CHAPTER 2

LITERATURE REVIEW

This chapter critically reviews the techniques available in the literature for detection and diagnosis of breast cancer. The literature is categorized according to the identified research problem. It also deals with research gaps, objectives and its significance.

2.1 INTRODUCTION

With the development of low cost computing and economical storage capacity, many researchers (Bellotti et al 2006; Banik et al 2011; Biswas 2011; Chuang et al 2006; Tang et al 2009a) have been investigating different methods of incorporating computer analysis in the detection and diagnosis of breast cancer. Until now there have been only a few commercially available systems that are used for breast detection in conjunction with the mammographer’s assessment. The Imagechecker (R2 Technology Inc, Los Altos, CA during 1998), SecondLook (iCAD, Nashua, NH during 2002), and mammography CAD engine (Eastman Kodak company during 2004) MammoReader (Intelligent Systems Software Inc., Clearwater, FL) are approved by the Food and Drug Administration (FDA), which may assist radiologists in the mammographic image interpretation (Muralidhar et al 2008).
Mostly, the computerized analysis methods in mammography can be divided into two areas that may be conjoined to form a total analysis system: CADe and CADx. The CADe methods locate the abnormality, whereas CADx methods may help radiologists in the final assessment of benign or malignant prediction.

2.2 COMPUTER AIDED DETECTION (CADe) TECHNIQUES

Various techniques for segmentation of the suspected areas are presented by different researchers, and among them threshold is found to be much simpler, inexpensive and faster than the other segmentation techniques. Many researchers adopt global or local thresholding, which is based on global information of the image (Cheng et al 2003).

Oliver et al (2010) have reviewed different approaches that involve automatic and semi-automatic detection and segmentation of mammographic masses. Different types of segmentation techniques such as region-based mammographic detection and segmentation, contour-based methods, clustering methods, model-based mammographic detection and segmentation are implemented and tested with two different mammographic datasets. In order to segment the image or to detect the ROI, various features such as texture, gray level, gradient and morphological features are employed. The performances of the different segmentation algorithms are compared using Receiver Operating Characteristics (ROC) curve which shows that the best performances, of 0.762 and 0.780 are obtained when applying the Laplacian approach over an enhanced version of the mammogram and the thresholding approach after applying Iris filter respectively. It is reported that the clustering methods are most widely used for segmenting the ROI.
Region growing algorithms have been widely used in mammographic mass segmentation with the aim of extracting potential lesions from the background of the image. Mencattini et al (2010) have developed a semi-automatic region growing approach, in which the growing step is automatically computed after a radiologist has manually placed the seed point.

Due to the contrast present in mammographic images, fuzzy logic has been introduced for the segmentation of ROIs. This algorithm first assigns a fuzzy membership value to each pixel and then calculates an error value. Fuzzy membership is updated taking into account neighboring pixels. The algorithm stops when a zero error is reached indicating that each pixel has been assigned either to bright, microcalcification or to dark, background region (Salvado & Roque 2005).

Oliver et al (2008) have used Fuzzy C Means (FCM) for segmenting the image into two clusters namely fatty versus dense mammographic tissue and considered both clusters for feature extraction. The study has yielded a correct classification rate of 86% and 77% for Mammographic Image Analysis Society (MIAS) dataset and Digital Database for Screening Mammography (DDSM) dataset respectively.

The FCM algorithm classifies pixels, which can belong to multiple classes with varying degrees of membership. This has benefits when compared to hard segmentation methods like K-means clustering (Martins et al 2009). However, the conventional FCM algorithm does not consider spatial and contextual information, which makes it sensitive to noise and intensity inhomogeneties (Pham & Prince 1999).
Chuang et al (2006) have modified the conventional FCM by incorporating the spatial information to segment the MRI images. Likewise Ojeda-Magana et al (2009) have used Possiblistic Fuzzy C Means (PFCM) clustering algorithm for the sub segmentation of mammograms.

Similarly, Chaira (2011) has introduced Intuitionistic Fuzzy C Means (IFCM) clustering for segmenting the computer tomography scan brain images for finding abnormalities. It is found that the IFCM is far better as compared to FCM algorithm. Hence this IFCM clustering is studied and taken for this research to segment the ROI from the mammogram image.

2.3 COMPUTER AIDED DIAGNOSIS (CADx) TECHNIQUES

The CADx system consists mainly of three steps: feature extraction, feature selection and classification. The existing studies related to diagnosis of breast cancer, that is feature extraction, feature selection and classification are reviewed in the following sections.

2.3.1 Feature Extraction

A typical mammogram contains a vast amount of heterogeneous information that depicts different tissues, vessels, ducts, chest skin, breast edge, film and X-ray machine characteristics. In order to build a robust diagnostic system towards accurately classifying normal and abnormal regions of mammograms and then to distinguish between benign and malignant regions, all the relevant information in mammograms are to be presented to the diagnostic system so as to enable it to discriminate between different pathologies effectively. In forth coming section various types of features and methods used for diagnosis of microcalcification, mass, architectural distortion and bilateral asymmetry are reviewed.
2.3.1.1 Diagnosis of microcalcifications

Cheng et al (2003) have listed about 200 studies on computer aided detection and classification of microcalcifications, including the methods for the visual enhancement of microcalcification, segmentation, analysis of malignancy and strategies for the evaluation of detection algorithms.

Kim et al (1998) have proposed statistical textural features based on Surrounding Region Dependence Method (SRDM) for the detection of clustered microcalcifications. This method defines four textural features to classify ROI into positive ROIs containing clustered microcalcifications and negative ROIs of normal tissue. In terms of the Free-response Receiver Operating Characteristic (FROC) curve, a sensitivity of more than 90% with low FP detection rate of 0.67 per cropped image is reported. The experimental results are quite promising due to the number of 140 ROI from 100 mammogram images.

Kim & Park (1999) have compared the SRDM features with the other conventional second order features like Gray Level Cooccurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM) and Gray Level Difference Method (GLDM) and found that the SRDM features outperform the other texture features.

Markov Random Field (MRF) method hybridized with Ant Colony Optimization (ACO), Genetic Algorithm (GA) and backpropagation network is used for the detection of microcalcification in digital mammogram by Thangavel et al (2005). Conventional textural analysis methods, namely Spatial Gray Level Dependency Method (SGLDM), SRDM, GLRLM and GLDM are used to extract features from the segmented image. It is found in the study that the SRDM features are superior to the other textural features by
producing 94% of accuracy with 161 pairs of digitized mammograms from MIAS database.

In the same way, Karahaliou et al (2008) have developed a system for breast cancer diagnosis based on the features such as gray-level texture, Laws’ texture energy measures and wavelet coefficient texture features. In this system, probabilistic neural network is used for classifying the mammogram and achieved area under ROC curve of 0.989 for 85 mammographic images. The limitation of this work is that the training and test samples are selected by leave-one-out methodology. So, the correlation between the data of the same patient may have favorably biased the reported classification performance. In addition, the system is evaluated only with the limited size of dataset.

Podsiadly-Marczykowska et al (2009) proposed a set of 27 shape descriptors to classify the microcalcifications into BI-RADS morphological types. The authors reported the accuracy ranging from 84% to 88% with SVM classifier.

Yu & Huang (2010) also have proposed combined model-based and statistical textural features for microcalcification cluster recognition in digital mammograms. In the first stage, the method detects microcalcifications, adopting a wavelet filter and two thresholds. In the second stage, textural features based on MRF and fractal models together with statistical textural features based on the SRDM are extracted from the neighborhood of microcalcifications and are classified by a three-layer neural network. It is found that a true positive rate of about 94% is achieved at the rate of 1.0 FP per image and a true positive rate of about 90% is achieved when reducing the FPs per image to 0.65 FPs per image. The experimentation is done only on 25 images from MIAS data repository.
Similarly, Malar et al (2012) have investigated a method to discriminate the microcalcifications from the normal tissue based on wavelet features. It is reported that 94% of classification accuracy is obtained by using extreme machine learning classifier.

Tsai et al (2011) also have used wavelet transform and Renyi’s information theory to reconstruct the suspicious microcalcification regions in the X-ray image by eliminating the most normal tissue pixels and background noise. Forty nine descriptors, which mainly include shape inertia, compactness, eccentricity and gray-level co-occurrence matrix features, are used to define the characteristics of the suspicious microcalcification clusters. Principal Component Analysis (PCA) is employed to reduce the dimension of the feature set. Finally, back propagation neural network classifier is used to classify the system and achieving the TP rate of about 97.12% and the FP rate of 7.89%. In this study, 716 clusters are considered out of 26 images.

2.3.1.2 Diagnosis of masses

Hadjiiiski et al (1999) have used combination of features from GLCM and GLRLM matrices. These matrices are computed from the ROI. Stepwise linear discriminant analysis is applied to reduce the dimension of the feature vector. Combination of unsupervised adaptive resonance theory and supervised linear discriminant analysis classifier is used for classification. Area under the ROC curve of 0.81 and 0.78 are achieved for the hybrid classifier and stepwise linear discriminant analysis respectively.

Bellotti et al (2006) have proposed a completely automated CAD system for mass detection which includes three techniques: 1) using an edge based segmentation algorithm to select the suspicious regions, 2) deriving eight gray tone independent texture features for each ROI from GLCM at four angles and 3) A supervised two layer feed forward neural network, with the
gradient-descent learning rule to classify the masses from normal tissue. A database of 3369 mammographic images, which includes 2307 negative cases and 1062 positive cases with at least one confirmed mass, has been diagnosed. It is reported that the area under ROC curve is 0.783 ±0.008 for the ROI based classification. For mammographic images diagnosed by expert radiologists, 4.23 FPs per image is found at 80% of the sensitivity of mass detection.

Mu et al (2008) have used shape, edge sharpness and texture characteristics to discriminate between benign and malignant masses and reported that area under the ROC curve of 0.95 with 111 ROIs; 46 malignant and 65 benign images.

Texture features such as photometric features, discrete texture features, run-length texture features and fractal texture features are used by Sameti et al (2009) to classify mammograms from manually marked regions. The mammograms are taken 10 to 18 months in advance subject to the classification for cancer detection. A stepwise discriminant analysis is also performed to identify the best discriminating features. This system results in an average classification of 72% with the real dataset, but fails to identify the ROI automatically.

Mencattini et al (2010) have developed a method to classify the ROI, based on 25 features; 11 geometric features and 14 textural features from GLCM for the selected ROI. Experiments are carried out with 16 mammographic images from DDSM database achieving an Area Under Curve (AUC) of 0.88. Predominant features are selected manually by ranking the features and the reduced feature set are evaluated with the help of Monte Carlo simulation.
Samulski & Karssemeijer (2011) have developed a method by considering both MLO view and CC view. First for each view the region based features like region contrast, roughness of the boundary, linear texture, and relative location in the breast, contour smoothness and lesion size are extracted for ROI. Then the ROIs in both views are matched based on region matching techniques, and the features are extracted from the matched ROIs. This method is evaluated by using 454 mammograms with mass and architectural distortion and reported the increased mean sensitivity by 4.7% in the range of 0.01 to 0.5 FP per image.

Eltoukhy et al (2012) have presented a two-stage classifier based on multiresolution approach, namely wavelet and curvelet. Initially, the ROI is manually cropped and wavelet or curvelet coefficient is extracted based on the statistical t-test method. Then the ROI is classified into normal or abnormal. The abnormal tissue is again classified into benign or malignant using SVM classifier. It is found that the classification accuracy achieved using wavelet coefficient is 96.56% with 150 features and that of curvelet coefficient it is 97.30% with 333 features.

2.3.1.3 Diagnosis of architectural distortion

Matsubara et al (2003) have used mathematical morphology to detect architectural distortion around the skin line, and a concentration index to detect architectural distortion with mammary gland and reported a sensitivity of 94% and 84% with 2.3 FPs per image and 2.4 FPs per image, respectively.

Size of ROI, the mean pixel value, the mean concentration index, the mean isotropic index, the contrast, and four other features based on the power spectrum are employed by Ichikawa et al (2004) to detect architectural
distortion. It is reported that the classification accuracy of 76% and the sensitivity of 80% with 0.9 FP per image are obtained.

Use of Fractal Dimension (FD) to characterize the presence of the architectural distortion in mammographic ROIs has been explored recently. Guo et al (2005) have investigated the characterization of architectural distortion using Hausdorff dimension and a Support Vector Machine (SVM) classifier to distinguish between mammographic ROIs exhibiting architectural distortion and those with normal mammographic patterns. A set of 40 ROIs is selected from MIAS database which is classified with an accuracy of 72.5%.

Eltonsy et al (2006) also have proposed a method for the detection of masses and architectural distortion based on the identification of points surrounded by concentric layers of image activity. A test dataset of 80 images containing 13 masses, 38 masses accompanied by architectural distortion, and 29 images exhibiting only architectural distortion, is used in the evaluation of the method. An overall sensitivity of 91.3% with 9.1 FPs per image is reported. A sensitivity of 93.1% in the detection of pure architectural distortion is also reported with the same level of FPs per image in the overall dataset.

Tourassi et al (2006) have explored the use of FD to differentiate between normal and architectural distortion patterns in mammographic ROIs. The area under the ROC curve of 0.89 with 112 ROIs related to architectural distortion and 1388 ROIs exhibiting normal tissue patterns is reported. It is observed that the average FD of ROIs exhibiting architectural distortion is lower than that of ROIs with normal patterns, and that the observed difference is statistically significant under an independent-sample and two-tailed t-test.
Rangayyan et al (2008) have investigated a method based on Gabor filters and phase portrait analysis to detect the initial candidates for the sites of architectural distortion. FD, entropy, sum entropy and inverse difference moment features are calculated from each candidate site. A database of 386 ROIs, with 21 ROIs related to architectural distortion is used. The ROC curve of 0.80 with Bayesian classifier and a sensitivity of 0.79 at 8.4 FPs per image are obtained.

In the same way Prajna et al (2008) have investigated a method based on Gabor filter and phase portrait analysis to detect the potential candidates of architectural distortion. A database of 386 ROIs, with 21 ROIs related to architectural distortion is used. The FD and fourteen textural features are calculated for each ROI. The ROC curve of 0.74 and 0.70 is reported using the feature FD and fourteen textural features respectively.

Nemoto et al (2009) have developed a method to detect architectural distortion with radiating spiculation on 25 digital mammograms and attained a sensitivity of 80.0% at 0.8 FP per image.

Rangayyan et al (2010) have proposed a method for the detection of architectural distortion based on linear phase portrait analysis, FD and Haralick’s texture features. A database of 4224 ROIs are automatically extracted from 106 prior mammograms of 56 interval cancer cases with 301 true positive ROIs associated with architectural distortion and from 13 TN ROIs from 52 mammograms. A sensitivity of 0.8 at 7.6 FP per image is reported.

Banik et al (2011) have enhanced the method proposed by Rangayyan et al (2010) for the detection of architectural distortion by adding the Gabor filter, method for analysis of angular spread of power, Laws’ texture energy measure in addition to phase portrait analysis, fractal analysis,
and Haralicks’ texture features. The area under the ROC curves obtained using the features selected by stepwise logistic regression and the leave one ROI out method are 0.76 with Bayesian classifier, 0.75 with Fisher linear discriminant analysis and 0.78 with a single layer feed forward neural network. A sensitivity of 0.80 and 0.90 at 5.8 and 8.1 FPs per image respectively are obtained with the Bayesian classifier and leave one image out method.

In another study, Banik et al (2013) have extended their work to the detection of architectural distortion by adding entropy measures and reported an area under the ROC curves of 0.75. Also, they achieved FROC indicated a sensitivity of 0.80 at 5.2 FPs per patient.

2.3.1.4 Diagnosis of bilateral asymmetry

One of the cues used by radiologists to detect the presence of breast cancer is bilateral asymmetry, where the left and right breasts differ from each other in overall appearance in the corresponding mammographic images. Lau & Bischof (1991) have devised a method for the detection of breast tumors, using a localized definition of asymmetry that encompasses measures of brightness, roughness and directionality. This method is evaluated using 10 pairs of mammograms where asymmetry is a significant factor in the radiologist’s diagnosis. A sensitivity of 92% is obtained with 4.9 FPs per mammogram.

Miller & Astley (1993) have presented a method for the detection of bilateral asymmetry that comprises a semi-automated texture based procedure for the segmentation of the glandular tissue, and the measures of shape and registration cost between views for detecting the occurrence of asymmetry. An accuracy of 86.7% is reported on a test dataset of 30 mammogram pairs.
In another study, Miller & Astley (1994) have proposed a technique for the detection of bilateral asymmetry based on measures of shape, topology and distribution of brightness in the fibroglandular disk. An accuracy of 74% with 104 mammogram pairs is reported.

Ferrari et al (2001) have presented a procedure based on the detection of linear directional components. A multiresolution representation based on Gabor wavelets is used. The fibroglandular disk is segmented, and the resulting image is decomposed using bank of Gabor filters at different orientations and scales. The Karhunen-Loeve transform is employed to select the principal components of the filter responses. For representing the quantitative and qualitative analysis of the oriented patterns the rose diagram are used. A database of 80 images from MIAS database containing 20 normal cases, 14 asymmetric cases and 6 architectural distortion cases is used to evaluate the method reporting the accuracy up to 74.4%.

Rangayyan et al (2007b) have proposed a technique to analyze bilateral asymmetry in mammograms by combining directional information, morphological measures and geometric moments related to density distributions. Eighty-eight mammograms from the Mini-MIAS database are used and achieved the classification accuracies of 84.4% with sensitivity and specificity rates of 82.6% and 86.4% respectively.

Karnan & Thangavel (2007) have devised a method to analyze the bilateral asymmetry based on GA. GA is used to find the breast border and the nipple position based on which, the mammogram images are aligned and subtracted to extract the suspicious region. The overall detection rate of 90.6% with 114 abnormal mammograms from MIAS dataset is reported.
2.3.2 Feature Selection

Stepwise logistic regression (Banik et al 2011; 2013; Rangayyan et al 2010), PCA (Ferrari et al 2001; Buciu et al 2011), stepwise discriminant analysis (Sameti et al 2009), sequential forward selection (Oliver et al 2008) and so on are used for feature selection achieving an improved classification accuracy in breast cancer classification.

In the recent years, nature inspired algorithms are used for feature selection. GA, ACO, Particle Swarm Optimization (PSO), and Simulated Annealing (SA) are used in numerous applications for both feature selection and also in optimization problems (Mu et al 2008; Hendrawan & Murase 2011; Jona et al 2012; Babaoglu et al 2010).

Artificial Bee Colony (ABC) is a stochastic, nature inspired, swarm intelligent algorithm proposed by Karaboga (2005) for handling constrained optimization problems. Since its proposal, ABC has been proved to be successful in solving optimization problems in numerous application domains (Karaboga et al 2012). Moreover, it is proved to give promising and enhanced results in the areas where GA, ACO, PSO, DE algorithm and evolution strategies have used (Karaboga et al 2009). Hence ABC is used in the present research work for feature subset selection.

2.3.3 Classification

After extraction and selection, the features are input into a classifier to classify the detected suspicious areas into normal, benign or malignant. Applications of machine learning techniques for classification of medical data are becoming increasingly popular. Among various classification methods, neural network based classifiers have been found to be successful in a number of applications like medical image analysis (Hwang & Bang 1997; Wei et al
Radial Basis Function Network (RBFN) has also been widely applied in many science and engineering fields. An RBFN uses the radial basis functions as the activation functions of the network and has three layers, namely input layer, a hidden layer and a linear output layer. Suresh et al (2010) have proposed a new sequential learning algorithm named SRAN. This SRAN classifier uses Radial Basis Function (RBF) as a basic building block and problem independent self-regulated control parameters.

Usually, the CAD system integrates common steps: image preprocessing, image enhancement, segmentation of ROI, feature extraction, feature selection, and classification of lesions. There are plenty of dissimilar approaches to different phases. These approaches can still be improved and new approaches or even distinct combination of the approaches can be used to create better algorithms for more robust and efficient computer aided detection and classification of breast tumors.

CAD can play a key role in the early detection of breast cancer and help to reduce the death rate among women with breast cancer. Hence, these, CAD systems and related techniques have attracted the attention of both researchers and the radiologists in the recent years. Though various techniques exist for the detection of cancer, many techniques do not consider all the four signs together. Moreover, these techniques are found to less accuracy. An increasing need has been felt for detecting and classifying the occurrence of breast cancer at an early stage. So a novel approach to detect all the signs of cancer in early stages is necessary. These situations have laid a foundation for the current research.
2.4 OBJECTIVES OF THE RESEARCH

The present research aims at developing an effective and efficient cancer detection and classification technique that can produce a high level of accuracy and performance. Its main objectives are

- Automatic segmentation of the suspicious region
- Proposing novel features to classify all the signs of abnormalities into benign or malignant
- Enhancing and introducing a feature selection method
- Reducing the false positive and increasing the classification accuracy
- Reducing the learning time

It investigates and improves CAD techniques for the detection and the classification of microcalcifications, masses, architectural distortion and bilateral asymmetry into benign or malignant.

2.5 CONTRIBUTION OF THE RESEARCH

The research in focus proposes the following approaches for cancer detection, which are

- Segmentation of suspicious region using IFCM with spatial information (sIFCM)
- Feature extraction based on MSRDM, Gabor filters, multifractal analysis, directional and morphological analysis
- Feature selection using modified ABC optimization and
- Classification of ROI using SRAN classifier
In general, the methods for segmentation, feature extraction, selection and classification are evaluated to build an effective CAD system to discriminate between the indicative patterns associated with normal, benign and malignant parenchyma. Figure 2.1 shows the phases of the proposed research work.

Figure 2.1 Phases of the proposed methodology
2.6 SUMMARY

In this chapter, a range of existing CAD techniques for the early detection of breast cancer is reviewed. A brief taxonomy has been presented by dividing these techniques into mammographic image segmentation, feature extraction techniques; to diagnose mass, to diagnose microcalcification, to diagnose architectural distortion and to diagnose bilateral asymmetry, feature selection and classification techniques. There is a substantial research on the detection and classification of microcalcifications and masses, certain areas of research in CAD of breast cancer still require attention. Only a small number of researchers have focused on detecting architectural distortions and bilateral asymmetry and no features are identified to detect all the signs of abnormalities together. Hence, the development of new CAD for breast cancer detection and classification, by considering all the abnormalities in mammograms is required.