CHAPTER 1

INTRODUCTION

1.1 BREAST CANCER

Breast cancer is formed when the cells in the breast are in an abnormal growth or out of control. The cells are formed as a tumor and it can be seen by X-ray techniques or felt as a lump. The tumor is termed as a malignant and its cell is grown into surrounding tissue or it metastasizes to other parts of the body. In women, breast cancer forms in different parts of the breast; ducts, glands, etc. First, the breast cancer starts from ducts, the passages that drain milk from lobules to nipple and is called as ductal cancer. Some breast cancer begins in the cells of lobules which are milk producing glands and is called as lobular cancer. The other types of cancer produced in different tissues in the breast are called as sarcomas and lymphoma. Figure 1.1 illustrates the breast tissue and their parts.

![Figure 1.1 Normal Breast Tissue](image-url)
The breast cancer spread through the lymph system, it consists of lymph nodes, lymph vessels and lymph fluids. Lymph nodes are small in size, and it is comprised of immune system cells. The Immune systems are connected by Lymph vessels it looks like a small vein and it consists of clear fluid away from the breast. So, Lymph consists of fluids, immune system cells and some waste products. First, the breast cancer enters into Lymph vessels and it grown into Lymph nodes.

1.1.1 Statistics about Breast Cancer

Breast cancer is the most common cancer in women for worldwide. In the USA, an estimated amount of 231840 women is affected with breast cancer in 2015 (Torre et al. 2015). In the USA, breast cancer situates rank second after the lung cancer and it is leading cause of premature mortality for women (Siegel et al. 2015).

An American woman is most affected by the breast cancer and about 12% in the US will affected by the invasive breast cancer during their lifetime. The American cancer society estimates for breast cancer in the United States for 2016 are:

- About 246,660 new cases of invasive breast cancer will be diagnosed in women.
- About 61,000 new cases of Carcinoma In Situ (CIS) will be diagnosed (CIS is noninvasive and is the earliest form of breast cancer).
- About 40,450 women will die from breast cancer.
1.1.2 Breast Cancer Symptoms

There are different types of symptoms for breast cancer, one of the most common symptoms of breast lumps are benign. Other symptoms are, changes in the size and shape of the breast, changes in the nipple feels, changes in the skin color, a nipple discharge other than breast milk and is discharged from the breast and the nipple turned towards the breast. These changes are illustrated in Figure 1.2.

![Breast Cancer Symptoms](image)

Figure 1.2 Breast Cancer Symptoms

1.2 MAMMOGRAM

Mammogram is an x-ray image of the breast and is used to detect the abnormalities in the breast cancer. Screening mammography is an important factor to reduce the breast cancer mortality. The two types of mammograms are Screening Mammogram and Diagnostic Mammogram.

- Screening Mammogram: This technique is used to analyze the signs of breast cancer in women, the person who doesn’t have any breast symptoms or problems. Two different angles of the breast cancer are represented in X-ray.
Diagnostic Mammogram: The Diagnostic mammogram is used if there is any change present in the screening mammogram or the women affects by any breast problem. If the woman was affected by breast cancer in the past, then diagnostic mammogram is used to screen.

1.2.1 What do mammogram shows?

Mammogram can’t state that an abnormal area in cancer, however it is helpful for a health care provider. In mammogram, the two types of breast changes are found as calcifications and mass.

**Calcifications:** It is represented by tiny materials and is deposited with in the breast tissue and looks like small white spots on the picture. Calcifications may or may not be affected by cancer. The two types of calcifications are micro calcification and macro calcification

**Mass:** It is an important change in the mammogram image is called as tumor and it may or may not have calcifications.

1.2.2 Working Principle of Mammogram:

Figure 1.3 illustrates the block diagram of Film-screen and Digital mammography. The two types of detection in digital mammography are indirect detection and x-rays. X-rays pass through the patient breast and hit the scintillator. The conversion of x-ray energy into visible light is obtained using scintillator. It is coupled with a photo detector array or tiles of Charge-Coupled Device (CCD) using optical fibers. Scintillator is used by crystal of cesium iodine. The Photodiode is used to form the Amorphous Silicon Detector (ACD), ACD along with a Thin-Film Transistor (TFT) is used to read out circuitry.
Figure 1.3 Digital Mammogram

The direct method is illustrated in the Figure 1.3 where amorphous selenium is used whenever the x-ray strikes it; electron-hole pairs are formed. These pairs are collected by TFT array and produce the output image in the form of an array. Film-screen mammogram is used for detection in early stage of breast cancer and it saves many lives. Excellent image quality, ease access to image and computer aided diagnosis is obtained by digital mammography compared to film-screen mammography (Pisano et al. 2005).

Breast tomosynthesis (Friedewald et al. 2014) or 3D mammography is the new invention of mammogram techniques. In this type the breast is compressed and the machine takes only low dose as it passes through a mammogram. The computer provides the output of the mammogram image in 3D visualization. This type also used more radiation compared to standard mammogram because of clearance.
Table 1.1 Critical and Important Outcomes of Screening Mammography and Clinical Breast Examination (CBE) in the Systematic Evidence Review

(Source: Oeffinger et al. 2015)

<table>
<thead>
<tr>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Critical outcomes</strong></td>
</tr>
<tr>
<td>Breast Cancer mortality: Breast cancer deaths prevented by screening</td>
</tr>
<tr>
<td>Quality of life: Quality adjusted life gained by screening</td>
</tr>
<tr>
<td>Life Expectancy: Life-years gained by screening</td>
</tr>
<tr>
<td>False positive finding: Recall for additional testing (imaging and/or biopsy) after abnormal CBE or mammography, in which further evaluation determines that the initial abnormal finding was not cancer</td>
</tr>
<tr>
<td>Over diagnosis: Screen-detected cancers that would not have led to symptomatic breast cancer if undetected by screening</td>
</tr>
<tr>
<td>Over treatment: Cancer therapies (surgery, radiation, chemotherapy) performed for screen-detected cancers that would not have led to symptomatic breast cancer if undetected by screening</td>
</tr>
<tr>
<td><strong>Important but not critical outcomes</strong></td>
</tr>
<tr>
<td>Breast cancer stage: Tumor characteristics at diagnosis (including stage, tumor size, and nodal status)</td>
</tr>
<tr>
<td>Short- and long-term emotional effects: Anxiety, depression, quality of life associated with positive results (i.e., true and false positives)</td>
</tr>
</tbody>
</table>

1.3 BREAST CANCER LESION

Breast cancer has some characteristic lesions such as microcalcifications, masses, architectural distortions and bilateral asymmetry.
1.3.1 Microcalcifications

Microcalcifications are small deposits of calcium of size from 0.33 to 0.7 mm and are slightly brighter than surrounding tissues. These lesions are difficult to detect in mammography because it appears with low contrast due to their small size, although have high inherent attenuation properties. Associated with extra cell activity in breast tissue, microcalcifications may show up in clusters or in patterns. A typical mammogram from the Mammographic Image Analysis Society (MIAS) database with microcalcifications and its ground in truth is shown in Figure 1.4 (Chang et al. 2005; Kavitha & Kumaravel 2007).

![Figure 1.4](source)

(Source: Chang et al. 2005; Kavitha & Kumaravel 2007).

**Figure 1.4 (a) Original mammography image (b) Correspondent ground truth (from MIAS Database)**

A microcalcifications cluster is normally more detectable than isolated microcalcifications, and contributes for diagnosis of early stages of breast cancer. These clusters may have three or more microcalcifications present in a mammogram region with an area around 1 to 2cm. Once microcalcifications may be a sign of malignancy and it is important to be able to distinguish benign and malignant microcalcifications, Table 1.2 presents the grade, degree of suspicion and mammographies appearance (Kavitha & Kumaravel 2007)
Table 1.2 Grading of imaging reports of microcalcifications according to risk of malignancy

<table>
<thead>
<tr>
<th>Grade</th>
<th>Degree of suspicion</th>
<th>Mammogram appearance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal</td>
<td>No abnormality seen</td>
</tr>
<tr>
<td>2</td>
<td>Consistent with a benign lesion</td>
<td>Popcorn, ring, micro style or diffuse bilateral calcification</td>
</tr>
<tr>
<td>3</td>
<td>A typical or indeterminate but probably benign</td>
<td>Localized cluster of round, fine or punctuate calcification</td>
</tr>
<tr>
<td>4</td>
<td>Suspicious of malignancy</td>
<td>Localized cluster of granular calcification</td>
</tr>
<tr>
<td>5</td>
<td>Consistent with malignancy</td>
<td>Comedo calcification</td>
</tr>
</tbody>
</table>

1.3.2 Masses

It is an another type of lesion and is very difficult to find in the mammogram than microcalcifications because the features of a mass are resemblance to those of the normal breast parenchyma.

Figure 1.5 BI-RADS standardized description of masses
Basically, masses have several shapes. They are round, oval, lobulated or irregular and margin can be formed circumscribed to Spiculated (Jatoi & Kaufmann 2010) and is illustrated in Figure 1.5. It is very difficult to distinguish between benign and malignant in the mass but the features of the mass are different. Benign masses are smooth and distinct and it is round in shape, where as malignant mass is irregular in shape and it has blurry in their boundary. If the mass has a regular shape with the highest probability, then it is considered as benign while the mass with irregular shape has a high probability, then it is termed as malignant (Saki et al.2010; Sun et al. 2010; Zhao et al. 2011).

1.3.3 Architectural distortions

The anatomy of the breast included several linear structures that cause directionally oriented texture in mammograms. So, a way to detect architectural distortions is the change of the normal texture of the breast. Architectural distortion could be categorized as malignant or benign. The former includes cancer and the latter includes scar and soft-tissue damage due to trauma. Due to its subtle appearance and variability in presentation, architectural distortion is the most common missed abnormality in false negative cases (Ayres et al. 2003; Banik et al. 2009).

1.3.4 Bilateral Asymmetry

Bilateral asymmetry of breast means a difference between corresponding regions in left and right breast and can be classified into global asymmetry and focal asymmetry. The former happens when a greater volume of fibroglandular tissue is present in one breast compared to another in the same region. The latter corresponds to a circumscribed area of asymmetry seen on two views, and usually is an island of healthy fibroglandular tissue that is superimposed with surrounding fatty tissue (Bozek et al. 2009)
Table 1.3 BI-RADS report final assessment categories

<table>
<thead>
<tr>
<th>Category</th>
<th>Definition</th>
<th>Recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Incomplete assessment</td>
<td>Additional imaging workup</td>
</tr>
<tr>
<td>1</td>
<td>Negative</td>
<td>Routine screening</td>
</tr>
<tr>
<td>2</td>
<td>Benign findings</td>
<td>Routine Screening</td>
</tr>
<tr>
<td>3</td>
<td>Probably benign</td>
<td>Short term follow-up (6 months)</td>
</tr>
<tr>
<td>4</td>
<td>Suspicious abnormality</td>
<td>Biopsy may require</td>
</tr>
<tr>
<td>5</td>
<td>Highly suggestive</td>
<td>Biopsy required</td>
</tr>
<tr>
<td>6</td>
<td>Known (biopsy-proven) cancer</td>
<td>Appropriate action</td>
</tr>
</tbody>
</table>

1.4 CONTENT BASED IMAGE RETRIEVAL

Computer-Aided Diagnosis (CAD) systems are termed as computer software that used to analyze the medical images and find the lesions in the medical image and it is helpful to clinicians for further diagnosis. In the past two decades the CAD system was activated and provided promising results. CAD system is applied in mammography, Chest CT and CT colonography. But still there is a debated going on the conflicting evidence concerning the clinical benefits of a CAD system and radiologist. To improve the accuracy of the radiologist in the CAD results, the CAD system should provide more interactive supporting evidence.

Content Based Image Retrieval (CBIR) plays an important role in the CAD application because it has an advantage of vast image database to facilitate the clinical decision by showing similar cases interactively and it is applicable for false positive reduction and lesion characterization. It is a second classifier or post processing step for a CAD system.
CBIR system has a benefit of finding of images or collection of image with similar contents. With the help of large image database and retrieving techniques of a CBIR system efficiently find the images with pathologies or imply particular diseases.

Research and development issues in CBIR cover a range of topics, many shared with mainstream image processing and information retrieval. Some of the most important are:

- Understanding image user’s needs and information-seeking behavior
- Identification of suitable ways of describing image content
- Extracting the features from raw images
- Providing compact storage for large image databases.
- Matching query and stored images in a way that reflects human similarity judgments
- Efficiently accessing stored images by content
- Providing usable human interfaces to CBIR systems

Key research issues in video retrieval include:

- Automatic shot and scene detection
- Ways of combining video, text and sound for retrieval
- Effective presentation of search output for the user.
Figure 1.6 Overview of Content Based Image Retrieval Block diagram

Figure 1.6 illustrates the block diagram and its overview of CBIR system. The CBIR system consists of two databases are image database and feature database. The collections of features of all images in the given database are stored in the image feature database. While adding a new image in the image database, image features are extracted and stored in the feature database. The features are represented in a convenient format before storing them appropriately for faster search. The feature database contains the query features and is compared with image database using similarity measure.
CBIR system module consists of Input and output interface, Image database and its interface, image features database and its interface, feature extraction, representation, indexing & storing modules and Similarity searching & image retrieval.

- **Input and output interface**

  Input interface provides the mammogram image from the image database. The output interface provides or displays the retrieved output image based on the similarity measure.

- **Image database and its interface**

  The collection of mammogram images is available in the image database. The accessibility to the mammogram image database provides by the interface.

- **Image feature database and its interface**

  This block consists of collections of features for all images in the given database. The accessibility to the image feature database is given by corresponding interface.

- **Feature Extraction**

  It is most important in the CBIR system. The relevant features are extracted from the given image database using feature extractor modular. These features are compared to determine similarity.

- **Representation, Indexing & Storing modules**

  The extracted features are represented appropriately to facilitate storing and indexing.
• **Similarity searching & Image retrieval**

In this module similarity between the query features and the stored image features in the given image feature database are obtained by using distance calculation measure.

### 1.4.1 Medical Image Retrieval

CBIR is a most important application in the medical domain area because, increase in numbers of digital images are introduced for the analysis of diagnostics and therapies. For example, in the year of 2002 (Müller et al. 2004), totally 12,000 images are produced by the Radiology department of the university Hospital of Geneva and in the same year the same hospitals produced around 1TB of cardiological image.

The goal or aim of the medical domain is to deliver the relevant medical information to the right person at the right place and also improve the efficiency of diagnostics in medical domain. The goal of the medical domain needs more than a query by patient name, patient ID or image ID.

Due to the advantage of “Digital Imaging and Communications in Medicine” (DICOM), a standard image communication, a patient information is needed with their actual image. CBIR is helpful for supporting clinical decision and improve the management of clinical data. This also provides scenarios for the integration of content-based image retrieval methods into Picture Archiving and Communication Systems (PACS). Some efficient CBIR systems are case-based reasoning (LeBozec et al. 1998) and evidence based medicine (Boissel et al. 2003) which are clinical decision support techniques. The overview of the clinical importance of an imaging system is given in Kaplan and Lundsgaarde (2006).
1.4.2 Various CBIR systems

Various CBIR systems are given as follows:

**QBIC:** IBM developed the Query BY Image Content System (Flickner et al. 1995).

**Ultimedia Manager Product:** It is also developed by IBM based on QBIC (Flickner et al. 1995).

**VisualSEEK:** Developed at Columbia University (Smith & chang, 1996)

**Photobook:** Developed by Media Laboratory, Massachusetts Institute of Technology – MIT [Photobook, online], incorporating a unique feature of interactive learning agent, named FourEyes for selecting & combining feature-based models

**MARS:** Multimedia Analysis and Retrieval Systems

**FIRE:** Flexible Image Retrieval Engine

**PicSOM:** Picture & Self-organizing Map (Laaksonen et al. 1999) implemented using tree structured SOM

**NeTra:** A toolbox for navigating large image databases (Ma et al. 1997)

1.5 SIMILARITY MEASURE

Similarity measure is used to calculate the similarity between the query image and the images in the given database. A Number of similarity measures are introduced to image retrieval system based on their distribution of features. Some similarity measures will affect the performance of the retrieval...
system significantly. Some commonly used similarity measures are described in this section are:

- Minkowski-Form Distance:
- Quadratic Form Distance
- Mahalanobis distance
- Euclidean Distance
- Kullback- Leibler (KL) Divergence and Jeffrey-Divergence (JD)

The above similarity measures are described as follows:

1.5.1 Minkowski-Form Distance

If each dimension of the image feature vector is independent of each other and is of equal importance, the Minkowski-form distance is appropriate for calculating the distance between two images. This distance is defined as

\[ S_d(i, j) = \left( \sum_n |f_n(i) - f_n(j)|^{p} \right)^{1/p} \]  \hspace{1cm} (1.1)

Where \( S_d(i, j) \) denotes the distance measure between the query image \( i \) and the image present in the database \( j \); \( f_n \) denotes the number of pixels in the query image \( i \) and the database image \( j \).

If the distance measure between the two histogram images \( i \) and \( j \) is calculated using the equation below,

\[ H(i, j) = \frac{\sum_{n=1}^{N} \min(t_n(i)-f_n(j))}{\sum_{n=1}^{N} f_n(j)} \] \hspace{1cm} (1.2)

Where \( H(i, j) \) denotes the distance between the histogram of query image \( i \) and the histogram of the image database \( j \).
1.5.2 **Quadratic Form (QF) Distance**

The Minkowski distance has the disadvantage that it treats all the bins present in the query and image database of the feature histogram entirely independently, but it does not give the account that certain pairs of bins present in the query and database features which are perceptually more similar than other pairs. The below equation gives about the quadratic distance form

\[ QF_d = \sqrt{(f_i - f_j)^T A (f_i - f_j)} \]  \hspace{1cm} (1.3)

Where \( QF_d \) denotes the quadratic distance measure between the query image \( i \) and the image in the database \( j \); \( A = [a_{ij}] \) it defines the similarity matrix and it denotes the similarity between the bin present in the query image and database images.

Quadratic form distance is mostly used for the application of color histogram based image retrieval system (Hafner et al. 1995 and Niblack et al. 1993).

1.5.3 **Mahalanobis Distance**

The Mahalanobis distance is appropriate when each dimension of the feature vector is dependent of each other and is calculated as follows

\[ M_d = \sqrt{(f_i - f_j)^T C^{-1} (f_i - f_j)} \]  \hspace{1cm} (1.4)

Where \( C \) denotes the covariance matrix of given feature vectors.

If the feature vector is independent of each other then the Mahalanobis distance is calculated as follows
\[ M_d = \sum_{n=1}^{N} \left( f_i - f_j \right)^2 / v_i \]  

(1.5)

Where \( v_i \) denotes the variance of each feature component in the query and the given database.

### 1.5.4 Kullback-Leibler (KL) Divergence and Jeffrey-Divergence (JD)

The Kullback-Leibler (KL) divergence measures how compact one feature distribution can be coded using the other one as the codebook. The distance measure between the query image \( i \) and the image in the database \( j \) using KL divergence is given as follows:

\[ KL_d = \sum f_n(i) \log \frac{f_n(i)}{f_n(j)} \]  

(1.6)

Where as Jeffrey-Divergence (JD) similarity measure calculation for texture is given below:

\[ JD_d = \sum f_n(i) \log \frac{f_n(i)}{f_n(j)} + f_n(j) \log \frac{f_n(j)}{f_n} \]  

(1.7)

Where \( \hat{f}_n = [f_n(i) + f_n(j)]/2 \)

### 1.5.5 Euclidean Distance

It is used to calculate the distance between the query image \( i \) and the database image \( j \).

\[ E_d = \sqrt{\sum_{l=1}^{n} (q_i - ID_i)^2} \]  

(1.8)

Where \( q_i \) defines the feature of the query image and \( ID_i \) represent the features of the database image.
1.6 APPLICATIONS OF CBIR

CBIR system is applied in many fields apart from medical applications are given as:

- Crime prevention (fingerprint, face recognition)
- Military (radar, aerial, satellite target recognition)
- Space observation (satellite observations of agriculture, deforestation, traffic, etc.)
- Intellectual property (trademark, image copy detection (Chang et al. 1998; Chang et al. 1999; Wang & Wiederhold 1998)
- It is used in the application of CAD database such as architectural and engineering database.
- Commercial (fashion catalogue, journalism).
- Cultural (museums, art galleries).
- Educational and training (lecture slides, graphs)
- Entertainment (photo, video, movie)
- Image classification (filtering of adult-only objectionable images and Web sites)
- Image security filtering (locate images with certain critical patterns)

1.7 CHALLENGES IN MEDICAL IMAGE RETRIEVAL

- Application of CBIR is mostly useful in the medical domain.
• Feature extraction from medical images in a robust one is a difficult problem.

• In medical diagnostics CBIR is used as important key even though it is difficult to realize.

• To be used as a diagnostic tool, the CBIR systems need to prove their performance to be accepted by the clinicians.

• In medical application domain many systems have been proposed where database consists of images of various anatomical regions with a variety of image modalities such as an image CLEFmed database (Hersh et al. 2009). Such databases are useful as a benchmark to test various approaches in a general image retrieval framework and these approaches are not useful for diagnostics support systems where high precision is required.

1.8 MOTIVATION

The following describes about the motivation of content based image retrieval system:

Image retrieval provides an efficient tool for managing the large database. In CBIR, the query depends on texture, color and shape. Many hospitals obtain the benefits of the CBIR system to diagnose the diseases. Due to this there is an increasing advantage in the diagnosis of the diseases in a medical domain. The aim of the CBIR system is to retrieve the relevant information from the medical imaging database. The objective of the CBIR system is to improve the effectiveness of the diagnosis in the medical domain.

Several types of techniques or acquisition method provides the medical information such as Magnetic Resonance Imaging (MRI), Magnetic
Resonance Spectroscopy (MRS), Computed Tomography scanners (CT), Single Photon Emission Computer Tomography (SPECT), Positron Emission Tomography (PET), Electrical Impedance Tomography (EIT), Ultrasound Probes (US), need to be adequately analyzed.

CBIR system is used to search and retrieve the image from the large database based on the visual content of the image. Therefore, retrieval of image from the large database is based on the combination of feature extraction and similarity measure. One important idea for supporting the clinical decision-making process is to supply the medical doctor with cases that offer a similar visual appearance.

1.9 SCOPE OF THE RESEARCH

The simple browsing method is enough for small a collection of images, however this is not possible for large collection of images. The image retrieval problem is the problem of searching and retrieving images that are relevant to a user’s request from a database.

In this research images are retrieved from a large database with reference to the content of the query images and the database images. In the retrieval process, features are extracted from the query image and it compared with features obtained from the large database. The primitive features of the basic CBIR system are shape and texture features. In this thesis shape & margin features are extracted to detect the various scales and orientation in mammogram image. The properties of the texture features are analyzed through two types of techniques are Gray Level Co-occurrence Matrix (GLCM) and Gabor filter. Along with above features Local Binary Pattern (LBP) features are extracted from a mammogram image.
1.10 OBJECTIVE OF THE RESEARCH

The main objective of this research is to increase precision, recall and accuracy of Content Based Mammogram Image Retrieval (CBMIR) system. To achieve that, two systems are developed.

- Mammogram retrieval based on Hybrid classifier is proposed. In this approach the hybrid classifier of Artificial Neural Network with Multilayer Feed-Forward Back Propagation (MLFFBP-ANN) classifier with PSO is used to retrieve the mammogram images based on query image. The shape & margin, texture and density features are used to analysis the performance of this approach. The performance of this approach is to be compared with the existing method.

- Content based mammogram image retrieval using Fuzzy Neural Network (FNN) is proposed. In this method the Fuzzy Neural Network is used to increase the performance of the CBMIR and optimal features are selected by using Modified Fisher’s Linear Discriminant Analysis (MFLDA) which improves the overall classification accuracy. In this approach, texture features, Gabor features and LBP features are used to analysis the performance. The Wiener filter is to be applied to reduce the noise present in the Mammogram image to increase the performance of this method. The performance of the proposed hybrid classifier approach, proposed fuzzy based approach and existing method are analyzed based on precision, recall and accuracy.
1.11 ORGANIZATION OF THE THESIS

Chapter 2 presents the survey of the literature associated with the CBIR mammogram image. This chapter covers introduction about CAD system where it consists of image preprocessing, image segmentation, feature extraction, feature selection, classification and evaluation. Following CAD system, survey on mammogram preprocessing is given by the image enhancement method. The literature survey carried over for CBIR mammogram system is described in this chapter where several types of feature extractions are involved. Finally, the classification of mammogram image is given in this chapter.

Chapter 3 describes about the detailed explanation of the techniques for the detection of the mammogram image using feature extraction by three types of features, feature selection by optimization method, similarity measure gives the retrieval output based on features and hybrid classifier is used to classify the mammogram image as normal or abnormal image. This chapter gives the performance metrics in terms of recall, precision and accuracy.

Chapter 4 presents the detailed explanation of technique for retrieval and classification of the mammogram image using fuzzy neural network classifier. This chapter consists preprocessing, segmentation, feature extraction, feature selection, similarity measure and classification. This chapter provides the overall performance metrics of proposed Hybrid classifier and FNN classifier and compares the results with existing methods.

Chapter 5 summarizes the conclusion of the proposed framework along with future scope.
1.12 SUMMARY

This chapter describes about the breast cancer introduction with their statistics. The several symptoms of the breast cancer are given. The tool or device to detect the breast cancer is referred as mammogram is given in this chapter with their working principles. The differences between the screening and diagnostic mammograms are explained. Types of breast cancer lesions are discussed in this chapter. A basic of CBIR systems with their block diagram is given. The motivation, scope and objective of the proposed framework along with the organization of the thesis are given in this chapter.