CHAPTER 5
METHODS AND IMPLEMENTATIONS OF PREPROCESSING

The literature discussed in chapter 3 gives the state of the art of image processing and algorithms applied for the detection of Tumor in Mammogram image. In this chapter we have presented our work in detail. Figure 18 below illustrated an overview of the basic work developed in this research. For detailed illustration of the proposed framework are mammogram images, whereas output of the system indicates that the Input image intensity and abnormality change after applying the step by step algorithm in input mammogram image.

Figure 18. Overview of the proposed framework.

The proposed system will aid radiologists in their diagnosis by indicating suspicious abnormalities in mammograms. Thus, the system will act as a second reader after the radiologists. The proposed system will substantially reduce the number of false positives which will eliminate the need of performing unnecessary biopsies and save cost. This system will reduce patient examination time by inspecting mammograms and reporting the findings within a few seconds.
5.1. Preprocessing Methodology

At present, mammography is the method of choice for early breast cancer detection (Grady, 2006 and Mencattini et al., 2008). Although automatic analysis of mammograms cannot fully replace radiologists, an accurate computer-aided analysis method can help radiologists to make more reliable and efficient decisions.

This section describes the methods for constructing a series of image processing techniques for Mammogram Image. The algorithm stages I implemented for image preprocessing steps are

1. Image segmentation
2. Image Binarization
3. Image Thinning
4. Gray Scale Extending

In this section, I discussed about the methodology for each stage of the image preprocessing algorithm, including modifications that have been made.

5.1.1. Segmentation

The main objective of segmentation is to simplify and/or change the representation of an image into meaningful image that is more appropriate and easier to analyze. Segmentation is basically a collection of methods that allow spatially partitioning close parts of the image as objects. “Image segmentation” is an important aspect of digital image processing. Image segmentation may be defined as a process of assigning pixels to homogenous and disjoint regions which form a partition of the image that share certain visual characteristics (Pichel et al., 2006).

Extracting breast tumors accurately from a mammogram is a kernel stage for mammography, due to significantly influencing the overall analysis, accuracy and processing speed of the whole breast tumor analysis. For this reason, tumors have to be identified and segmented from breast region in a mammogram before further analysis.
In the breast region of a mammogram, the gray intensity of a pectoral muscle region is similar to that of the breast tumor cells and the pectoral muscle’s texture may also be similar to some abnormalities. Segmentation algorithms generally are based on one of the two basic properties of intensity values (Gonzalez and Woods 2002).

- Discontinuity: to partition an image based on sharp changes in intensity
- Similarity: to partition an image into regions that is similar according to a set of predefined criteria.

That means image segmentation include identifying objects in a scene for object-based measurements such as size and shape.

Image segmentation is used to divide images into functional or structural subunits and help to identify and separate out areas that are of interest for further investigation and diagnosis. The aim of segmentation in this project is to 1) delineate border and separate foreground area from background; 2) classify perfusion level and give areas that doctors are concerned about.

A gray level image consists of two main features, namely region and edge. Segmentation algorithms for gray images are generally based on two basic properties of image intensity values, discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principle approach in the second category is based on partitioning image into regions that are similar according to a set of predefined criteria. Thresholding, region
growing and region splitting and merging are examples of the methods in this category. A mammogram contains two distinctive regions, the exposed breast region and the unexposed air-background (non-breast) region. The principal feature on a mammogram is the breast contour, otherwise known as the skin-air interface, or breast boundary. The breast contour can be obtained by partitioning the mammogram into breast and non-breast regions. The extracted breast contour should adequately model the soft-tissue/air interface and preserve the nipple in profile (Indra Kanta Maitra et al., 2011).

In mammograms, background objects may even appear brighter. So in this work, preparation phase is needed in order to improve the image quality and make the segmentation results more accurate. Objective of this process is to improve the quality of the image to make it ready for further processing by removing the irrelevant and unwanted parts in the background of the mammogram image.

The segmentation stage is primarily used to accurately segment the masses and distinguish malignant from benign tumors of the breast images. Thus it provides the following goals:

1. Specifying the locations of suspicious areas to assist radiologists during the diagnosis.
2. Classifying the abnormalities of the breast as benign or malignant.
3. Spotting salient regions in mammograms such that salient regions corresponding to distinctive areas that may include the breast boundary, the pectoral muscle, masses and some other dense tissue regions.

Segmentation is the process of separating the foreground regions in the image from background regions. Thus, Segmentation is employed to discard these background regions, which gives the reliable features of an image.

In an image the background regions generally exhibit a very low gray-scale variance value, whereas the foreground regions have a very high variance. Hence, a method based on variance thresholding is used to perform the segmentation. First, the image is divided into 8×8 blocks and grayscale variance is calculated for each block in the image. The input image is segmented into 8×8 block of pixels. The reason for segmenting into 64 pixels is based on the operating system used for our application.
Segmented image separates the pixels into 64 pixels. This helps us to carry further investigation in each pixel value.

If the variance is less than the threshold, then the block is assigned to be a background region; otherwise, it is assigned to be part of the foreground. The gray scale variance for a block of size 8×8 is defined as:

\[
V(x) = \frac{1}{8^2} \sum_{i=0}^{8-1} \sum_{j=0}^{8-1} (I(i,j) - M(i,j))^2
\]  

(1)

\[
M(x) = \frac{1}{8^2} \sum_{a=1}^{8} \sum_{b=1}^{8} J(a,b)
\]

(2)

Where \(V(x)\) is the variance for block \(x\), \(M(x)\) is the mean gray-level value for the block \(x\). \(I(i,j)\) and \(J(a,b)\) are the gray-level value for pixel \(i,j\) and \((a,b)\) respectively in block \(k\).

The output illustrates the result of segmenting a mammogram image based on variance thresholding. Hence, a variance threshold is used to separate the mammogram image foreground area from background regions. The final segmented image is formed by assigning the regions with a variance value below the threshold to a gray-level of zero. These results show that the foreground regions segmented by this method effective in discriminating the foreground are from the background area.

In this method of segmentation threshold fixing is very important. If the threshold value is too large, results have shown that foreground regions may be incorrectly assigned as background regions. Vice versa, if the threshold value is too small, background regions may be mistakenly assigned as part of the foreground region. Hence variance threshold gives result in terms of differentiating between the foreground and background regions.
5.1.2. Image Binarization

Image Binarization is the process of separating of pixel values into two groups, white as background and black as foreground. In Binarization, the gray scale image is converted into binary image. Binarization is a process that converts a gray level image into a binary image and in a binary image each pixel value is either 0 or 1(255). Binary images are easy to process. The basic principle of converting an image into binary is to decide a threshold value, and then the pixels whose value are more than the threshold are converted to white pixels, and the pixels whose value are below or equal to the threshold value are converted to black pixels. This improves the contrast between the ridges and valleys in a fingerprint image, and consequently facilitates the extraction of minutiae.

The threshold in local variance technique for binarization of the image is calculated based on the local mean \( m(x, y) \) and standard deviation \( \delta(x, y) \) within a window of size \( w \times w \) (Niblack, 1986). In this method the local threshold value \( T(x, y) \) at \((x, y)\) is calculated within a window of size \( w \times w \).

\[
T(x, y) = m(x, y) + k \delta(x, y) \tag{3}
\]

Where \( m(x, y) \) and \( \delta(x, y) \) are the local mean and standard deviation of the pixels inside the local window and \( k \) is a bias. The result is satisfactory at \( k = -0.2 \) and \( w=15 \). The local mean \( m(x, y) \) and standard deviation \( \delta(x, y) \) adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. The bias \( k \) controls the level of adaptation varying the threshold value. In this method the threshold value selection has more trial process and takes more time to complete.

Local adaptive thresholding method is used to binarize the image (Nalini et al., 1995). In this process we transform the 8-bit gray image to a 1-bit image with 0-value for ridges and 1-value for furrows. After the operation, ridges in the fingerprint are highlighted with black color while furrows are white. In this locally adaptive method, image is divided into blocks of 32 ×32 pixels. A pixel value is then set to 1, if its value is larger than the mean intensity value of the current block to which the pixel belongs.
The binary image can be processed well than gray scale image. In this work thresholding method is used to convert the gray scale image in to binary for further processing.

Robust binarization gives the possibility of a correct extraction of the sketched line drawing from its background. For the binarization of images many algorithms have been implemented. Thresholding is a sufficiently accurate and high processing speed segmentation approach to monochrome image. Thresholding method to extract the binary image adaptively from the degraded gray-scale image with complex and inhomogeneous background.

Binarization can be seen as the separation of the object and background. It turns a gray scale picture into a binary picture. A binary picture has only two different values. The values 0 and 1 are represented by the colors black and white, respectively. To perform binarization on an image, a threshold value in the gray scale image is picked. Everything darker (lower in value) than this threshold value is converted to black and everything lighter (higher in value) is converted to white.

The basic idea in thresholding is to select a threshold (T) to extract an object or several objects with the same value of background. Here we have used one level thresholding to convert gray scale image into binary image.

The difficulty with binarization lies in finding the right threshold value to be able to remove unimportant information and enhance the important one. It is impossible to find a working global threshold value that can be used on every image. The variations can be too large in these types of mammogram images that the background in one image can be darker than the background in another image. Therefore, algorithms to find the optimal value must be applied separate on each image to get a functional binarization. Mean value or the median of the pixel values in the image is used as a global threshold. Average of mean value of each block back ground and foreground pixels are selected as a global threshold.
Threshold value of each 8×8 block was calculated by using each block.

\[ T = \frac{\mu_1 + \mu_2}{2} \]  

\( \mu_1 \) is the mean value of the object, \( \mu_2 \) is the mean value of the background. The outcome is a binary image containing two levels of information, the foreground and background. During this phase the gray scale image is transformed into a binary image by computing the mean value of each 8×8 input block matrix and transferring the pixel value to 1 if larger than the mean or to 0 if smaller.

5.1.3. Image Thinning

Thinning is a process of reducing a shape to a simpler one that still retains the essential features of the original object (Serra 1982). It preserves the topology (extent and connectivity) of the original region while throwing away most of the original foreground pixels (Jang and Chin 1992 & Gonzalex and Woods 2002). More number of thinning algorithms was performed earlier. A type of different thinning algorithm is discussed below.

![Figure 20. Thinning process view.](image)
In this thesis Binary digital image can be represented by a matrix, where each element in matrix is either zero (white) or one (black) and the points are called pixels. Thinning is a process that deletes the unwanted pixels and transforms the image pattern one pixel thick. In parallel binary image processing, the value of the pixel element at the n iteration depends on the current pixel value and its neighbor at the (n -1)th iteration. We define non-zero pixels as representing objects and zero-valued as pixels representing the background. To avoid connectivity paradoxes, we define objects with eight-connectivity and background with four connectivity, our algorithm uses the $3 \times 3$ mask as shown in Figure-1. We define W1, W3, W5 and W7 are four connectivity representing the background and W2, W4, W6, W8 are eight connectivity representing the object. New image thinning algorithm is divided into two iterations.

In this work we have applied skeletonization algorithm for thinning the Mammogram image after Binarization (Saad Harous and Ashraf Elnagar 2009). It is a parallel method that means the new value obtained only depend on the previous iteration value. It is fast and simple to be implemented. This algorithm is made by two sub-iterations. In the first one, a pixel $I(i, j)$ is deleted if the following conditions are satisfied:

1. Its connectivity number is one.
2. It has at least two black neighbours and not more than six.
3. At least one of $I(i, j+1)$, $I(i-1, j)$, and $I(i, j-1)$ are white.
4. At least one of $I(i-1, j)$, $I(i+1, j)$, and $I(i, j-1)$ are white.

In the second sub-iteration the conditions in steps 3 and 4 change.

1. Its connectivity number is one.
2. It has at least two black neighbours and not more than six.
3. At least one of $I(i-1, j)$, $I(i, j+1)$, and $I(i+1, j)$ are white.
4. At least one of $I(i, j+1)$, $I(i+1, j)$, and $I(i, j-1)$ are white.
Thinning process increases the speed of extraction. Parallel thinning will work on all pixels simultaneously. This parallel thinning algorithm has two sub iterations. A binary digitized picture is defined by matrix where each pixel \( g(x, y) \) is either 1 or 0. Iterations are applied to matrix point by point according to the values of small set of neighbors of point \((i, j)\). In this processing the new value given to a point at the \( n \)th iteration depends on its own value as well as those of its eight neighbors at the \((n-1)\)th iterations, all the pixels will be processed selecting \(3 \times 3\) matrix window, in this each element connected with its eight neighboring elements (Kamaljeet and Mukes, 2013 & Peter, 2007) as shown in Figure 21.

![Figure 21. Places of Nine pixels in a 3×3 window.](image)

**First sub iteration**

The contour point \( w_1 \) is deleted from the digital pattern if it satisfies the following

a) \( 2 \leq B(w_1) \leq 6 \)

b) \( A(w_1) = 1 \)

c) \( w_2 \times w_4 \times w_6 = 0 \)

d) \( w_4 \times w_6 \times w_8 = 0 \)

Where \( A(w_1) \) is the number of 01 patterns in the ordered set \( w_2, w_3, w_4, w_5, w_6, w_7, w_8, w_9 \) that are neighbors of \( w_1 \), and \( B(w_1) \) is the number of nonzero neighbors of \( w_1 \) that is

\[
B(w_1) = w_2 + w_3 + w_4 + w_5 + w_6 + w_7 + w_8 + w_9.
\]

If any above condition is not satisfied then \( w_1 \) is not deleted from the window.
For example

<table>
<thead>
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<th></th>
<th></th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>w1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

In above example A (w1) =2 (01 pattern), Therefore w1 is not deleted from the window. In Condition (c) and (d) w4=0 or w6=0 or (w2=0 and w8=0). So the point w1, which has been removed, might be a South-East boundary point or a North-West Corner points. By condition (a) the end points of the line are preserved. Also condition (b) prevents the deletion of those points that lie between the endpoints of a line. Since the entire set of non-zero pixels w that satisfying the conditions i) and ii) are deletable in parallel. With this, the objects of two pixels width completely disappear. This difficulty cannot be solved by using the conditions i) and ii) only. To overcome this problem, conditions iii) and iv) are checked and if it is found to be true, its central pixel is saved, or equivalently, all non-zero pixels w that satisfies the conditions (iii) and (iv) can be deleted in parallel. Let us now illustrate the iteration 2.

**Second sub iteration**

a) $2 \leq B(w1) \leq 6$

b) $A(w1)=1$

c) $w2 \times w4 \times w8 = 0$

d) $w2 \times w6 \times w8 = 0$

The condition (c) and (d) only changes in second sub iteration. Because the first sub iteration removes only the south-east boundary points or a North-West Corner points. But the second sub iteration removes north-West Boundary points or a South-East corner points which do not belonging to the line.
At the end, pixels satisfying these conditions will be deleted. If at the end of either sub-
iteration there are no pixels to be deleted, then the algorithm stops. Thinning algorithm
with a 2-iterations is able to

a) Reduce the number of iterations and the time complexity of each iteration.
b) Produce a perfect 8-connected thinned image.
c) Prevent the excessive noise and erosion.

The meaning of these objectives will be clarified in the subsequent sections. According
to the algorithm described in above section, a pixel is deletable by analyzing the values
of its neighboring pixels within the area of (3×3) mask in the first iteration. If the
conditions specified in first iteration are not satisfied, then the same process is carried
out in the second iteration

**5.1.4. Image gray scale extending**

After preprocessing, mammogram image is extended by intensity variance. This will be
done by post processing step of mammogram image processing to find the cancer cell
location in Breast.

It can be approached in different ways such as background subtraction (Su et al., 2010),
water flow model (Hwa et al., 2005), mean and standard derivation of pixel values
(Sauvola and Pietikainen, 2000) and local image contrast (Su et al., 2010). The Global
thresholding techniques are used when the background is uniform. But in cases where
different parts of a document have different backgrounds or foregronds varying in
darkness, local thresholding methods can be very useful.

**The Bersen’s local thresholding**

The Bersen’s local thresholding method is a widely used local thresholding method
(Bernsen, 1986). The local threshold value of each pixel \((x, y)\) is calculated by this
equation. If the window is centered at the pixel \((x, y)\) the threshold for \(I(x, y)\) is defined
by

\[
T(x, y) = \frac{Z_{(\text{max})} + Z_{(\text{min})}}{2}
\] (6)
Where $Z_{(\text{max})}$ and $Z_{(\text{min})}$ are Maximum and Minimum Intensity level in a $R \times R$ window centered at $(x, y)$ respectively. This threshold works properly only when the contrast is large. The contrast is defined as; if the contrast is less than a specific value $k$ the pixel within the window may set to background or to foreground according to the class (Wei-Chih Hsu et al., 2012). This blog entry is about Java implementation of this method. This algorithm is dependent on K value and also on the size N of window $R \times R$.

This method can achieve good results even on severely degraded process, but it is slow since the computation of local mean, max and min from the local neighborhood is to be done for each block of image pixels. Above threshold value calculation is without ghost removal. If the contrast is greater than a specific value $k$ global thresholding method is used (Bernsen, 1986).

\[
T(x, y) = \begin{cases} 
\frac{Z_{(\text{max})} + Z_{(\text{min})}}{2}, & \text{if } Z_{(\text{max})} - Z_{(\text{min})} > k \\
GT, & \text{if } Z_{(\text{max})} - Z_{(\text{min})} \leq k 
\end{cases}
\]  

(7)

Where $k$ is a contrast threshold, threshold the image according to the thresholding curved surface $T(x, y)$. If the intensity difference is greater than the threshold means local thresholding method is applicable else global thresholding technique is useful to extend the image. GT is Global threshold value calculated when the contrast is lesser than the threshold $k$. We are moving in to global threshold method. In our work we have implemented the technique of Otsu to the entire image.

**Otsu’s method**

In Otsu’s method we exhaustively search for the threshold that minimizes the intra class variance (the variance within the class), defined as a weighted sum of variance of the two classes:

For every possible $t$ from 1 to maximum intensity:

Calculate within group variance:

Separate the pixel into two clusters according to the threshold

100
1. Probability of being in group 1; probability of being in group 2
2. Determine mean of group 1; determine mean of group 2
3. Calculate variance for group 1; calculate variance for group 2
4. Calculate weighted sum of group variance

Remember which t gave rise to minimum.

\[ q_1(t) = \sum_{i=0}^{t} p(i) \]  
\[ q_2(t) = \sum_{i=t+1}^{\text{max}} p(i) \]  

Where \( q_1(t), q_2(t) \) probability of each group and \( p(i) \) is the class probability; the total number of pixels in the image divided by the pixels in the class.

\[ p(i) = \frac{n_i}{N}. \]  

Class mean is calculated as

\[ \mu_1(t) = \frac{\sum_{i=0}^{t} p(i)}{q_1(t)} \]  
\[ \mu_2(t) = \frac{\sum_{i=t+1}^{\text{max}} p(i)}{q_2(t)} \]

The Variance of individual group is

\[ \sigma_1^2(t) = \frac{\sum_{i=0}^{T} [i - \mu_1(t)]^2 p(i)}{q_1(t)} \]  
\[ \sigma_2^2(t) = \frac{\sum_{i=t+1}^{\text{max}} [i - \mu_2(t)]^2 p(i)}{q_2(t)} \]

The weighted sum of group variance

\[ \sigma_w^2(t) = q_1(t) \sigma_1^2(t) + q_2(t) \sigma_2^2(t) \]  

Threshold t is chosen, so that the between class variance \( \sigma_w^2 \) is maximized that is

\[ t = \left\{ \text{Max} \sigma_w^2(t) \right\}, \quad 0 \leq t \leq \text{max} \]
We take the threshold that produced minimum intra class variance as a global threshold. In Otsu method extension of Multi threshold is possible.

When different methods are being applied on mammogram of tumor data base, most of the algorithms binarized the whole image without properly detecting the region of interest and the black background, so some methods failed to give appropriate binarization. Thus the problem of variation in intensity level of foreground to the background is totally overcome. Combination of these algorithms produces very good results for all type of Mammogram images. Output of these algorithms also proved that our proposed method produces better results visually as well as metric wise compared to the other established image binarization. These methods are very much simple and can be easily implemented in any platform.