CHAPTER 6
MASS DIAGNOSIS USING NEW GRAY LEVEL GRADIENT BUFFERING WITH REGION OF INTEREST EXTRACTION

6.1 INTRODUCTION

This is the final approach developed in this research work. It was developed with the whole experience of previous two approaches with the goal of overcoming the drawbacks and pitfalls of previous approaches. The ultimate aim of this research work is developing a fully automatic flawless Computer Aided Diagnosis system with nearly 100% accuracy in mass diagnosis. This final approach has five main processes such as,

- Region Of Interest Extraction
- Preprocessing
- Segmentation
- Feature Extraction
- Classification

Unlike previous approaches in this approach Region of Interest Extraction is the initial process which extracts the necessary major part alone from the mammogram image leaving the unnecessary details. Then the mammogram is enhanced with preprocessing. The noise in the mammogram is removed using Median filtering and the contrast of the mammogram is enhanced using CLAHE. Edge detection was not used in the previous approaches. But the edge detection is important operation in image processing which improves the segmentation result. Hence edge detection is implemented in this approach using Sobel Operator.
So far in this research work some existing standard algorithms has been modified and used for mammogram segmentation. But in this approach a new algorithm is designed specifically for mammogram segmentation. The newly invented algorithm is named as ‘Gray Level Gradient Buffering’ algorithm which shows the greater improvement in the classification result. Segmented mammogram undergoes feature extraction process. In this approach instead of one, combination of two feature extraction processes were used to extract the features of the mammogram. Result of the two feature extracted values have been given for the classification process. SVM is found to be optimal classifier for the mammograms. Hence Classification is performed with SVM classification method. The result of the classification is given as the message box. Due to the inclusion of Region of Interest extraction process, it is named as Malignancy Detection Technique with Region of Interest extraction (MDTR). In this chapter all the processes of this approach are given in detailed manner.

6.2 DATA COLLECTION

The data used in the experiments of the proposed work was taken from MIAS (Mammography Image Analysis Society) database and DDSM (Digital Database for Screening Mammography). MIAS is an organization of UK research groups interested in understanding of mammograms. It contains left and right breast images of 161 patients. Totally 322 images are there which are selected from United Kingdom national screening programme. DDSM database provides two different views such as Crasino Caudal view (CC) and Medio Lateral Oblique (MLO) view of left and right breast images. It contains 2620 cases acquired from Massachusetts general
hospital wake forest University. Some real time mammograms collected from Tamilnadu Government hospital also used in this research work.

Fig 6.1 Original raw Mammogram (MDTR)

6.3 REGION OF INTEREST EXTRACTION

The interested region is extracted to reduce the processing time. Normally masses appear as whiter region in mammogram. There is no possibility of detecting the mass region from the darker region of mammogram, hence darker region can be simply ignored during processing. Thus the process of extracting the brighter region alone neglecting the darker region is called as Region of Interest Extraction. Since it extracts the interested region alone from the mammogram there is no need to process the unwanted region which reduces the processing time. In addition to that separate artifact removal process is not needed due to this ROI extraction process.

In this approach the Region of Interest of the mammogram image is extracted using newly developed abnormal center based RoI selection
method. Research mammograms such as MIAS and DDSM gives all the
details about each mammogram such as character of background tissue,
class of abnormality, x and y coordinate value of centre of abnormality,
radius of circle enclosing the abnormality. In the proposed algorithm for
ROI extraction process x, y coordinate value and radius value of abnormal
region will be given as input for each mammogram. In real time
mammograms abnormal region can be selected based on the gray level
values. The algorithm will extract the abnormal region alone from the
mammogram as follows,

Let

\[ X_c \] is center point of X coordinate
\[ Y_c \] is centre point of Y coordinate
\[ R \] is radius of abnormal region

\[
nX_c = R - X_c \quad (6.1)
\]
\[
nY_c = n \times Y_c \quad \text{where } n = 1 \quad (6.2)
\]

\[ \text{TOP}_X, \text{TOP}_Y, \text{BOTTOM}_X, \text{BOTTOM}_Y \] are the values of four sides of ROI
rectangle region. which can be calculated as follows,

\[
\text{TOP}_X = nX_c - \text{side} \quad (6.3)
\]
\[
\text{TOP}_Y = nX_c - \text{side} \quad (6.4)
\]
\[
\text{BOTTOM}_X = nX_c + \text{side} \quad (6.5)
\]
\[
\text{BOTTOM}_Y = nY_c + \text{side} \quad (6.6)
\]

By computing the above four values for each mammogram, region of
interest image can be obtained. Sample of Region of Interest extracted
image is shown in Fig.6.2.
6.4 PREPROCESSING

Mammogram is the medical image which has lot of noises like digitization noise, noise occurred during image capturing process. Hence it is difficult to interpret it. In the proposed method median filter is used to remove the noise. In 2D Median filtering process each output pixel will be replaced with Median value in 3-by-3 neighborhood around the corresponding pixel in the input image. Median filter provides comparatively better results than other noise removal process. Edges are more important factor in segmentation process. Median filter can remove the noises without disturbing the edges, which is one more advantage of using Median filter. The detailed explanation of Median filtering is given in 3.2.2.3. Result of Median filtering processing for the ROI extracted image (shown in Fig 6.2.) is shown in Fig 6.3.
6.4.1 Contrast Enhancement

Contrast enhancement is performed using Contrast Limited Adaptive Histogram Equalization method. CLAHE operates on small regions in the image called tiles rather than the entire image. It adds intensity values over different segments by using adaptive histogram equalization method. Contrast of each pixel relative to its local neighborhood is adaptively enhanced during this process. As a result, improved contrast will be produced for all levels in the image. CLAHE also helps to reduce the noise produced in homogenous area. The detailed explanation of CLAHE process is given in 3.2.3.2. Fig.6.4. shows the result of Contrast enhancement process.
6.4.2 Edge detection

Edge detection is a useful process in understanding the image features. Edges occur in image boundaries, hence edge detection is very supportive process for image segmentation. Particularly in mammogram segmentation it helps to enhance the tumor area. Sobel operator has been proved to be better than any other methods such as Prewitt, Kirsch and watershed algorithm for medical images. Sobel operator performs a 2D spatial gradient measurement on the image. It emphasizes the region of high spatial frequency that corresponds to the edges. It is used to find absolute gradient magnitude at each pixel of input image.

\[
\begin{array}{ccc}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1 \\
\end{array}
\]

\[
\begin{array}{ccc}
-1 & -2 & -1 \\
0 & 0 & 0 \\
1 & 2 & 1 \\
\end{array}
\]

\( S_X \)

\( S_Y \)

Fig.6.5 Convolution kernels of Sobel operator
The operator consists of 3X3 convolution kernels as shown in Fig.6.5. Convolution is the process of multiplying together two arrays of numbers of different size. The convolution is performed by multiplying the kernel shown in Fig.6.5 over the image. Each kernel position corresponds to single output pixel, which is calculated by multiplying together the kernel value and underlying image pixel value for each of the cells in the kernel. Let i, j implies row and column of kernel. I, J implies row and column of image. Then the output image will have (I-i+1) rows and (J-j+1) columns. Mathematically convolution operation can be written as shown in Eq.6.7.

\[ C(x,y) = \sum_{m=1}^{i} \sum_{n=1}^{j} M(x+y-1, y+n-1) N(m,n) \quad (6.7) \]

Where x runs from 1 to (I - i+1) and y runs from 1 to (J - j+1)

Sobel operator is partial derivative of f(x,y) and derivatives in x and y direction are given as shown in eqn.(6.8 and 6.9)

\[ G_x = \{f(x+1,y-1)+2f(x+1,y)+f(x+1,y+1)\} - \{f(x-1,y-1)+2f(x-1,y)+f(x-1,y+1)\} \quad (6.8) \]

\[ G_y = \{f(x-1,y-1)+2f(x,y+1)+f(x+1,y+1)\} - \{f(x-1,y-1)+2f(x,y-1)+f(x+1,y-1)\} \quad (6.9) \]

Generally the size of the gradient is calculated as,

\[ G(x,y) = \sqrt{G_x^2 + G_y^2} \quad (6.10) \]

By applying the sobel operator S_x and S_y row wise two gradient matrices can be obtained as original image. Total gradient value can be obtained by using Eq.6.10. If G > TH (Threshold value) then it means that edge pixel has been found out. If G < TH then there is no edge pixels. The algorithm is not only identifies the presence of edges but also identifies the
direction of the edge. Result of edge detection process is shown in Fig 6.6.
The detailed explanation of Sobel Operator is given in the section 3.2.4.3.

![Edge detection Image](image)

**Fig.6.6 Image after Sobel Edge detection**

6.5 SEGMENTATION WITH GRAY LEVEL GRADIENT BUFFERING ALGORITHM

Gray Level Gradient Buffering Algorithm is newly designed algorithm specifically used for segmenting the mammogram. The basic concept of this algorithm is gray level measurement. Since in mammogram segmentation, the ultimate aim is to find out and extract the mass region alone from the entire mammogram. The typical identification of mass region is it would be brighter than the other regions. Other than mass some other brighter regions will be there in the mammogram such as microcalcification, nerve systems and normal tumors. So these can be misclassified as mass region. Microcalcification is nothing but the collection of calcium cells which oftenly misclassified as mass region. So that the Computer Aided Diagnosis system should be intelligent enough to overcome all these
chances of misclassification. Proper Segmentation and classification is essential to overcome this problem.

Hence special algorithm has been designed specifically for this approach. As a result a new algorithm has been designed which suits specially for mammogram segmentation. The newly designed algorithm is named as “Gray Level Gradient Buffering algorithm”. This produces greater result with maximum accuracy over the other methods. Edge detection with Sobel operator should be combined with Gray Level Gradient Buffering algorithm to achieve the maximum result.

\[ G(x) \text{ and } G(y) \text{ calculated using eqn.6.8 and eqn.6.9 respectively.} \]

By fixing the minimum and maximum value, pixel value will be set in the image. Initially the maximum and minimum value will be set to 0. Then the values will be changed according to the gray level value. \( X \) denotes the pixels in the row wise. Hence the limitation for the variation is set from 0 to width of the edge detected mammogram image. \( Y \) denotes the pixels in the column wise. Hence the limitation for the variation is set from 0 to height of the edge detected mammogram image. The value of \( G(x) \) and \( G(y) \) will be calculated iteratively for the whole image. The value of the pixel is calculated using the equation 6.11. Every time the value of each pixel will be compared with that updated value of max and min. Max and min value will be set accordingly in each iteration. The whole process will be performed iteratively for the whole image. The above process is described as follows,

Initially \( \text{max} = 0 \text{ and } \text{min} = 0 \)

\( Y \) value varies from 1 to height of input image

\( X \) value varies from 1 to width of input image.
If \( G(x,y) > \max \) then \( \max = G(x,y) \)

If \( G(x,y) < \max \) then \( \min = G(x,y) \)

Output value obtained by following the three steps given below,

1. For \( y \rightarrow 0 \) to height of input image,
2. For \( x \rightarrow 0 \) to width of input image,
3. Value should be calculated by using Eq.6.11:

\[
\text{Value} = \frac{(\text{buffer} \ [y \times \text{width} + x] - \min)}{(\max - \min) + 255} \tag{6.11}
\]

Result of GLGB segmentation process is shown in Fig.6.7.

![Image after GLGB segmentation](image)

**Fig.6.7. Image after GLGB segmentation**

### 6.6 FEATURE EXTRACTION

The segmentation output is given as input to feature extraction. In this approach two different methods such as GLCM and LBP is used in combined manner to extract the features. The segmentation output is given as input to both GLCM and LBP. The result of both feature extraction methods are given for the classification. So that more features will be extracted which will increase the accuracy of diagnosis.
6.6.1 Feature Extraction by GLCM

Texture feature measures the variation in the surface of the image. Texture feature used to differentiate normal and abnormal pattern. Two types of measures are there first order and second order. Statistics calculated from individual pixel gives the first order relationship. Statistics calculated between two neighbor pixels gives the second order relationship. Gray level Co-occurrence Matrix used in the proposed method comes under the second order texture measure. Segmentation output value is given as input to GLCM.

GLCM is the joint probability of occurrence of gray levels \( i \) and \( j \) for the two pixels with a defined spatial relationship in an image. Spatial relationship is defined in terms of distance \( d \) and angle \( \theta \). GLCM is constructed at distance \( d = 1, 2, 3, 4 \) and for angles \( \theta = 0^\circ, 45^\circ, 90^\circ \) and \( 135^\circ \). Two points at distance \( d \) will have similar gray levels if the texture is coarse. If the texture is fine then the points will have different gray levels. Using GLCM features like contrast, energy, homogeneity and correlation can be derived. Contrast is the contrast between a pixel and its neighbor. Energy is the sum of squared elements in GLCM or uniformity. Homogeneity is closeness of the distribution of elements in GLCM. Correlation shows how correlated a pixel is to its neighbor over the whole image. GLCM features can be calculated by using the following equations,

\[
\text{Contrast} = \sum_{i,j=0}^{n-1} pij (i - j)^2 \tag{6.12}
\]

\[
\text{Energy} = \sum_{i,j=0}^{n-1} (pij)^2 \tag{6.13}
\]

\[
\text{Homogeneity} = \sum_{i,j=0}^{n-1} \frac{pij}{1+(i-j)}^2 \tag{6.14}
\]
Correlation = \[ \sum_{i,j=0}^{n-1} (P_{ij}) \frac{(i-\mu)(j-\mu)}{\sigma^2} \] (6.15)

\[ P_{ij} = \text{Element } i, j \text{ of the normalized symmetrical GLCM} \]

\[ N = \text{number of gray levels in the image} \]

The GLCM mean is calculated as: \[ \mu = \sum_{i,j=0}^{N-1} iP_{ij} \] (6.16)

The variance of the intensities is calculated as: \[ \sigma^2 = \sum_{i,j=0}^{N-1} P_{ij} (i - \mu) \] (6.17)

Where,

Contrast is the contrast between a pixel and its neighbor.

Energy is the sum of squared elements in GLCM or uniformity.

Homogeneity is closeness of the distribution of elements in GLCM.

Correlation shows how correlated a pixel is to its neighbor over the whole image. The detailed explanation about GLCM method is given in 3.4.1

The sample results of the Feature Extraction process for 20 mammograms are shown in Table.6.1. Results of 10 benign and 10 malignant mammograms are taken for the sample.
Table 6.1. Feature extraction result of GLCM (MDTR)

<table>
<thead>
<tr>
<th>Image id</th>
<th>Image</th>
<th>Contrast</th>
<th>Correlation</th>
<th>Energy</th>
<th>Homogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mam1</td>
<td>Cancer</td>
<td>0.0447</td>
<td>0.7598</td>
<td>0.8870</td>
<td>0.9817</td>
</tr>
<tr>
<td>Mam2</td>
<td>Cancer</td>
<td>0.1083</td>
<td>0.7607</td>
<td>0.8922</td>
<td>0.9755</td>
</tr>
<tr>
<td>Mam3</td>
<td>Cancer</td>
<td>0.1100</td>
<td>0.5923</td>
<td>0.6129</td>
<td>0.9400</td>
</tr>
<tr>
<td>Mam4</td>
<td>Cancer</td>
<td>0.0302</td>
<td>0.6548</td>
<td>0.9435</td>
<td>0.9945</td>
</tr>
<tr>
<td>Mam5</td>
<td>Cancer</td>
<td>0.1270</td>
<td>0.7345</td>
<td>0.7675</td>
<td>0.9456</td>
</tr>
<tr>
<td>Mam6</td>
<td>Cancer</td>
<td>0.1273</td>
<td>0.7450</td>
<td>0.7564</td>
<td>0.9345</td>
</tr>
<tr>
<td>Mam7</td>
<td>Cancer</td>
<td>0.1289</td>
<td>0.6656</td>
<td>0.6970</td>
<td>0.9893</td>
</tr>
<tr>
<td>Mam8</td>
<td>Cancer</td>
<td>0.0129</td>
<td>0.6267</td>
<td>0.7691</td>
<td>0.9673</td>
</tr>
<tr>
<td>Mam9</td>
<td>Cancer</td>
<td>0.1569</td>
<td>0.6567</td>
<td>0.7234</td>
<td>0.9389</td>
</tr>
<tr>
<td>Mam10</td>
<td>Cancer</td>
<td>0.1527</td>
<td>0.7465</td>
<td>0.6568</td>
<td>0.9390</td>
</tr>
<tr>
<td>Mam11</td>
<td>Normal</td>
<td>0.4404</td>
<td>0.7356</td>
<td>0.4067</td>
<td>0.8704</td>
</tr>
<tr>
<td>Mam12</td>
<td>Normal</td>
<td>0.3741</td>
<td>0.7720</td>
<td>0.5340</td>
<td>0.8772</td>
</tr>
<tr>
<td>Mam13</td>
<td>Normal</td>
<td>0.1472</td>
<td>0.7500</td>
<td>0.4500</td>
<td>0.9026</td>
</tr>
<tr>
<td>Mam14</td>
<td>Normal</td>
<td>0.2333</td>
<td>0.7204</td>
<td>0.3143</td>
<td>0.8825</td>
</tr>
<tr>
<td>Mam15</td>
<td>Normal</td>
<td>0.3273</td>
<td>0.7107</td>
<td>0.2886</td>
<td>0.8699</td>
</tr>
<tr>
<td>Mam16</td>
<td>Normal</td>
<td>0.2596</td>
<td>0.6700</td>
<td>0.4003</td>
<td>0.8866</td>
</tr>
<tr>
<td>Mam17</td>
<td>Normal</td>
<td>0.2800</td>
<td>0.7059</td>
<td>0.3416</td>
<td>0.8768</td>
</tr>
<tr>
<td>Mam18</td>
<td>Normal</td>
<td>0.2095</td>
<td>0.6095</td>
<td>0.3749</td>
<td>0.8451</td>
</tr>
<tr>
<td>Mam19</td>
<td>Normal</td>
<td>0.1925</td>
<td>0.6549</td>
<td>0.4457</td>
<td>0.9218</td>
</tr>
<tr>
<td>Mam20</td>
<td>Normal</td>
<td>0.2100</td>
<td>0.7210</td>
<td>0.4672</td>
<td>0.9459</td>
</tr>
</tbody>
</table>

6.6.2 Feature extraction process by Local Binary Pattern

Local binary pattern is a type of feature used for classification. It labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as binary number. It is unifying approach to divergent statistical and structural models of texture analysis. The important property of LBP is its robustness to monotonic gray scale changes caused. Another advantage of LBP is its computational simplicity which makes it possible to analyze images in real time settings. Again Segmentation output value is given as input to LBP separately.
LBP worked with the eight neighbors of a pixel, using the value of the center pixel as a threshold. LBP code for a neighborhood was produced by multiplying the thresholded values with weights given to the corresponding pixels and summing up the result. It is implemented by an orthogonal measure of local contrast. The average of gray levels below the center pixel is subtracted from that of gray levels above the center pixel. Two dimensional distributions LBP and local contrast measures are used as features. The detailed explanation about LBP method is given in 3.4.2.

6.7 CLASSIFICATION

Classifiers used to diagnose data in shorter time and in more detailed manner. Support Vector Machine produces comparatively better result than any other classifiers particularly for medical image analysis. Results obtained from both GLCM matrix and Local Binary Pattern is given as input data to SVM classifier. Based on the statistical learning theory SVM classifies the given input data into two separable classes \{1, -1\}. SVM uses separating hyper plane to classify the classes. Training data is given as input to SVM classifiers. It consists of N datum \((x_1, y_1), \ldots, (x_n, y_n)\), \(x \in \mathbb{R}^n, y \in \{1, -1\}\).

\[ D(x) = (w \cdot x) + w_0 \]  \hspace{1cm} (6.18)

The inequality \(y_i (w \cdot x_i) + w_0 \geq 1\) is produced for both \(y=1\) and \(y=-1\). Hyper planes are performed by using eqn.6.19.

\[ Y_i \left[ (w \cdot x_i) + w_0 \right] \geq 1, \ i=1, \ldots, n \]  \hspace{1cm} (6.19)

If data points satisfy the above inequality condition then they form support vectors. Classification process is performed based on the support vectors. Margins of hyper plane obey the following inequality,
\[
\frac{y_k \cdot D(x_k)}{||y||} \geq \Gamma, \ k=1,2,\ldots,n
\]

(6.20)

We can maximize the margin by minimizing \( w \) by using the eqn.6.21.

\[
\Gamma \times w = 1. \quad k = 1,2,\ldots,n.
\]

(6.21)

In the case of non separable data slack variable \( \xi \) is added as follows,

\[
Y_i [(\ w \times x_i \ ) + w_0] \geq 1 - \xi
\]

(6.22)

In the case of non linear data, non linear input should be converted to high dimensional linear feature via kernels. In the proposed method RBF kernels are used which is given in eqn.(6.23)

Where RBF kernels = \( k(x,x') = \exp (-\|x-x'\| / \sigma^2) \)

(6.23)

Where \( \sigma \) is positive real number

All 400 mammograms were taken into account for the classification process. 200 mammograms were used for training the classification process and 200 mammograms were used for testing process. The detailed explanation about SVM classification method is given in 3.5.4.

The classification result obtained from SVM classifier is shown in Table 6.2.
6.8 RESULTS AND DISCUSSION

Experiments are conducted on the images taken from both MIAS and DDSM database. 400 mammograms have taken for experiments in which 150 are normal and 250 are abnormal. 50% of images are used for training and 50% of the images are used for testing phase. Samples of the results for both benign and malignant classes are shown in this section.

One of the main advantages of this method is, it interprets the final result in simpler manner as a message box. The result of the classification process will be analyzed automatically and according to the result any of the two message boxes will be displayed. If the given mammogram has no abnormal regions then the result will be displayed as shown in Fig. 6.8 and if the given mammogram has cancerous tissue then the result will be displayed as shown in Fig. 6.9. So for each mammogram input the output can be obtained simply as message box. Thus the easy interpretation of the result makes the system more user friendly.

![Fig.6.8. Result of the output message for benign image](image-url)

<table>
<thead>
<tr>
<th></th>
<th>True positive</th>
<th>True Negative</th>
<th>False Positive</th>
<th>False Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cases</td>
<td>246/250</td>
<td>149/150</td>
<td>4/250</td>
<td>1/150</td>
</tr>
<tr>
<td>Percentage</td>
<td>98.8%</td>
<td>99.3%</td>
<td>1.6%</td>
<td>0.7%</td>
</tr>
</tbody>
</table>

Table 6.2: Result of Classification Process (MDTR)
Fig. 6.9. Result of the output message for malignant image

6.9 PERFORMANCE EVALUATION

Perfect test method is one of the methods in ROC curve method. Perfect test method is used to evaluate the performance of the designed algorithm. The result obtained from the classification process is given as input. The result is shown as graphical representation in Fig.6.10 which also gives the sensitivity and specificity of the proposed method. Efficiency of the algorithm is decided by major factors TP, TN, FP, FN. Which are described as follows,

True Positive (TP): mass region is present and algorithm shows the same result

True Negative (TN): mass region is absent and algorithm shows the same result

False Positive (FP): mass region is absent and algorithm shows that mass region is present

False Negative (FN): mass region is present and algorithm shows that mass region is absent
Fig. 6.10. Graphical representation of the result (MDTR)
The summarization of the overall process in the proposed method is given as flowchart in Fig. 6.11.

Fig. 6.11. Flow chart of the MDTR
MDTR is the final approach developed in this research work. In this approach a new algorithm is designed and implemented to segment the suspected region. Each process in MDTR is built with optimal method to improvise the final result. Region of Interest is the initial process of this system which is designed by ‘Abnormal center based RoI selection’. It helps to improve the performance by reducing unnecessary computations. In preprocessing median filtering is used to reduce the noise in mammogram as in the previous approaches since it is the only optimal filtering for mammogram noise removal. Then the tumor region is enhanced using Contrast Limited Adaptive Histogram Equalization method.

The CLAHE helps to enhance the edges of the tumor which maximizes the result of edge detection process performed by Sobel operator. The newly designed algorithm ‘Gray Level Gradient Buffering’ helps to segment the suspected region in perfect manner with the Sobel edge detection. The segmented regions are given as input to Feature Extraction Process. The Features of the suspected regions are extracted using two different methods such as GLCM and LBP. The results of both methods are given as input to Classification process. The classification is performed by Support Vector Machine which is found to be optimal for Medical Image Classification.

The experience and knowledge gained in the whole research work helps to find out the optimal methods to design the best Computer Aided Diagnosis system. The main objective of the system is to assist the radiologists. Hence their feedback and suggestions were collected before designing this technique. The designed approach has 99.3% Sensitivity and
98.1% Specificity. The accuracy of the diagnosis system is found to be 99.1%. This result is comparatively better than the previous approaches.

Another important advantage of this approach is it is completely automatic Computer Aided Malignancy Diagnosis system which does not need any human interruption from the initial process to final result. By simply giving the mammogram input we can get the output result as message. Thus the designed system gives the satisfactory result in all aspects.

Since all the three approaches are implemented with different set of mammograms the efficiency measurement will vary. Hence for the comparative study of efficiency all the three approaches were tested with same set of mammograms. In the next chapter the result of this comparative study is given in detailed manner.