity of bilateral asymmetry is 52.4% were incorrectly classified. In fig 6 shows the graphical representation of specificity performance in types of CAD system.

Table 2: Performance of Specificity in different CAD system

Types of CAD Systems	Specificity
Microcalcification	70.6
Masses	71.4
Architectural distortion	79.1
Bilateral Asymmetry	52.4

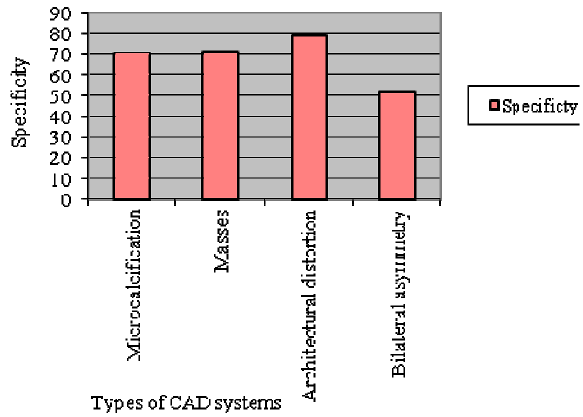

Fig 6: Performance of Specificity in different CAD System

3.3. Comparative analysis based on accuracy

In table III shows the average accuracy of types of CAD system. It was found that accuracy for masses and microcalcification is high when compared to architectural distortion and bilateral asymmetry CAD systems. The masses have high accuracy 84.8% and low accuracy rate of 67.4% in case of bilateral asymmetry. In fig 7 shows the graphical representation of average accuracy in types of CD Systems.

Table 3: Performance of Average Accuracy in different CAD system

Types of CAD Systems	Average Accuracy
Microcalcification	82.1
Masses	84.8
Architectural distortion	81.6
Bilateral Asymmetry	67.4

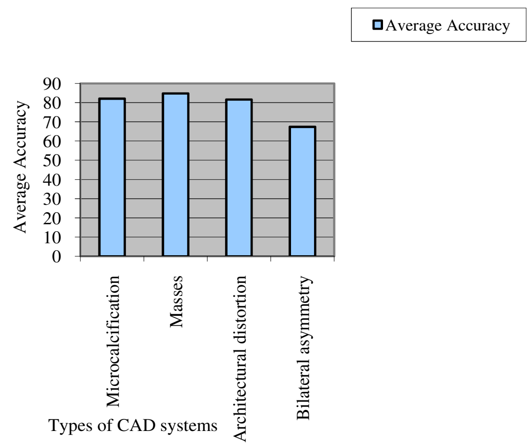

Fig 7: Performance of Average Accuracy in different CAD System

Upcoming work on computer-aided breast cancer detection should focus on the consideration in improving the performance of CAD systems. Even though present CAD systems have not been fully doing well, we believe that advance studies on CAD systems and related technique should help develop their performance, and in this manner facilitate them to gain more widespread adoption in breast care clinics. For MC detection, the last two decades have witnessed a great number of MC detection algorithms developed for mammograms. In current years, several CAD systems that support MC detection have been deployed for clinical use.

4. CONCLUSION

Computer-Aided-Detection (CAD) is a vital system for early detection of breast cancer. A noteworthy amount of work has been done in this area over the past 20 years. On the other hand, the performance of current CAD systems still needs improvement to fully meet up the requirements for everyday clinical applications. This paper has discussed an outline of the recent advances in CAD systems and related techniques, described some fundamental concepts related to breast cancer detection, including comparative analysis of detection of masses, calcification, architectural distortion and bilateral asymmetry in mammograms. Even though important improvement has been made more than the last 20 years, a large amount of work still needs to be done to build up more effective CAD systems.

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