AN IMPROVED CLIPPED SUB-HISTOGRAM EQUALIZATION TECHNIQUE USING OPTIMIZED LOCAL CONTRAST FACTOR FOR MAMMOGRAM IMAGE ANALYSIS

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FACULTY OF ENGINEERING
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KUALA LUMPUR

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING SCIENCE

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[AN IMPROVED CLIPPED SUB-HISTOGRAM EQUALIZATION TECHNIQUE USING OPTIMIZED LOCAL CONTRAST FACTOR FOR MAMMOGRAM IMAGE ANALYSIS]

ABSTRACT

Mammography has been known worldwide as the most common imaging modalities utilized for early detection of breast cancer. The mammographic images produced are in greyscale, however they often produced poor contrast images, non-uniform illumination, and the image often contain artefacts and noise. These limitations can be overcame during the pre-processing stage by improving the image enhancement process. Therefore, in this research an optimized enhancement framework is developed where the local contrast factor is manipulated to preserve details of the image. This technique aims to improve the overall image visibility without altering histogram of the original image, which will affect the segmentation and classification processes. Unwanted pixel removal is performed in the image histogram at early stage to increase the efficiency of mean histogram calculation. Then, the histogram is separated into two partitions to allow histogram clipping process to be conducted individually for underexposed and overexposed areas. Consequently, the local contrast factor optimization is conducted to preserve the image details. The proposed method is tested on 322 MIAS database images, and the results from the proposed method are compared with other methods such as HE, CLAHE, DPPLHE, BPPLHE, and QPLBHE by the quantitative measurement of peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), average contrast (AC), and average entropy (AE) difference. The results portrayed that the proposed method yield better quality over the others with highest peak signal-to-noise ratio of 32.676. In addition, in terms of qualitative analysis, the proposed method depicted better lesion segmentation with smoother shape of the lesion.

Keywords: Mammography, Histogram Clipping, Histogram Equalization, Mammogram Enhancement, Local Contrast.

[TEKNIK SUB-HISTOGRAM TERPOTONG MENGGUNAKAN FAKTOR KONTRAS TEMPATAN YANG DIOPTIMUMKAN UNTUK ANALISIS GAMBAR MAMOGRAM]

ABSTRAK

Mamografi dikenali di seluruh dunia sebagai kaedah pengimejan yang paling biasa digunakan untuk pengesanan awal kanser payudara. Gambar mamografi yang dihasilkan berada dalam skala kelabu, namun ia sering menghasilkan kontras yang kurang, pencahayaan tidak seragam, dan mengandungi artifak serta bunyi bising. Masalah ini dapat diatasi semasa peringkat pra-pemprosesan dengan memperbaiki proses peningkatan gambar. Oleh itu, dalam penyelidikan ini, kerangka penambahbaikan optimum telah dilakukan di mana faktor kontras tempatan dimanipulasi untuk mengekalkan perincian gambar. Teknik ini bertujuan untuk meningkatkan tahap penglihatan gambar secara keseluruhan tanpa mengubah histogram gambar asal, yang akan mempengaruhi proses segmentasi dan klasifikasi. Penghapusan piksel yang tidak diingini telah dilakukan dalam histogram gambar pada peringkat awal untuk meningkatkan kecekapan pengiraan histogram rata-rata. Kemudian, histogram dipisahkan menjadi dua partisi untuk membolehkan proses pemotongan histogram dilakukan secara individu untuk kawasan yang tidak terdedah dan terlalu terbuka. Seterusnya, pengoptimuman faktor kontras tempatan dilakukan untuk mengekalkan perincian gambar. Kaedah yang dicadangkan telah diuji ke atas 322 gambar daripada pangkalan data MIAS, dan hasilnya telah dibandingkan dengan kaedah lain seperti HE, CLAHE, DPPLHE, BPPLHE, dan QPLBHE dengan pengukuran kuantitatif nisbah isyarat-ke-bising puncak (PSNR), indeks kesamaan struktur (SSIM), rata-rata kontras (AC), dan rata-rata perbezaan entropi (AE). Hasil menunjukkan bahawa kaedah yang dicadangkan menghasilkan kualiti yang lebih baik daripada yang lain dengan nisbah isyarat-ke-bising puncak tertinggi iaitu 32.676.

Selain itu, dari segi analisis kualitatif, kaedah yang dicadangkan menggambarkan segmentasi lesi yang lebih baik dengan bentuk lesi yang lebih halus.

Kata kunci: Mamografi, Pemotongan Histogram, Pemerataan Histogram, Peningkatan Imej Mamogram, Kontras Tempatan.

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LIST OF SYMBOLS AND ABBREVIATIONS

HE	:	Histogram Equalization
CLAHE	:	Contrast-Limited Adaptive Histogram Equalization
BPPLHE	:	Brightness Preserving Plateau Limits Histogram Equalization
DPPLHE	:	Detail Preserving Plateau Limit Histogram Equalization
QPLBHE	:	Quantized Plateau Limits Bi-Histogram Equalization
PDF	:	Probability Density Function
CDF	:	Cumulative Distribution Function
IQ	:	Image quality
PSNR	:	Peak Signal-to-Noise Ratio
SSIM	:	Structural Similarity Index Measurement
AC	:	Average Contrast
AE	:	Average Entropy
MIAS	:	Mammography Image Analysis Society
ROI	:	Region of Interest

CHAPTER 1: INTRODUCTION

1.1 Background

Breast cancer is well known to be one of the most common cancers diagnosed among women worldwide. It is acknowledged to be the second main cause of cancer amongst women after lung cancer. In the year 2018, it was found that approximately 2.1 million people were diagnosed with breast cancer and mortality rate in more than 100 countries has escalated due to this disease (Bray et al., 2018). The incidence and mortality rate of breast cancer reported in Bray et. al., (2018) shows that the highest rate for breast cancer incidence occurred in Australia, Western Europe, and Northern Europe. Meanwhile, the greatest mortality rate occurred in Melanesia with 25.5%, although their incidence rate is only 49.7% (ranked 8-th in the report by Bray et. al., 2018).

Malaysia as a developing country with population estimation of 32.6 million with 48.6% of women, has also suffered from cancer cases (WorldBank, 2020). According to The Global Cancer Observatory (GLOBOCAN, 2019), 23,218 Malaysian women are identified as the victims of cancer, with statistics of 32.7% breast cancer case, 12% colorectum cancer case, 7.2% cervix uteri cancer case, 5.5% ovary cancer case, 5.4% lung cancer case, and 37.1% other cancer cases. The statistical data is illustrated in Figure 1.1. On the other hand, from Figure 1.2, it is reported that among the top 10 cancers in Malaysia, breast cancer has the highest incidence rate (47.5%), followed by colorectum cancer (19.95%) and lung cancer (15.3%) as the second and third top cases respectively. To add, breast cancer has the highest mortality rate (18.4%), followed by lung cancer (13.35%), and lung cancer (11.2%). Based on the statistics given, it can be observed that breast cancer cases are still occurring and the number is still high.

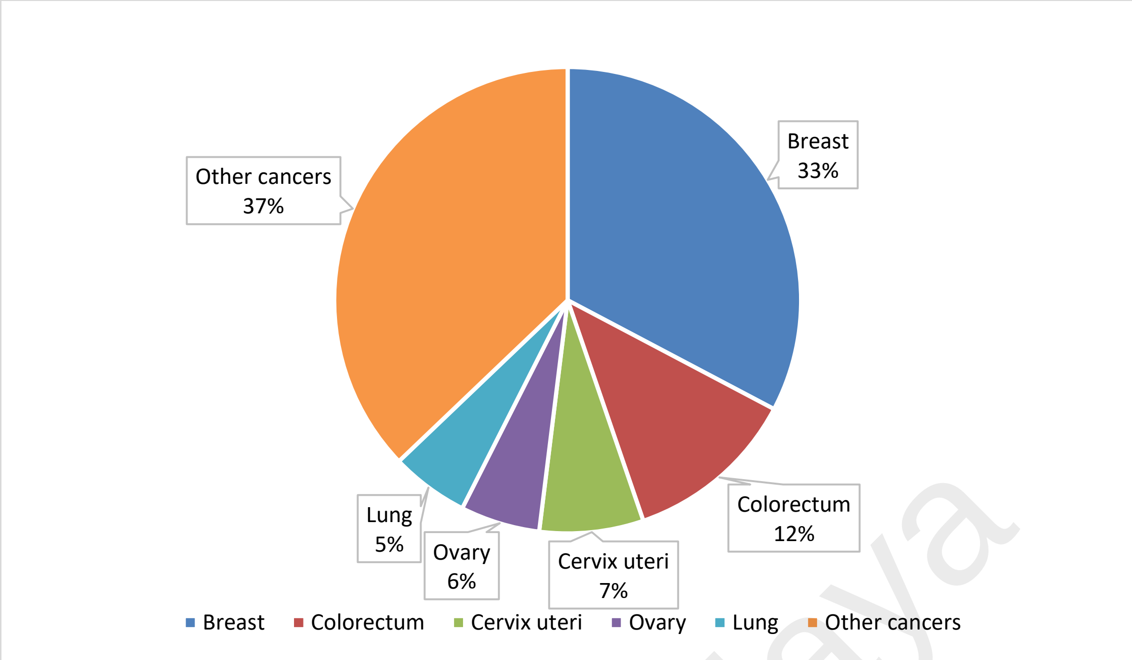


Figure 1.1. The number of new cancer cases for females in Malaysia (adapted from the Global Cancer Observatory, 2018)

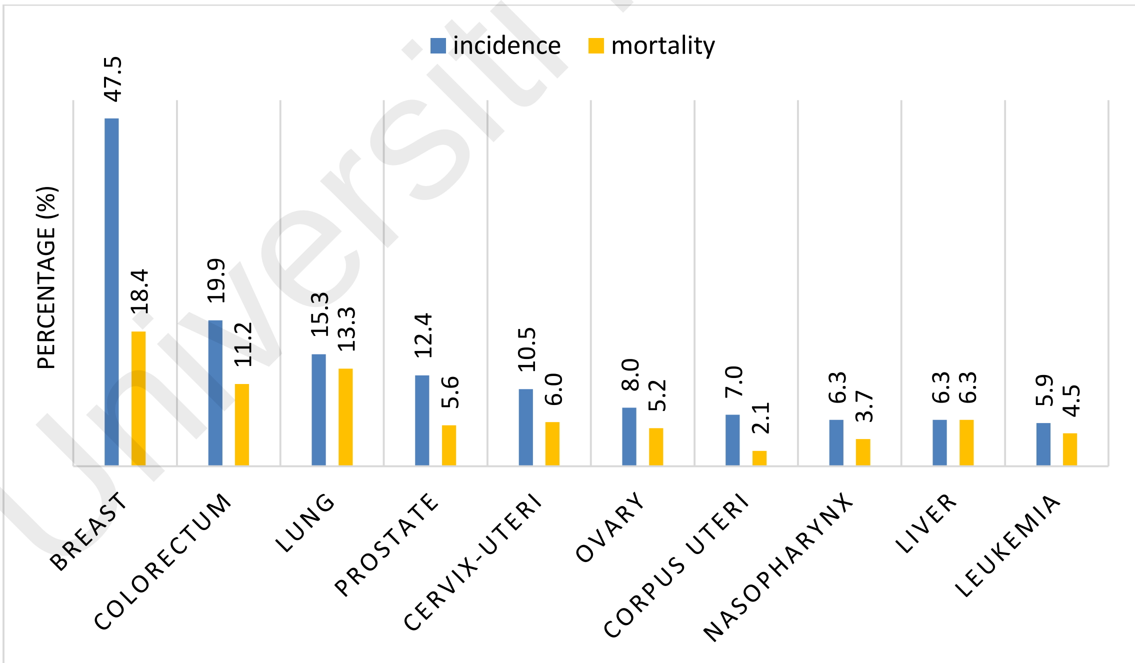


Figure 1.2. The age-standardized (world) incidence and mortality rate for top 10 cancers in Malaysia for male and female (adapted from the Global Cancer Observatory, 2018)

The key in reducing high death tolls caused by breast cancer can be realized through early diagnosis. The chance of survival for breast cancer patients are higher when the early detection is conducted. One of the ways for early cancer detection is by performing early breast screening, which can be conducted by various imaging modalities such as mammography, breast ultrasounds, computed tomography (CT), and magnetic resonance imaging (MRI) (Houssami et al., 2011). For breast screening, mammography has been the most reliable and effective screening tool due to its higher sensitivity and higher spatial resolution. It is commonly used by medical experts for early breast cancer intervention (Łuczyńska et al., 2015). In addition, mammogram screening acts consistently in declining the risk of death caused by breast cancer. Mammography is a process where x-ray is projected in the form of radio wave or light wave, directly to the patient's breast which will generate tiny radiation explosion. This trails to the breast image being recorded for analysis. This process is known to be non-invasive and comparing to screen film mammography technique, digital mammography performs better with high quality of precision and specification (Kerlikowske et al., 2011).

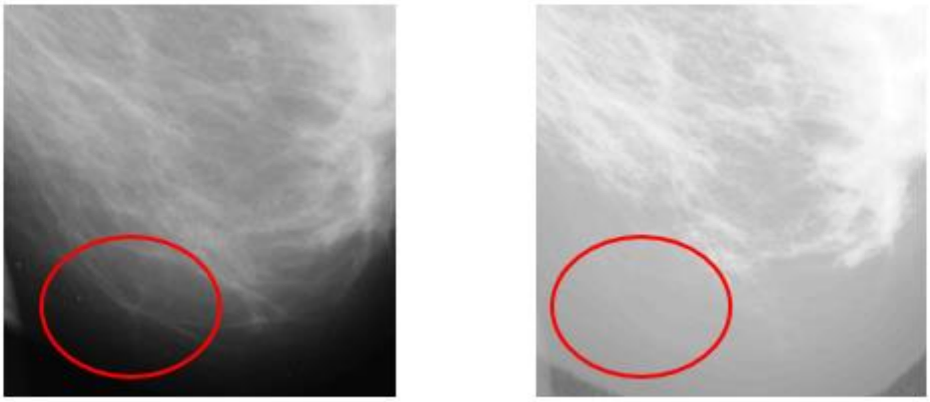
Mammogram readings can be toilsome and called for great experience of interpretation. In some cases, the presence of lesions in mammogram images are not detectable by medical experts during breast diagnosis due to the structure of dense breast tissue and fatty glandular layer (Nazari et al., 2018). Numerous mammographic images are required to be analyzed by different medical experts, making such analysis prone to be inaccurate. Study found that medical experts are susceptible for false analysis during diagnosis such as false positive and false negative, as upon retrieving the mammographic images, the images usually contain noises and artefacts, and low contrast images are also produced (Chaloeykitti et al., 2006). Breast lesions are presented in two different conditions which are benign and malignant. In most cases, medical experts are not able to differentiate between the two different lesions due to the presence of noises and low contrast image problem. Studies have shown that computer-aided diagnosis (CAD) system acts as a 'second reader' and helps medical expert in increasing the accuracy and efficiency of the mammogram image analysis (Henriksen et al., 2018). CAD system includes pre-processing and post-processing, where pre-processing is the stage which image features improvement are conducted before further processing. This research focused on pre-processing stage for image enhancement. To solve the aforementioned drawbacks of mammogram images, various contrast enhancement techniques have been developed to provide better visualization of the lesion and overall image.

Contrast enhancement technique can be classified into three domains, namely frequency domain, spatial domain and fuzzy domain. Precisely, this study focuses on exploiting spatial domain parameter to improve the visibility of the mammogram image without altering spatial shape of the histogram. Histogram equalization (HE) is the most popular method utilized for image contrast enhancement where it modifies the histogram of image. The simplicity of HE-based technique allowed it to be widely used in various fields. In addition, this method is simple, fast and more flexible in terms of the hardware development cost, thus it is implemented in the field programmable gate arrays (FPGA) (Alsuwailem et al., 2006). The detection of breast cancer during its early stages elevates the chances of survival and revamp the patient's life condition. It is significant to have an early diagnosis when the symptoms appeared to elevate the chances of successful treatment.

1.2 Problem Statement

Over the decades, mammography has been the most reliable modality for early breast cancer detection. However, most of the mammographic images obtained are poor in contrast where breast tissues, lesions and unwanted background are less visible. This leads to low visibility of breast lesions, which links to difficulty in mammogram image interpretation by medical experts. Since image deterioration occurred, possibility of obtaining wrong diagnosis such as false positive and false negative errors are most likely to occur. False positive error is a condition where radiologist detected a presence of lesion or abnormalities in mammographic image, but there is none exists in actual cases. On the other hand, false negative error is a situation where the mammographic image appeared normal, but actual lesions or abnormalities are presented. Both analyses are dangerous for the patient as the lesion will likely grow into higher stage where early intervention is delayed and thus no immediate action is taken on the patient. Therefore, enhancement of mammographic image is very significant to increase the contrast between the lesion, breast tissues and background.

Histogram Equalization (HE) is one of the key aspects of the image enhancement method, as the general description of the image can be derived from the image statistics embodied in the histogram. Therefore, the development of enhancement method mostly includes the utilization of HE-based method. In addition, HE-based method has been chosen for this research due to its simplicity and flexibility. Although this technique is widely used in various fields, there still exists some problems with the contrast feature when this method is applied on mammogram images. HE method might produce unwanted artefacts such as over-brightness, over-intensity-saturation, and noise amplification. In addition, over-saturation will lead to loss of details which is needed for analysis by the medical experts. Figure 1.3 shows an example of image when HE method is applied to mammogram image. The area enclosed in the red circle is the area where breast tissues appeared in the original image in Figure 1.3 (a).



(a) Original image (b) HE image

Figure 1.3: Example of HE-ed mammogram image (adapted from MIAS database)

Referring to Figure 1.3 (a) and Figure 1.3 (b), the problem arose when HE method produced an over-brightness image where the breast tissue appeared to be loss, as shown in the red circle in Figure 1.3 (b). The issue with loss of details is a major drawback for mammogram image, as all fine details need to be preserved at the end of enhancement method for a thorough diagnosis by the medical expert. A successful enhancement method should allow higher visualization of the tiny details without causing over-saturating and over-bright the original image.

1.3 Aims and Objectives of the Study

This study aims to provide aid to the medical experts for interpretation and analysis of mammogram image, specifically to reduce false analysis during diagnosis. In order to attain an improved mammogram image, the objectives are constructed as follows:

1. To propose an optimization enhancement protocol by altering local contrast of the mammogram images.
2. To propose an adaptive and automated brightness improvement technique using an optimized local contrast factor for mammogram image analysis.

3. To evaluate the performance of the proposed method in terms of image quality and their performance metrics.

The algorithm development is steered towards poor contrast problem and preservation of local contrast that could highlight details of the image for improved mammogram image diagnosis.

1.4 Scope of Work

This research is carried out using samples of mammogram images which are retrieved from Mammography Image Analysis Society (MIAS)[1] database (Clark, 2012). 322 mammogram images are presented in this database and all images are utilized for algorithm testing. The images have been categorized into three different categories; normal, benign and malignant with different types of breast tissues such as fatty, fatty glandular and dense glandular. In addition, the abnormalities are further classified into few types such as circumscribed masses, calcification, ill-speculated mass, ill-defined mass, architectural distortion, and others.

The algorithm is developed using MATLAB R2016B using the greyscale MIAS database images. The viewpoint of the images is either in right view or left view, specifically in mediolateral oblique (MLO) position, with each image having 1024 × 1024 pixels. The proposed algorithm is developed and tested on 322 images.

1.5 Thesis Organization

The thesis structure consists of five chapters and each of its function is described briefly as follows:

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[1] MIAS refers to Mammography Image Analysis Society where it can be found at http://peipa.essex.ac.uk/info/mias.html

- Chapter 1 – Introduction

  An overview of breast cancer, mammogram imaging, and mammogram image enhancement is presented in this section, along with the problem statements, objectives, scope of work and thesis organization. This chapter holds a summary of explanation on the whole thesis.

- Chapter 2 – Literature Review

  In this chapter, analyses of different techniques for mammogram image enhancement are reviewed. The explanation includes review on anatomy and pathology of breast, trailed by principles of mammogram and lesion detection by mammogram. Eventually, various researches on mammogram image enhancement algorithm are reviewed in this section.

- Chapter 3 – Methodology

  The overall approach for this research is provided in this chapter. The main contributions are highlighted, including the techniques that elevate the quality of final mammogram image. The research approach is divided into two stages, which is stage 1: brightness improvement and stage 2: contrast preservation.

- Chapter 4 – Results and Discussions

  The discussion on the results obtained is presented here. The effectiveness of the proposed method is analyzed in terms of qualitative and quantitative measurements. All results are displayed and compared accordingly to allow the performance of proposed method to be evaluated.

- Chapter 5 – Conclusion and Future Work

The last chapter draws the conclusion and highlights the contributions of this research. The pros and cons of using this method are explained, study limitations are provided, and the improvement is described in future works.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The overview of breast cancer and mammogram image enhancement is presented in this section. This research study focuses on the development of HE-based algorithm with the ability to improve the brightness of the original image without over-enhancing or over-saturating, along with the preservation of the tiny details and its local contrast factor. Enhancement process is commonly known for its function during pre-processing stage. Normally, this process is applied to the grayscale image that is poor in contrast to allow the viewer to extract more information to be exploited for further processing. There are various state-of-the-art enhancement methods developed since decades ago, however not all enhancement algorithms are suitable to be applied to mammogram images.

As mentioned in Chapter 1, HE-based method is preferable as it is simpler to adjust its spatial information and could provide higher effectiveness in enhancing the contrast of the image. However, during the process, unwanted artefacts and noises are often exist during acquisition process. Due to these reasons, this study involved development of HE-based algorithm for mammogram image enhancement as there are more room for improvement based on the published state-of-the-art algorithms.

This chapter consists of an explanation on details pertaining breast anatomy and pathology in Section 2.2, mammogram screening and image analysis in Section 2.3, reviews on the image enhancement method and some HE-based state-of-the-art algorithms that were previously developed in Section 2.4, and a summary to conclude Chapter 2 is available in Section 2.5.

2.2 Pathology of Breast Cancer

It is crucial for the specialist to first understand the anatomical structure of normal human breast in order to avoid false mammogram diagnosis. The lists of possibility for diagnosis can be narrowed down by identifying the location of lesion or abnormalities in the breast anatomy.

2.2.1 Anatomy of Breast

Generally, it is known that the breast tissue can be found more in women than men, resulting in different size between the two genders. Jesinger (2014) described that the development of human breast is under the influence of genetic and hormone during the fourth week of embryonic life from the ectoderm. The breasts are situated on the right and left side of the upper ventral section of the body trunk with their base extended from second rib to the sixth rib, connected to deep pectoral fascia and pectoralis major. For men, the volume of breast is mostly made up of fat, along with few ducts and elements of stromal. Different for female, puberty leads to escalation of estrogen hormone which stimulates the growth of fats and periductal connective tissues accompanied by thickening and elongation of the ductal system, breast glandular tissues, and breast adipose tissues.

The anatomy of human breast can be referred to Figure 2.1. The breast is shortly presented as modified cutaneous exocrine gland, which made up of skin and subcutaneous tissues, a tube-like structure that carry milk to nipples called duct, breast parenchyma (breast tissues), gland that produces milk known as lobules (each lobule holds tiny, hollow sacs called alveoli), and supporting stroma (connective tissues). In addition, the composition of human breast also includes fat placed within a complex web of ligaments, arteries, veins, nerves, and lymphatic. In addition, the breast anatomical structure is also composed of areola and nipple. Areola is the brown circular area located in the middle of the breast surrounding the nipple. It consists of tiny sweat glands, which functions to secrete liquid moisture that acts as lubricant to ease breast-feeding. On the other hand, the nipple is the place where milk secretion occurs.

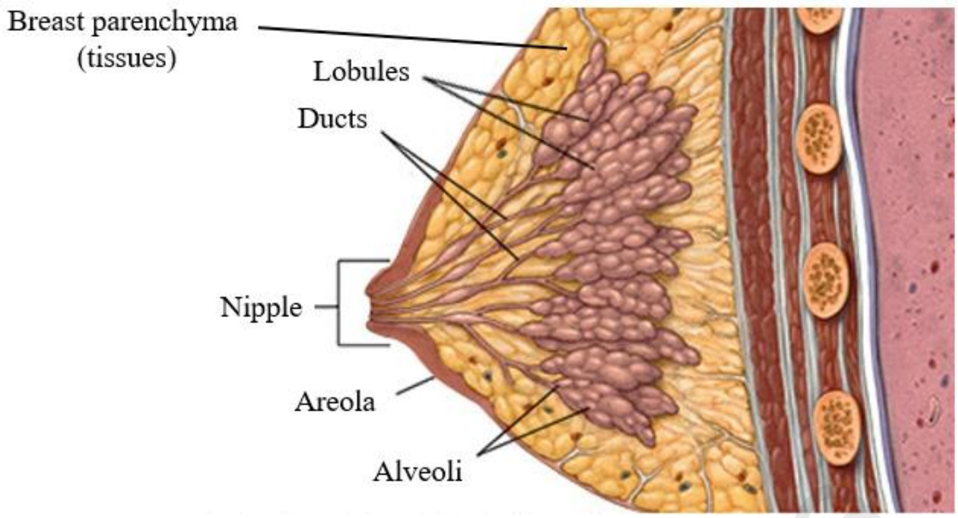


Figure 2.1: The female's breast anatomy (adapted online from American breast cancer foundation site)

Martini et al. (2009) explained that the composition of breast also includes blood and lymph vessels. As blood vessels function to carry bloods, lymph vessels act as a tube that collects and transfer the lymph fluids to the lymph nodes situated near the breast.

2.2.2 Breast Cancer and Abnormalities

Cancerous cell is known as a threat to human. This disease caused a change in body's cells and can grow out of control. Most cancerous cells possess the ability to form a lump or mass known as tumor or lesion. Normally, breast cancer is named after the part of breast in which it is originated. Development of breast tumor begins at lobules which is the milk-producing glands, and the duct connecting lobules to the nipple in the breast tissue (Bandyopadhyay et al., 2010). Breast cancer can be classified into two categories; invasive and non-invasive. Invasive breast cancer is the cancer that can break through the duct and lobular wall, leading to invasion of surrounding connective tissues of the breast. Cancer can be invasive even without spreading to the lymph nodes or other organs. On the other hand, non-invasive cancer is the cancer that confined in the ducts and do not invade the surrounding connective tissues of the breast. The most common form of non-invasive breast cancer is known as ductal carcinoma in-situ (DCIS). As the name implies, the cancer cell is confined within the ducts of the breast. The term 'in-situ' is an indication of cancer cell that has not spread far from the area where it originally developed. Lobular carcinoma in-situ (LCIS) is a less common cancer, therefore it is considered as a marker for the elevation of breast cancer risk. LCIS refers to the increase of cells within the lobules (milk gland) of the breast (Sharma et al., 2010). Figure 2.2 shows an illustration of DCIS and LCIS cancers.

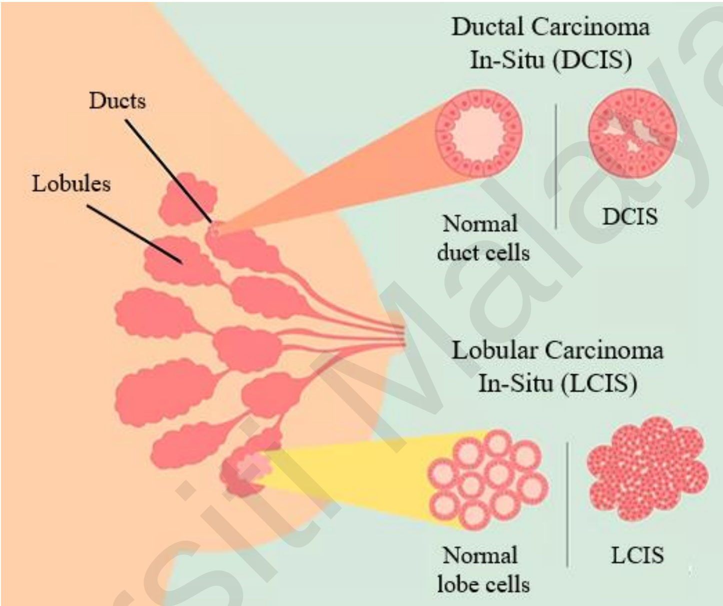


Figure 2.2. Examples of non-invasive cancers (adapted from Verywellhealth, 2019)

Breast tumor can be classified into two types; benign and malignant tumor, as shown in Figure 2.3. Most benign lesions are not cancerous, have a controllable growth, and does not threaten the life of the host as it has a protective sac that prevents invasion of surrounding tissues. On the other hand, most malignant lesions are invasive and infiltrating due to the absence of the protective sac, thus it is diagnosed as cancerous. Growth rate of both lesions are different. Benign lesion growth is slower compared to malignant as it takes months, in some cases years to grow and spread, while malignant lesion can grow within a week and invade other normal cells.

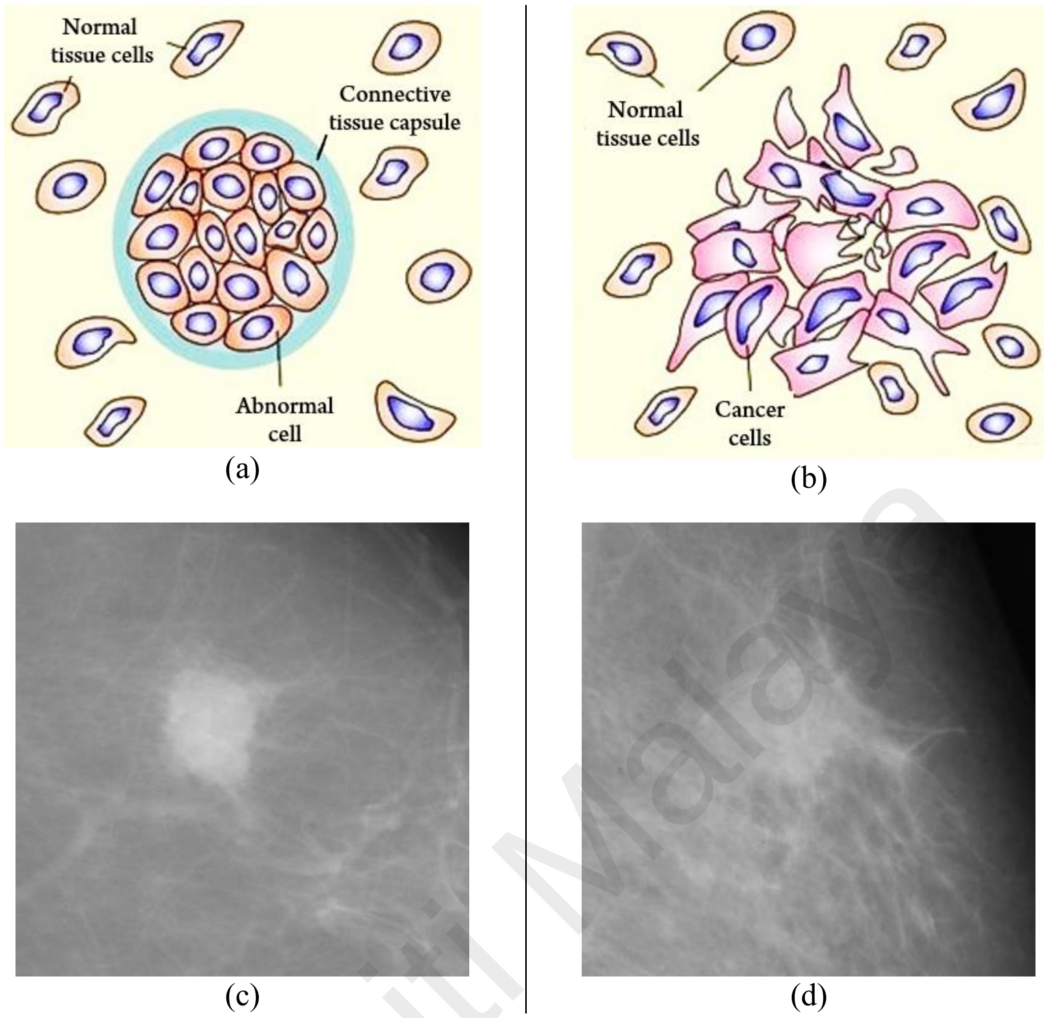


Figure 2.3: The illustration of (a) benign tumor; (b) malignant tumor (adapted from (Sinha, 2018)) and Mammogram image of (c) benign tumor; (d) malignant tumor (adapted from MIAS database).

The abnormalities within mass lesion varies according to its characteristics. Examples of breast lesions are microcalcifications, masses, and architectural distortion. Microcalcifications are tiny lesions found in breast, or also known as small deposits of calcium. On the other hand, it possesses a bright color, usually a bright dot shape compared to the background and have different shapes, sizes, and distribution as illustrated in Figure 2.4.

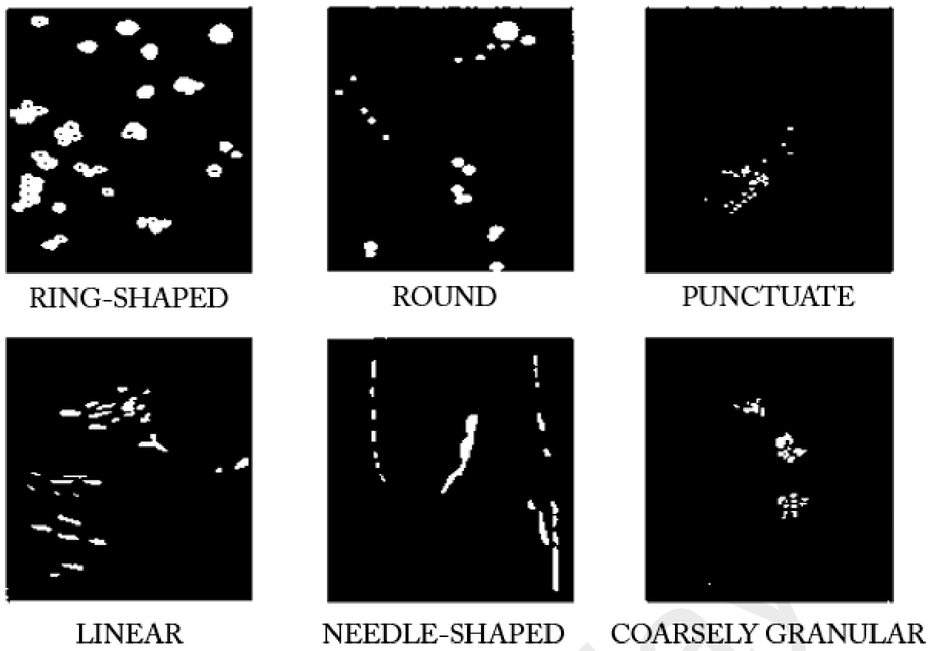


Figure 2.4: Types of microcalcifications (adapted from Gunderman, 2006)

It is often difficult to notice this microcalcification due to its small size, making it less visible to the viewer's eyes. In most cases, the lesions have poor contrast difference due to the less intensity difference between the suspicious lesion and surrounding area. In addition, the location of microcalcifications is often close to the surrounding breast tissues, sometimes superimposition occurred, making it harder to differentiate. In mammographic images, some anatomical structures tend to look like the microcalcifications, such as breast boundaries, fibrous strands, or lobules as shown in Figure 2.5. Presence of microcalcifications are often connected to breast cancer disease, especially if it appeared in clusters. Thus, high accuracy for lesion detection is significant for early detection.

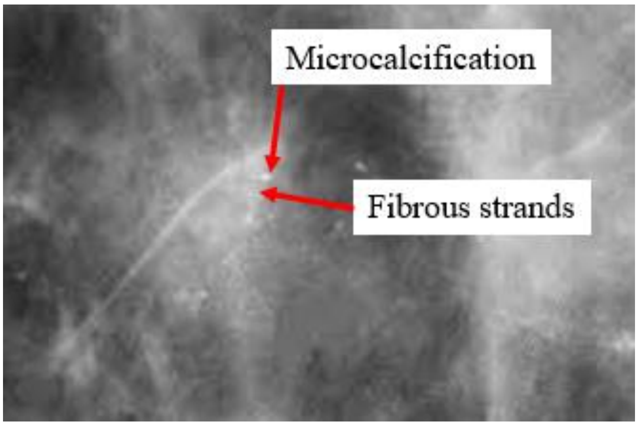


Figure 2.5. Example of microcalcification in mammogram image (adapted from Halls, 2019)

Masses are commonly found insight as dense areas, composed of different characteristics and sizes. Figure 2.6 shows few examples of masses with various shapes and borders such as circular, lobular, oral, and irregular shape. Their margins can be circumscribed, micro-lobulated, obscured, ill-defined or spiculated. Depending on its morphological structure, each mass has different chances of forming a malignant lesion. For instance, masses with ill-defined shape and spiculated borders have a higher probability of turning malignant. On the other hand, circular or oval shape masses are usually linked with benign lesion. The presence of variety mass appearance often leads to inaccurate analysis of mammographic images.

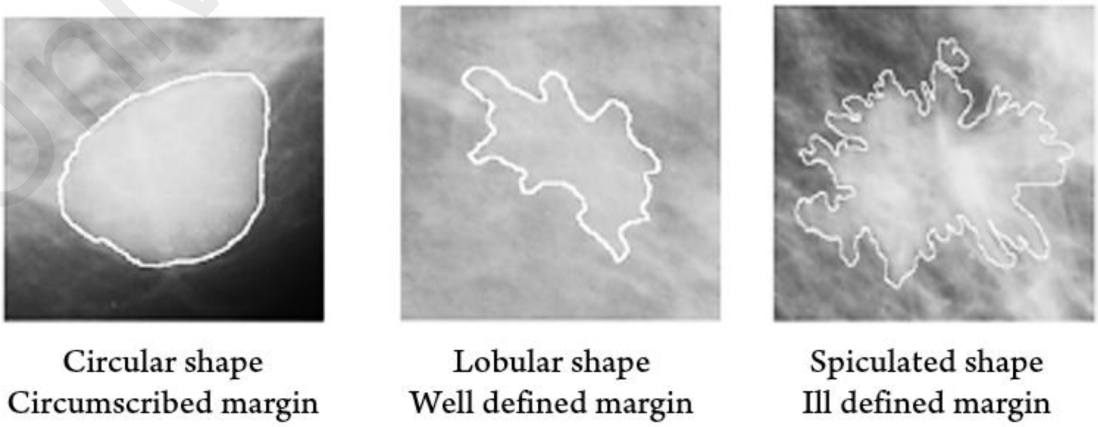


Figure 2.6: Examples of masses with various shapes and borders (adapted from Arnau, 2007)

Meanwhile, architectural distortion is a type of pattern disorder, where obstruction of the usual pattern of tissue strands occurred without any mass or associated center. Most cases varied accordingly, making it strenuous for lesion detection.

2.3 Mammography Image Analysis

Mammography has been the ‘gold standard’ for breast screening modality since decades ago. Numerous studies have shown that it is the most effective way for breast cancer diagnosis as it flattens the breast and allow breast parenchyma and ductal tissues easier to be differentiate while limiting the amount of X-ray radiation. Since X-rays radiation cannot penetrate the breast tissues easily, the mammogram machine is designed to have two plates that compressed and flattens the breast to spread the breast tissues which will generate breast image with higher accuracy and less radiation (Koch, 2016). Other imaging modalities that can be utilized for breast cancer screening includes computed tomography (CT) and magnetic resonance imaging (MRI). Both techniques are able to produce breast image similar with mammography, however they are not convenient for claustrophobic patient and for high risk breast cancer patient as any of the cancers that a mammogram could find may be overlooked by CT and MRI.

Commonly, radiologists will capture multiple mammographic views for detection and characterization of suspicious breast region with presence of lesion, and the typical views are craniocaudal (CC) and mediolateral oblique (MLO) views. Studies have reported that the use of multiple views in mammography sparks a positive effect on recall rate and improvement in performance of lesion detection compared to single view mammography (Timp et al., 2005).

Upon conducting the mammography process, the patient’s breast is compressed between two platforms, which are the film cassette and the compression plate along the direction of x-ray source (head to toe for CC view and over the shoulder to the hip for

MLO view). The patient is positioned upright throughout the process, with the breast compressed in between two plates to increase the contrast of projected image. Example of CC and MLO view mammography acquisition and their resulting image is shown in Figure 2.7. The act of breast compressing between the parallel plates aids in spreading of breast tissues, leading to less overlapping structure and consequently creating clearer breast structure (Hopp et al., 2015).

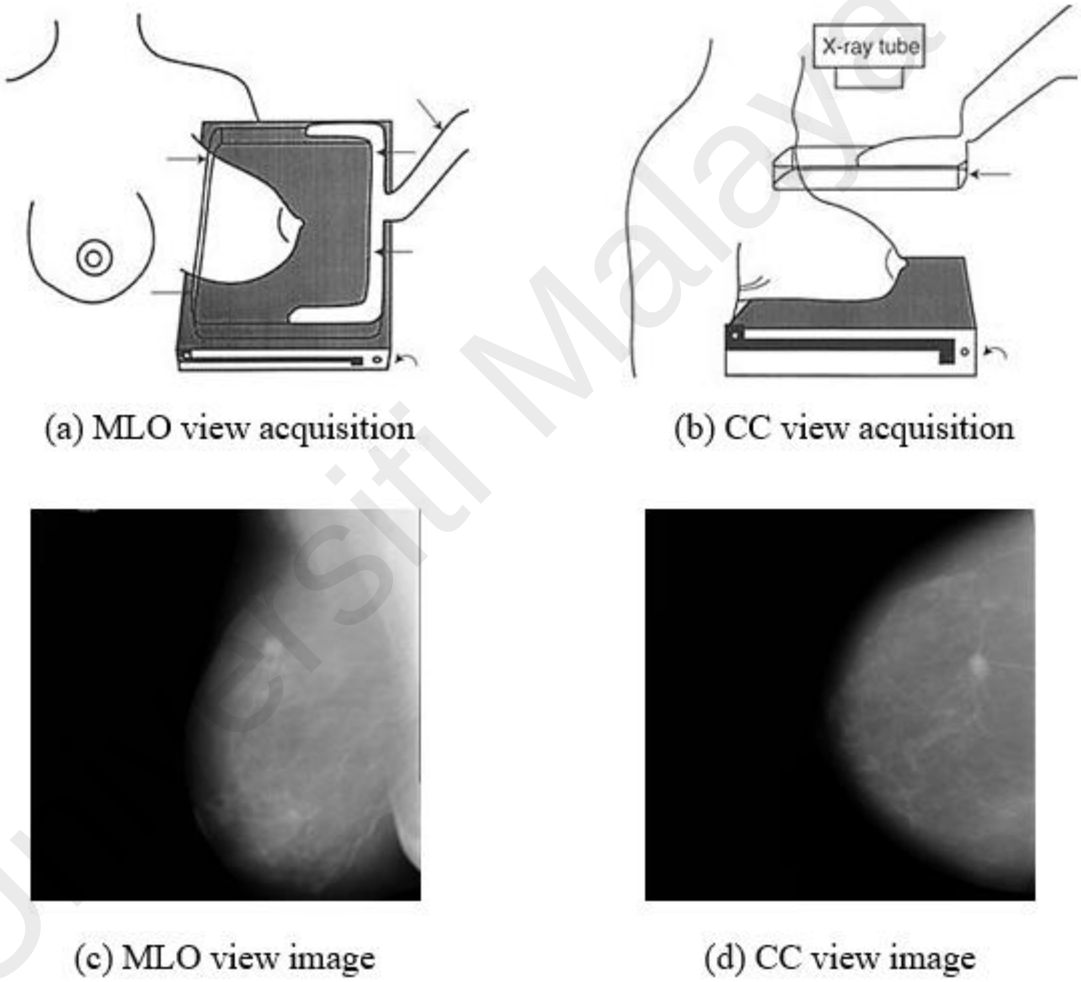


Figure 2.7: Acquisition of (a) MLO view; (b) CC view, and Mammogram image of (c) MLO view; (d) CC view (adapted from RadiologyKey, 2016)

Mammography technique uses lesser radiation dose during the breast compression between the two plates due to the reduction of distance between x-ray source and the receptor, thus decreasing the recall rate and biopsy rate (Markey, 2013). The x-ray tube releases the radiation of x-ray beam through the breast and x-ray detector will detect the radiation, producing an image. The illustration for the x-ray path is shown in Figure 2.8. The formation of x-ray image is caused by the different absorption of photons that passes through the breast tissues (Kopans, 2007). The grey level in mammographic images is the indicator of different tissues proportion in the breast column, as the breast tissue varies from the absorption of photons. The mammographic image will appear black when there is no x-ray photon absorption. On the other hand, the image will appear white when a total absorption takes place. In usual case, breast fibroglandular region produced brighter image due to high x-ray photon absorption, while fats are less bright (Molina et al., 2014)

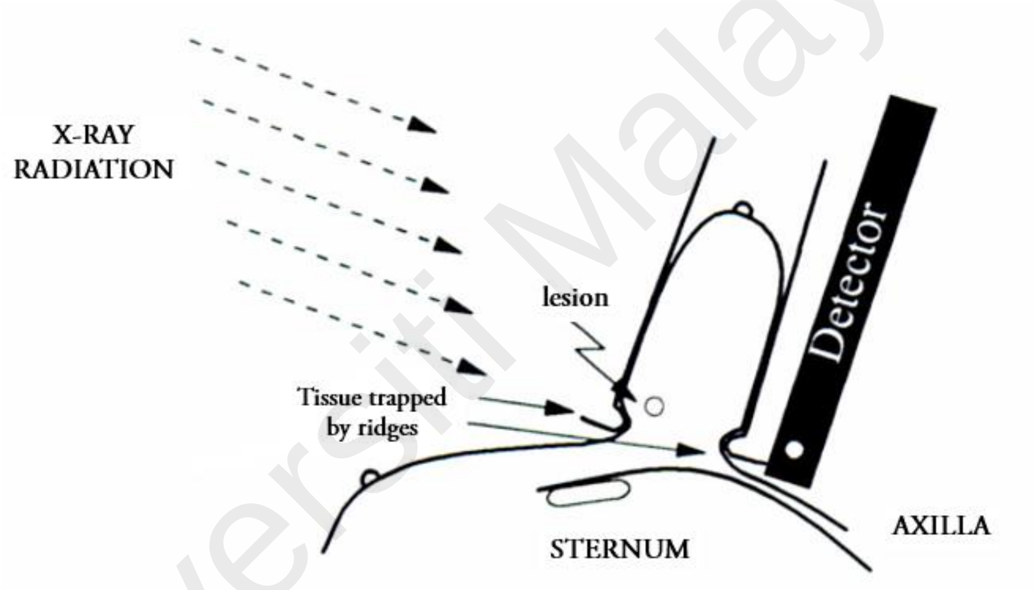


Figure 2.8: The x-ray radiation path in mammogram (adapted from Kopans, 2007)

Mammogram acquisition has many advantages, for instance, artefacts can be eliminated by signal processing technique, contrast enhancement can be conducted, and less acquisition time are required for each patient. On the other hand, the cost per each equipment is quite high, and the modality needs to be incorporated into the network. In addition, the image requires much computer and operating system processing power (Pisano et al., 2007). Although the advantages of digital mammography are quite promising, some improvements are needed with regards to high image resolution at lower cost.

2.4 Contrast Enhancement Technique

Mammogram screening is known to use low dose of x-ray during image acquisition. Due to this condition, major problem arose where the greyscale image produced tend to be poor in contrast, leading to difficulty in lesions and calcifications detection and clarification of their conditions. The features and details of breast lesions in poor contrast image are not clear due to the lower intensity difference between the object and its background (Akila et al., 2015). In order to aid the analysis of mammographic image and reduce false analysis in abnormalities detection, enhancement of image is needed during pre-processing to increase the image contrast and reduce the noise and artefacts presents.

Since the details of image are dependent on the x-ray density, less exposure leads to decrease in image contrast. To overcome this limitation, appropriate contrast enhancement technique is needed during pre-processing stage. Pre-processing stage is the process where image operations are at the lowest level of abstraction as input and output are magnitude images. It is needed to suppress undesirable distortions or to enhance some important image features for further processing (Sonka et al., 1993).

The image enhancement process aims to improve the difference of intensity between image's background and its characteristics, along with refining the visualization of details to the viewer's eyes (Abir, 2013). Contrast enhancement is one of the enhancement techniques, serving the purpose of providing better visualization as well as details extraction of an image. Contrast enhancement technique can be divided into three domains namely frequency domain, fuzzy domain, and spatial domain, as shown in Figure 2.9 (Mustafa et al., 2016).

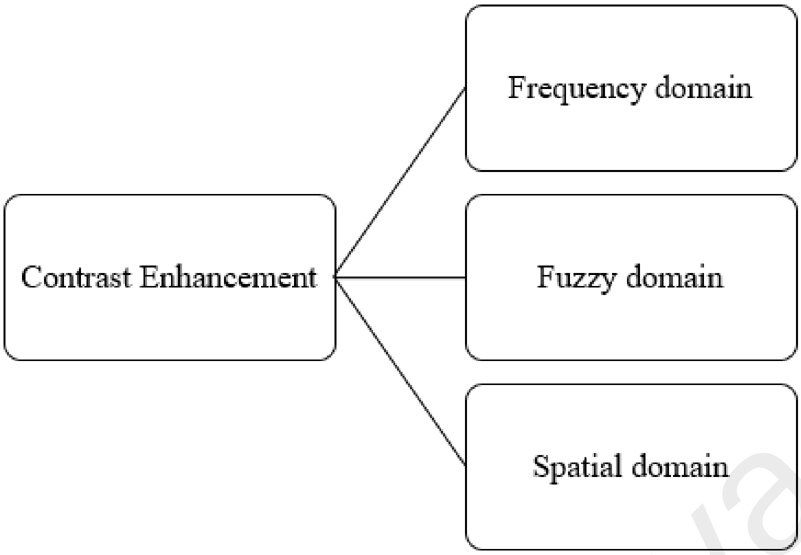


Figure 2.9: Domains for contrast enhancement technique (adapted from S. et al., 2017)

In addition, the contrast enhancement method also serves two different purposes, i.e. brightness preservation and detail preservation. These methods are commonly used to solve problems regarding poor contrast image, with objectives of maintaining the mean brightness and at the same time elevating the contrast of input greyscale image.

2.4.1 Frequency-based Enhancement Technique

Frequency domain method, or also known as transform domain is used to describe the mathematical functions or signals analysis in conjunction with its frequency. Frequency-based enhancement involves the modification of spectral image. Prior to that, image decomposition is conducted beforehand to prevent the formation of image artefacts, thus improving the quality of image (Lidong et al., 2015). Enhancement of image is carried out by manipulation of transform coefficients, which leads to operation on image frequency content, thus high frequency content such as boundaries, edges, and other details can be detected and enhanced easily. Specifically, two main components involved in the frequency-based algorithm are magnitude and phase components. Magnitude components are linked to the image frequency content, while phase components are used to change the image to spatial domain. The frequency value is represented by each point on the image, where high frequency indicates edges and sharp transition, while low frequency indicates smoother area on the images (S. et al., 2017). This method acts explicitly on image coefficients transform such as Fourier transform, discrete cosine transform (DCT) (Mohiddin et al., 2018), and discrete wavelet transform (DWT) (Azani Mustafa et al., 2019).

One way of conducting frequency-based image enhancement is by calculating the Fourier image transformation (Swaminathan et al., 2017). Fourier Transformation is a helpful image processing tool that can be used to disintegrate input images into the sine waves and provide details on the frequencies. This technique is computed by multiplying the outcome with a filter, and then implementing the Inverse Fourier Transform to create an enhanced image. An illustration of block diagram for Fourier transform is shown in Figure 2.10. The resulting output image, *g(x,y)* is in the Fourier domain, whilst the input image *f(x,y)* signifies the image in spatial domain. As Fourier transform only provide details about frequencies, the temporal data is lost during the transformation process. Therefore, the wavelet transformation was utilized to solve this problem.

Wavelet transform uses the same concept as Fourier transforms, where the input image is decomposed into wavelets rather than the sine waves. Different from Fourier transform, this technique provides data pertaining both time and frequency which is effective for image processing tool. Wavelet transform is found to have higher efficiency for noise removal compared to Fourier transform method (Pai et al., 2015). Various types of wavelet exists and utilized for image processing, such as Daubechies wavelet, Symlet wavelets, Coiflet wavelets, Haar wavelets, Spherical wavelets, and many more.

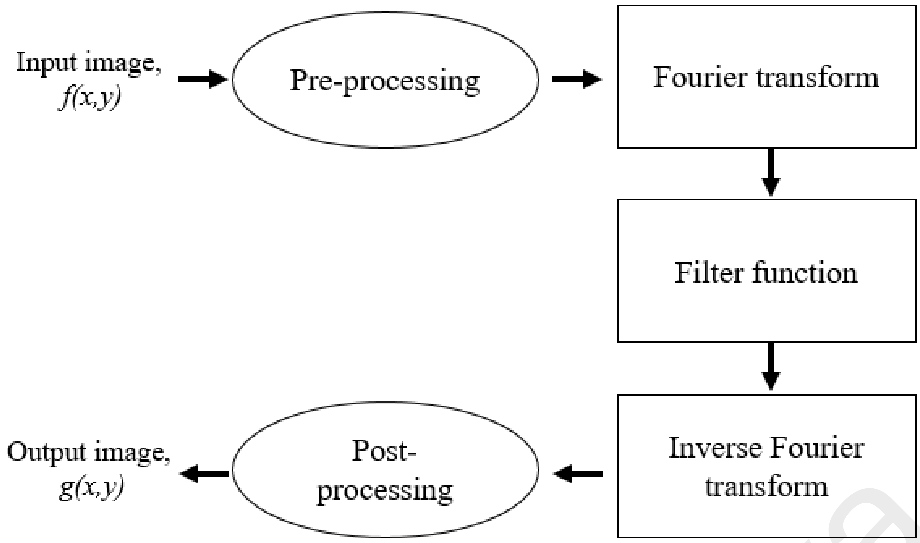


Figure 2.10: Block diagram of Fourier transform (adapted from Agrawal et al., 2014)

The commonly used wave is Haar wavelet as this method is simpler. Discrete wavelet transform (DWT) is introduced in 1989 by Daubechies (1988), Mallat (1989), and others, where it is a multi-resolution depiction of wavelet decomposition-based signals. The DWT breaks down a digital signal into various sub-bands, so that the lower frequency sub-bands have a greater frequency resolution and a shorter time resolution compared to those with higher frequency sub-bands (Acharya et al., 2005). This method can be conducted on few levels depending on the image enhancement, so that the original details and shape of image does not altered.

The study of mammogram enhancement which compares DWT techniques with other techniques are conducted by Moradmand et al. (2014), where five levels of discrete wavelets are utilized and the decomposition is facilitated by Daubechies Wavelet. The research outcome reveals that the most efficient technique for microcalcifications detection is DWT method, plus it is also effective in noise reduction in mammographic images. In contrast, this method has a drawback of sampling deficient and it is drawn to loss of details during the process of sampling. Liu et al. (2015) proposed a different method to solve the aforementioned problems by suggesting stationary wavelet transform (SWT) (Nason et al., 1995) for the purpose of image sharpening and image enhancement. Decomposition of input image into sub-bands are conducted using SWT, generating a sharper image. On the other hand, a combination of DWT and SWT is proposed by Yousefi (2015) where it involves three major steps. Transformation of image into frequency domain is conducted first, followed by manipulation of sub multi-resolution sub-groups, and eventually retransformation of image from frequency domain to spatial domain. DWT and SWT is utilized to transform the input mammographic image into frequency domain during the first stage, where SWT is needed as it helps in prevention of data elimination caused by DWT. The next stage serves the purpose of manipulation of image resolution, contrast enhancement and sharpening the image. The sub-bands that have been manipulated is combined and transformed back to spatial domain by inverse discrete wavelet transform (IDWT).

Despite all the advantages, frequency-based techniques generally have limitations, such as it has the inability to perform simultaneous enhancement well for all images parts, plus it has difficulty to conduct an automated enhancement procedure (S. et al., 2017). Furthermore, this technique requires complex procedure and time-consuming (Shrivastava et al., 2014).

2.4.2 Fuzzy-based Enhancement Technique

The fuzzy logic concept was first introduced in 1965 by Lotfi A. Zadeh with the Fuzzy Set Theory. Since the fuzzy logic has the ability to deal with approximate reasoning, it has been developed to handle the partial truth concept, which is the variation of truth value range between completely false and completely true. (Mahashwari et al., 2013). The broad use of fuzzy logic can be found in applications of image processing, where many ambiguous situations are developed. Ambiguity refers to the condition where uncertainty regarding boundary and non-homogenous region are found in the image. In addition, few edges, contrast and other features are in fuzzy condition as well (Cheng et al., 1999). Interpretation of bright and dark pixels are hard in cases of uncertainty and it can only be handled qualitatively by human visual system. Thus, fuzzy set theory is practical to be assimilated with the enhancement technique as it possesses the ability to imitate a human reasoning into machine system.

Fuzzy sets are defined as the sets at which its elements contains varying membership degree (Mahashwari et al., 2013). Fuzzy domain approach utilizes knowledge-based technique such as Fuzzy sets theory (FSs), logical Fuzzy sets, type I- Fuzzy sets, type II-Fuzzy sets, and intuitionistic Fuzzy sets (He Deng et al., 2016). The major principles of fuzzy enhancement process include three steps; image fuzzification, membership modification, and defuzzification (H. Deng et al., 2017). These methods effectively process the incomplete data resulting from uncertainty and vagueness, plus it is properly suited for automated adjustment of image contrast, leading to improvement of visual quality of the image. The block diagram illustrating the steps of fuzzy image processing is shown in Figure 2.11.

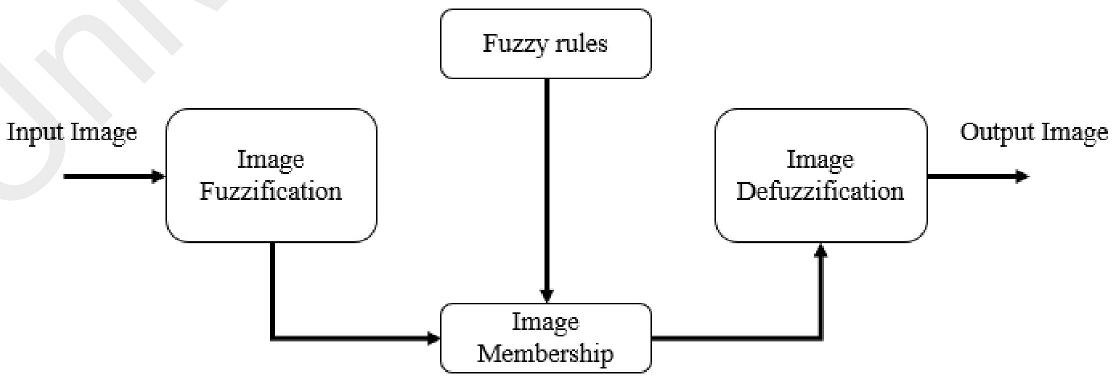
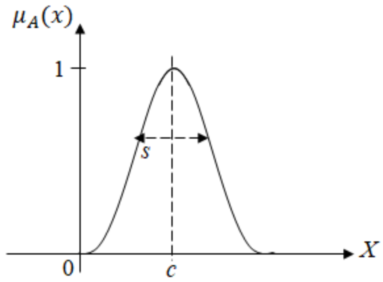


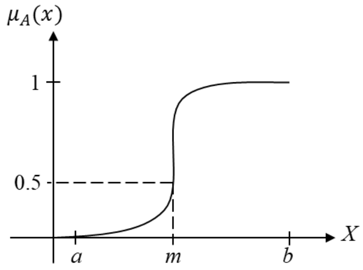
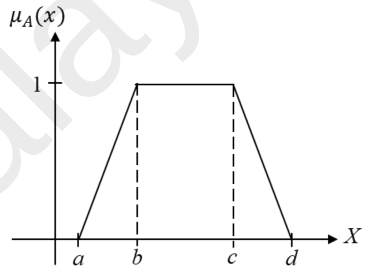
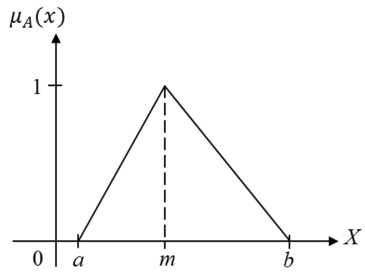
Figure 2.11: Process of fuzzy image processing (adapted from Mahashwari et al., 2013)

Image fuzzification process involves the coding of image information, where grayscale intensities of input image is converted to a fuzzy plane in the form of binary which is between 0 and 1. A conversion occurs where non-uniform illumination image in the spatial domain is transformed to fuzzy domain. On the other hand, the membership function is defined as a graphical description of fuzzy sets, where it is based primarily on the mapping of each element to the value of 0 and 1. Modifying the membership of the image is the core of this process, as it is necessary to change the value of the membership function resulting from the fuzzification process. The common membership functions used in image processing are listed in Table 2.1. Eventually, defuzzification process is responsible to transform back the image to spatial domain by mapping the algorithm back to grayscale intensities image. It is also known as the reverse process of fuzzification.

The applications of fuzzy domain in image processing has captured the eyes of researchers since decades. They have been developing variations of algorithms to increase the quality of images. As mentioned earlier, the most significant stage in fuzzy domain technique is the membership value modification, where the membership value can be altered by applying fuzzy approaches, such fuzzy rule-based system (FRBS) (Choi et al., 1995), fuzzy clustering (Tolias et al., 1998), or fuzzy morphology (Wirth et al., 2005).

Table 2.1: Lists of membership functions in fuzzy set theory (adapted from Samanta)

Membership Function	Descriptions	Plot
Gaussian	Represented by Gaussian (*x:c,s,m*) where *c* represents center and *s* is the standard deviation. The equation is given as: $\mu_A(x) = \exp[-\frac{1}{2}\frac{(x-c)^2}{s^2}]$	

Sigmoid	Defined by its lower limit, *a*, upper limit, *b* and value *m* or point of inflection so that *a* < *m* < *b*. The equation is given by: $\mu_A(x) = \begin{cases} 0 & if\ x \leq a \\ 2\{\frac{x-a}{b-a}\}^2 & if\ x \in (a,m) \\ 1-2\{\frac{x-b}{b-a}\}^2 & if\ x \in (m,b) \\ 1 & if\ x \geq b \end{cases}$	
Trapezoidal	Defined by its lower limit, *a*, upper limit, *d*, and the lower and upper limit of the nucleus, *b* and *c* respectively: $\mu_A(x) = \begin{cases} 0 & if\ (x \leq a), (x \geq d) \\ \frac{x-a}{b-a} & if\ x \in (a,b) \\ 1 & if\ x \in (b,c) \\ \frac{d-x}{d-c} & if\ x \in (b,d) \end{cases}$	
Triangular	Defined by its lower limit, *a*, upper limit, *b* and modal value *m* so that *a* < *m* < *b*.: $\mu_A(x) = \begin{Bmatrix} 0\ if\ x \leq a \\ \frac{x-a}{m-a}\ if\ a \leq x \leq m \\ \frac{b-x}{b-m}\ if\ m \leq x \leq b \\ 0\ if\ x \geq b \end{Bmatrix}$	

In these recent days, the use of fuzzy domain in mammogram enhancement is being developed in many ways. For instance, Amirpour et al. (2016) proposed an algorithm for mammogram contrast enhancement, utilizing a fuzzy based wavelet transform. In this technique, the input image is decomposed into four levels of wavelet sub-bands, and in order to increase the contrast, detail sub-bands coefficient are altered in enhance factor, and then the image is being reconstructed. As the enhance factor increase, the image contrast will also increase, however the image quality visual is getting poor. Hence, image denoising is conducted using the fuzzy system to eliminate the noises in details sub-bands. The results from the investigation shows that the final output image from this method has achieved a good contrast.

Jenifer et al. (2016) developed an algorithm for mammogram image enhancement using a combination of Fuzzy logic and contrast-limited adaptive histogram equalization (CLAHE) technique, where it is known as Fuzzy Clipped Contrast-Limited Adaptive Histogram Equalization (FC-CLAHE) method. The existing techniques limits the amplification contrast by allowing the histogram to be clipped at a particular limit. The clipping limit is crisp and invariant to the mammogram input data, causing all pixels in the window region of the mammogram to be affected at the same rate. FC-CLAHE method allows automation of clip-limit selection at the image histogram which is more relevant to the mammogram image and helps to enhance its local contrast. In this method, a fuzzy-based system is applied where the fuzzification is performed based on contrast and entropy of the input image. The fuzzy inference system is set to automate the selection of clip-limit, and it requires a limited control parameters number. This method are able to improve the image contrast and entropy without losing any details from the original image, at the same time elevating the detectability of microcalcifications. The original image and the enhanced image using FC-CLAHE is shown in Figure 2.12.

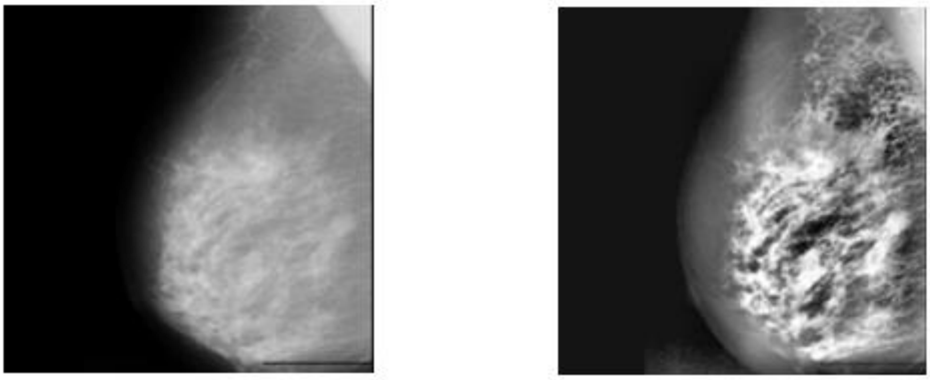


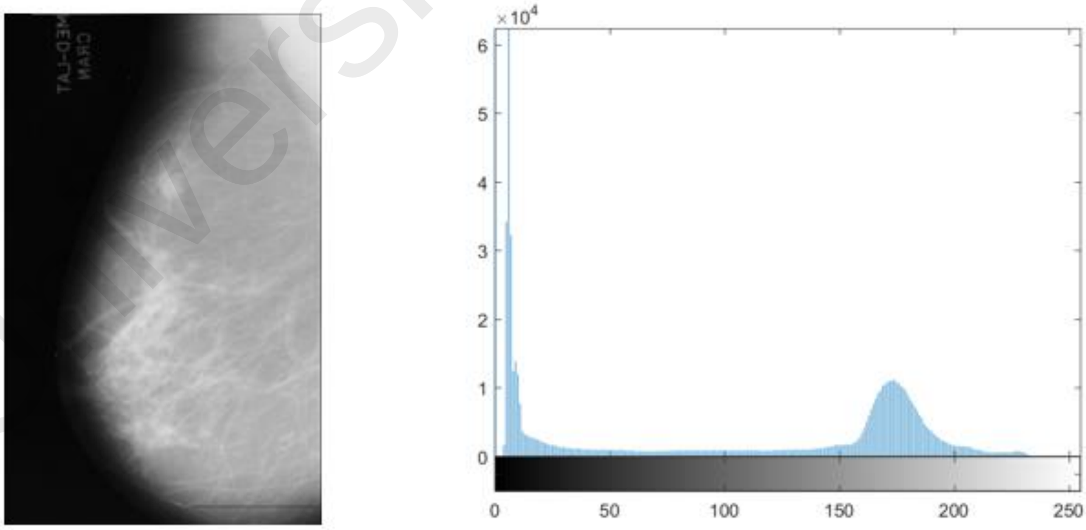
Figure 2.12: (a) original mammogram image (b) enhanced image using FC-CLAHE technique (adapted from Jenifer et al., 2016)

On the other hand, H. Deng et al. (2017) proposed a mammogram enhancement method using an intuitionistic fuzzy sets (MIFS) where this method can help to improve the image contrast and enhance the visual quality of the regions of interest (ROI) of the image. The algorithm initially performs image fuzzification using intuitionistic fuzzy membership function, followed by hyperbolization of membership degrees of background and foreground areas. Defuzzification operation is conducted to defuzzify the fuzzy plane and image is filtered by normalization method. Eventually, output enhanced image is achieved by fusing the original input image with the filtered image, also known as nonlinear fusion operators. Ironically, the authors addressed that the MIFS technique should be further explored in terms of its threshold, membership function and hyperbolization operator. In addition, it possesses relatively high processing time which is time consuming and not practical for industry uses.

2.4.3 Histogram Equalization (HE)-based method

Unlike frequency domain, spatial domain technique is simpler, as it operates directly on the pixels of image. It modifies the pixel values following the rules, which also dependent on the pixels value of the original image, such as local process or point process. This method has low complexity and mostly used for real time implementations. Various techniques exist for comparison or combination of pixel values with their immediate or surrounding pixels (S. et al., 2017). In order to decrease the complexity in the enhancement process, this research study focuses on spatial domain method, precisely Histogram Equalization (HE) – based method.

As discussed in Chapter 1, HE-based in one of the most popular method for contrast enhancement due to their simplicity and effectiveness. Image histogram is a significant feature, where description of an image can be derived from the image statistics displayed in the histogram such as mean, median, mode and image dynamic range. HE is presented in a form of graph where the x-axis refers to pixel intensity value, and the y-axis indicates the number of pixels. Commonly, an 8-bit grayscale image has 256 pixel intensities, thus the histogram portrays 256 numbers indicating pixels distribution between the greyscale values (Fisher et al., 2003). An example of a mammogram image and its histogram is shown in Figure 2.13.



(a) (b)

Figure 2.13: (a) Mammographic image (b) the image histogram

The aim of HE method is to generate a new image having redistribution of image intensities where the intensities appear to be almost uniformly distributed in the histogram. Uniform intensity values can be attained by using cumulative distribution function of the loaded input image (Garg et al., 2014). The basic HE equation can be defined in equation 2.1:

$$H(v) = round\left(\frac{CDF(v) - CDF_{min}}{(m \times n) - CDF_{min}} \times (L-1)\right) \tag{2.1}$$

where v as pixel intensity, $CDF(v)$ as cumulative distribution function depending on the value of pixel intensity, CDF_{min} is the minimum non-zero value of the cumulative distribution function, $m \times n$ is the maximum number of the cumulative distribution function, and L refers to the number of image intensity value (Rao et al., 2017).

Generally, HE can be classified into two main categories, which are Local HE (LHE) and Global HE (GHE). LHE method utilizes every image pixel, where it considers the neighborhood of each pixels using the sliding window method. Sliding window method is conducted by selecting a square window and move it from pixels to pixels in the image. For each of the square window selected, the histogram pixels is calculated, and the intensity proportional to the cumulative histogram at the actual pixel value is reassigned to one single pixel centered on each square window. (Joda et al., 2017) This results in better image enhancement, however, it may cause over contrast enhancement problem. On the other hand, GHE method conducted image enhancement by taking into account the whole input histogram image, leading to the entire histogram image being stretched and enhancement of overall image contrast. GHE is well-known as a simple but effective method for overall contrast enhancement, but ironically it has inability in conserving the contrast and brightness of original greyscale image due to the utilization of whole histogram details (Abdullah-Al-Wadud et al., 2007).

Development of LHE method has been conducted since decades ago. For instance, Adaptive Histogram Equalization (AHE) has been proposed as modification of HE conventional method which optimizes the contrast enhancement based on the local image information. The major drawback of this method is it causes noise over-amplification in homogenous regions of the image (Rao et al., 2017) The continuation of this method is referred as Contrast-Limited Adaptive Histogram Equalization (CLAHE) (Makandar et al., 2015). To prevent the problem of over-amplification of noise, CLAHE is developed to limit the noise amplification using clip limit, hence the resulting image appears more natural. CLAHE algorithm divides the image into rectangular contextual region, and it employs conventional histogram equalization in each region. A clip limit is introduced in the obtained histograms in each regions, and bi-linear interpolation is applied to reassemble the final image and artificial induced boundaries are removed. CLAHE method has the ability to prevent brightness saturation and overcome the problems regarding over-amplification of noises.

On the other hand, there are numerous GHE algorithm developed, such as Brightness Preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), Recursive Mean Separate Histogram Equalization (RMSHE), Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) and many more.

Pizer (2003) mentioned that limitation of HE method lies in preserving the image brightness due to the problem regarding 'mean-shift' situation. It happened when the value of mean intensity is relocated to the middle grey level of intensity range. BBHE method is proposed by Y. T. Kim (1997) to overcome the problem of deterioration of parameters in image, (i.e. brightness and image entropy) when using the conventional HE method and the problem regarding 'mean-shift'. BBHE technique works by dividing the original image histogram into two sub-histogram named lower sub-histogram (H_L) and higher sub-histogram (H_H), where the separation points for the two sub-histograms are determined by the value of its mean brightness. The illustration of the process are shown in Figure 2.14. Consequently, each of the separated histograms is equalized individually by equating their probability density function (PDF) and cumulative density function (CDF). The flowchart of BBHE process is drawn in Figure 2.15. The major drawback of BBHE method is that it tends to produce over-saturation in image intensity, leading to loss of information (Garg et al., 2014).

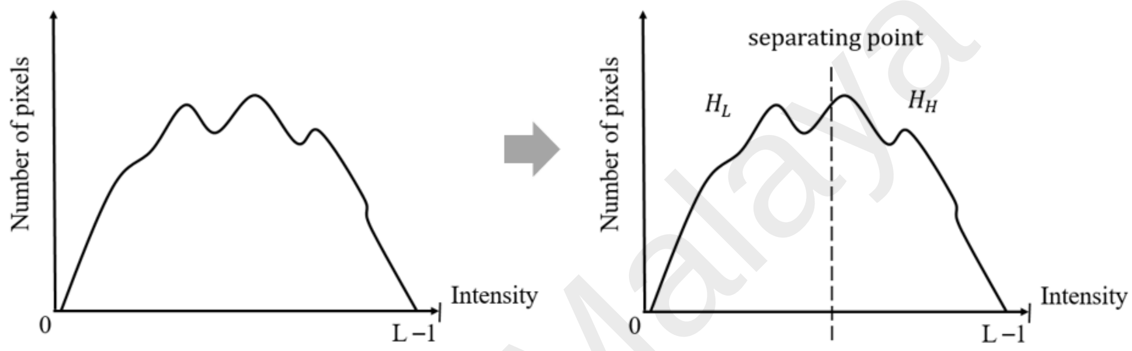


Figure 2.14: The separation of original histogram (left) into two sub-histogram (right) (adapted from Garg et al., 2014)

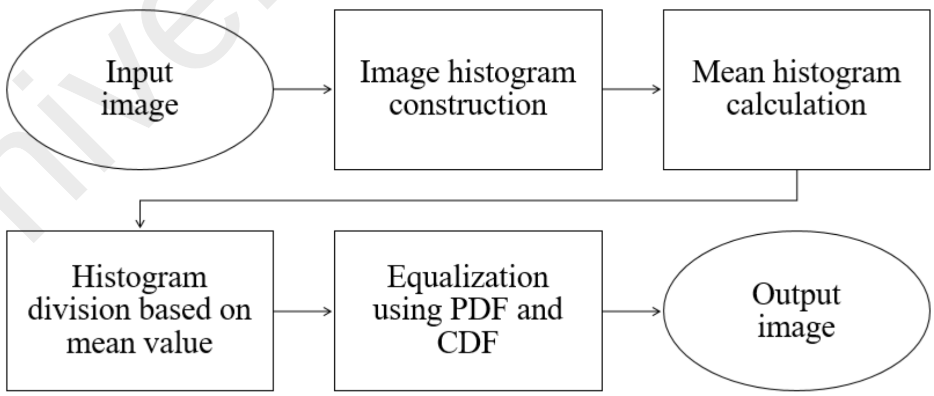


Figure 2.15: Flow chart of BBHE algorithm (adapted from Rao et al., 2017)

HE-based method is continued by (Ooi, 2010) namely Brightness Preserving Plateau Limits Histogram Equalization (BPPLHE) and Quantized Plateau Limits Bi-Histogram Equalization (QPLBHE). These methods have been demonstrated to outperform other prevalent techniques, allowing the output image to be clearer, with additional benefit of brightness preserving. Ironically, drawbacks exists in terms of image enhancement in low-light background. This is caused by the non-expandable side of the sub-histograms. Consequently, a technique named Detail Preserving Plateau Limit Histogram Equalization (DPPLHE) developed by Chen Hee Ooi (2010) is suggested to solve the mentioned drawbacks pertaining preservation of details. This method is sturdier in dispatching the image details in low contrast.

Conversely, Muneeswaran et al. (2019) utilized a tree seed optimization algorithm (TSA) to tune the parameter for local contrast regularized Contrast Limited Adaptive Histogram Equalization (LC-CLAHE) for mammogram image analysis. TSA algorithm comprises of three primary processes which are arbitrary tree location, looking seeds, and best arrangement determination. The best parameter for LC-CLAHE method are chosen by the TSA algorithm and the final outcome shows that mammogram images produced are enhanced successfully. This method managed to retain the information in original images and it can be used in wide range of mammogram images such as thick glandular breast image. On the contrary, this algorithm is developed mainly for mammogram images and yet to be tested on the other medical images.

Another HE-based algorithm has been developed by Dhamodharan et al. (2018) to enhance the contrast of mammogram images named Modified-Dualistic Sub-Image Histogram Equalization (M-DSIHE). The algorithm utilized the image histogram and divided them into two sub-histogram using the value from mid-point of the active dynamic intensity range of the input image. Subsequently, the sub-histograms are divided iteratively and HE is applied on each of them. M-DSIHE method has achieved a good result in enhancing the mammogram images without altering the originality of the input images. To add, this method is also applicable to other medical images.

On the flip side, Gupta et al. (2019) improved the overall contrast of mammogram image locally and globally by utilizing Linearly Quantile Separated Histogram Equalization-Grey Relational Analysis (LQSHE-GRA). This HE-based method sub divide the histogram of the input image into two or more sub-histograms where all spectrum of intensity levels is utilized. In consequent, the GRA algorithm modified the average brightness of the processed image to center grey level and image normalization is conducted to preserve the image brightness. The quantitative results for the proposed method are excellent, however, upon analyzing the output image, the mammogram image appeared to have unnatural looking image despite enhancement on the overall image.

2.5 Summary

This chapter describes the overview of breast cancer, including pathology of human breast with its anatomical structure and types of lesion which can be found in mammographic images. It is important for researchers to know the characteristics of breast lesion before analyzing the mammographic image to prevent false-positive and false-negative error usually made by human visual judgment.

In addition, this chapter also describes mammography acquisition method performed by mammogram screening machine, which includes the explanation of two main views in mammogram and description of movement of x-ray from the radiation source to the patient's breast. It is known here that mammography only utilizes low dose of x-ray, thus the image produced is low in contrast.

Various contrast enhancement method from three different domain are described in this chapter. From the discussions, all techniques possess their own functionality and disadvantages depending on its use. Over the decades, many state-of-the-art enhancement techniques are developed generally, however not all method is applicable to mammographic images. Some of them can be utilized with algorithm alteration to fit in the purpose of mammogram enhancement. Table 2.2 shows the summary of available techniques for image enhancement.

Based on the research conducted, HE-based method has an advantage of simplicity and flexibility compared to the other domain as the utilization of image histogram eases the process of algorithm development. It has low complexity and is used in real time implementations. HE-based techniques are widely used in applications of medical image enhancement as well as mammogram enhancement. For that, HE-based method is chosen for this research study and the algorithm is developed to improve the image brightness while preserving its original details as well as optimizing the local contrast factor.

Table 2.2: Summary of image enhancement techniques in different domains

Techniques		Description	Advantages	Disadvantages
Frequency-based	Fourier transform (Agrawal et al., 2014; Swaminathan et al., 2017)	• Transform input image to Fourier domain • Enhanced image by applying inverse Fourier transform	• Filter noise • Enhance image	• Only provide frequency details • Loss of temporal information
	DWT (Yousefi, 2015; Pai et al., 2015)	• Breaks down a digital signal into various sub-bands • Inverse DWT used to re-transformed enhanced image	• Noise reduction • Able to provide temporal and frequency details	• Sampling deficient • Loss of details during sampling
	SWT (Nason et al., 1995; Liu et al. ,2015)	• Decomposition of input image into sub-bands are conducted using SWT	• Generating sharper image • Details preservation	• Unable to properly grasp the curves and edges
Fuzzy-based	Fuzzy Denoising and Wavelet Transform (Amirpour et al. ,2016)	• Input image decomposed into 4 level of wavelet sub-bands • Detail sub-bands coefficient are altered in enhance factor • Image denoising by fuzzy system	• Eliminate noises in details sub-bands • Good contrast	• Not able to preserve brightness
	FC-CLAHE (Jenifer et al., 2016)	• Automation of clip-limit selection at the image histogram	• Enhance local contrast • Improve image contrast and entropy	• Not able to preserve the original image brightness

		• Fuzzification is performed based on contrast and entropy • Fuzzy inference system are set to automate the selection of clip-limit	• Prevent loss of details • Increase detectability of micro-calcification	
	MIFS (Deng et al., 2017)	• Image fuzzification using IFs membership function • Hyperbolization of membership degrees • Defuzzification operation • Fusing the original input image with the filtered image	• Improve image contrast • Enhance visual quality of ROI	• High processing time
Histogram-based	HE (Garg et al., 2014; Kaur et al., 2016)	• The image intensities is redistributed until it appears equally • Histogram is uniformly distributed	• Simple • Flexible • Less complex	• Low contrast enhancement • Poor brightness preservation • Poor visual quality • Produce unwanted artefact
	CLAHE (Makandar et al., 2015)	• Enhance the image contrast on each tile • The resulting tiles are matched back together	• Better image contrast • Reduce the over-amplified noise	• Intensity of background and foreground increased at same time • Background noise is increased
	BBHE (Rao et al., 2017)	• Extension from HE method	• Solve problem regarding mean-shift	• Intensity saturation increase • Some details might be loss

		• Divides the input image into 2 sub images based on mean value • Equalization of sub images separately	• Able to preserve brightness • Increase the poor contrast	• Over-enhancement problem
	M-DSIHE (Dhamodaran, 2018)	• Divide the histogram into 2 partition using mid-point of the active dynamic intensity range • Equalization of sub images separately	• Able to maintain the originality of image • Can be used in all medical images	• Not mentioned
	TSA-LC-CLAHE (Muneeswaran, 2019)	• Using TSA to find the best parameter for LC-CLAHE	• Able to maintain the originality of image. • Can be used for thick glandular mammogram image	• Only used on mammogram images. Not yet tested on other medical images
	LQSHE-GRA (Gupta et. al, 2019)	• Improved the overall contrast of mammogram image locally and globally	• Able to improve the image contrast and brightness	• Unnatural looking output image

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter presents the proposed methodology of research study. The improvement on image enhancement technique for mammogram images is still an active research study among researchers. The problems with mammogram images are the image produced often contains artefacts and noise, where some breast tissues are mistaken as microcalcifications. In addition, poor contrast and non-uniform illumination in the original mammogram image creates difficulty for analysis by human visual. Some of the state-of-the-art methods developed by researchers succeeded in increasing the local contrast in selected region of interest (ROI). However, there are cases where the final output image loses its originality in terms of brightness, creating over-saturated image, over-brightness, excessive contrast difference and loss of details. This creates an urge for improvement on mammogram enhancement method focusing on brightness improvement without creating an over-enhanced or over-saturated image and provide contrast preservation as well as prevention of features loss.

In this research, multi-stages approach has been proposed to resolve the aforementioned problems. The proposed technique is divided into two stages aiming to improve the overall image brightness in stage 1 while stage 2 focusing on preserving the image details and contrast as illustrated in flowchart in Figure 3.1. The experiment is conducted using Intel ® Core ™ i3-6006U CPU @ 2.00GHz 1.99 GHz with 64-bit operating system, where the algorithm is developed using MATLAB R2016B.

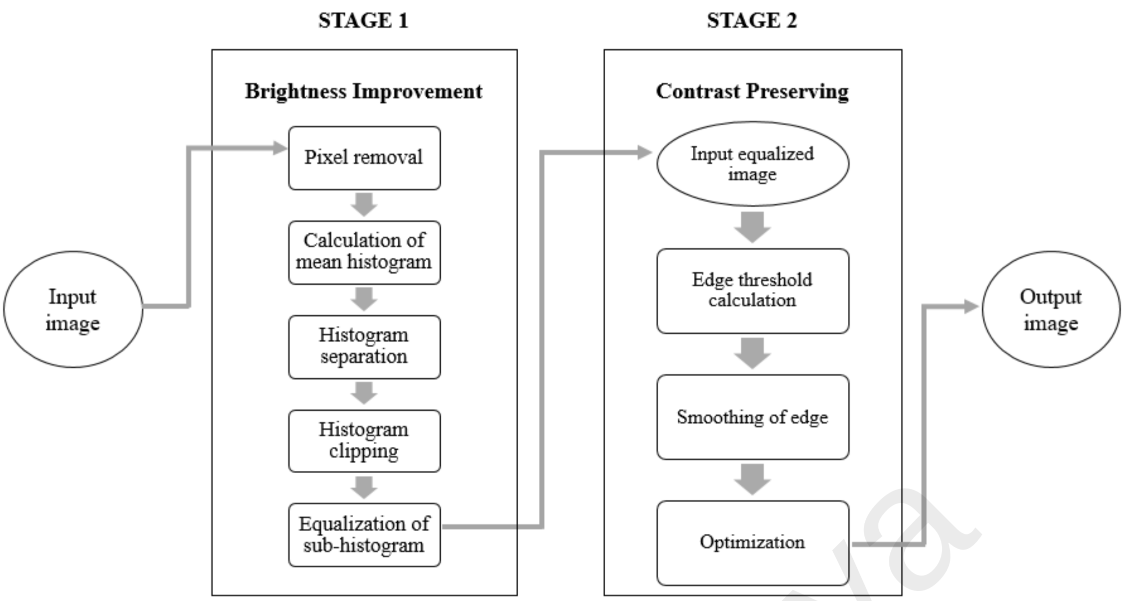


Figure 3.1: Flowchart of the overall proposed method

This section provides a detailed explanation on the database used in this research, which is the Mammographic Image Analysis Society (MIAS) database (Suckling et al., 1994). The MIAS database classified the abnormalities found in mammogram images into few categories such as normal, benign and malignant. Next, the proposed method for Stage 1: Brightness Improvement is further expounded in section 3.2. HE-based method is applied here where the steps include pixel removal, calculation of mean histogram, histogram clipping, and equalization of sub-histogram, as shown in Figure 3.1. Consequently, section 3.3 elucidates the algorithm for Stage 2: Contrast Preservation. The optimization of local contrast factor is conducted here, initiated with input equalized image, calculation of edge threshold, smoothing of edges, and optimization of edge threshold. Next, the image analysis method is described in section 3.4 where qualitative and quantitative analysis are demonstrated using various parameters. Eventually, a summary of chapter 3 is elaborated in section 3.5.

Data Acquisition

The mammogram images used for this research are obtained from the MIAS, which is an organization that provides databases for mammogram images, known as MIAS-database. This database contains 322 images of mammogram obtained from UK National Breast Screening Program, where MIAS has classified the images according to the patient's cancer condition which is normal, benign, and malignant tumor. Each mammogram images is constructed of different tissue types, such as fatty, fatty-glandular and dense-glandular. In addition, the MIAS-database also categorized the tumor found in the mammogram into some abnormalities; calcification, well-defined masses, spiculated masses, ill-defined mass, architectural distortion, and asymmetry. The ground truths of the images are provided and the locations of the abnormalities are verified by the radiologists. The viewpoint of the mammogram image is in mediolateral oblique (MLO), either left or right view and they are made up of 1024 × 1024 pixels. The mammogram images are in greyscale color with pixel range from 0 to 255 and it is stored in *.pgm* format.

The understanding of breast abnormalities is significant to differentiate the masses condition. Generally, calcifications are defined as small calcium formed within the breast tissues. Tiny calcium formation is known as microcalcifications, while formation of big white dot is called macrocalcifications. The determination of types of masses is dependent on the white dot formation or the shape of tissue growth in mammogram images. Benign masses are round or oval shape, and most malignant masses possess an irregular shape. On the other hand, the cause of architectural distortion is the uncertainty of medical experts when classifying the abnormal masses formation in the mammogram images. In case of breast asymmetry condition, it occurs due to the difference in shape of the left and right breast. This condition is normal to most women, however if the breast density and tissues are not the same with each other, there might be a presence of breast lesion. Figure 3.2 presents the shapes of lesion that can be found in breast images obtained from MIAS database, which are architectural distortion, asymmetry, circumscribed, ill-defined masses, spiculated, and calcifications.

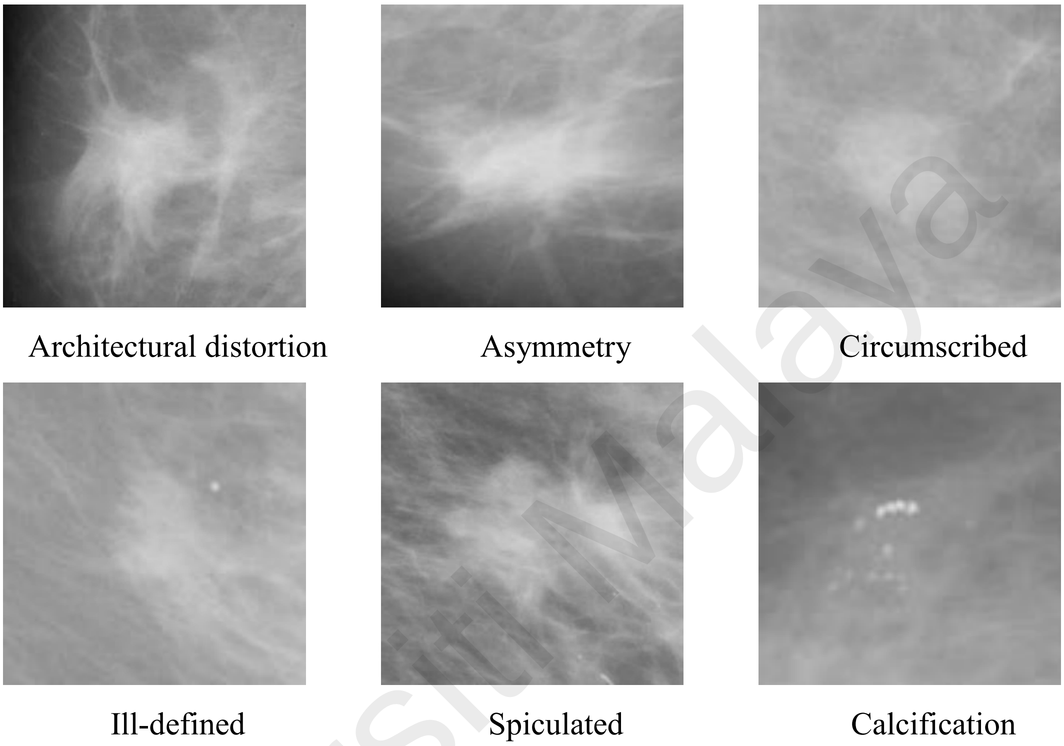
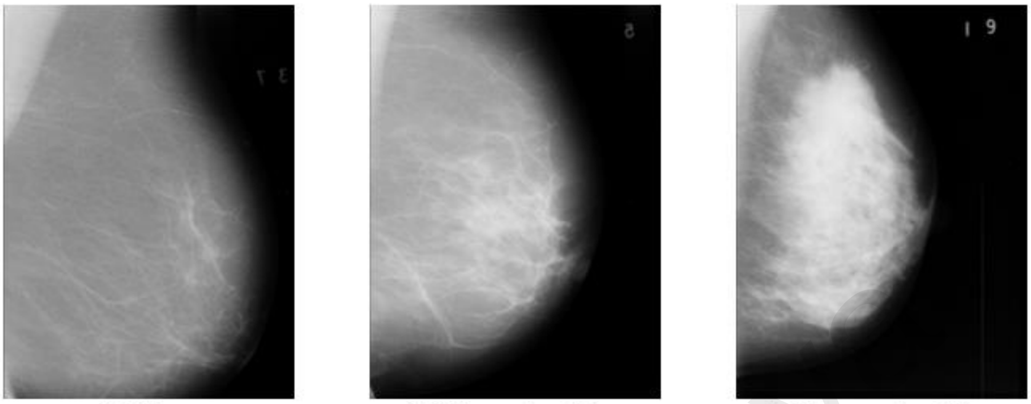


Figure 3.2. The shapes of lesion found in MIAS database images

Upon analyzing the mammogram images from MIAS database, there are some difficulties in detecting the abnormalities due to the poor quality of mammogram images, which might be caused by poor brightness, non-uniform illumination, low contrast problems and blurry image. These conditions will lead to high probability of gaining false-negative and false-positive errors. Furthermore, the breast structures also vary from fatty breast type, fatty-glandular breast type and dense-glandular breast type. The difference between these structures are shown in Figure 3.3. It can be observed that the structures differ in each case in terms of the presence of solid white area which indicates that the region are made up of dense tissues and muscles. It is difficult for analysis in breast images with dense structure as the lesion might be mistaken as a part of the tissues or it appears to be blurry.



(a) Fatty (b) Fatty glandular (c) Dense glandular

Figure 3.3. Different breast structures in MIAS database (a) Fatty breast structure; (b) Fatty-glandular breast structure; (c) Dense-glandular breast structure

Therefore, this research aims to provide a better output image quality with a clear visual of the abnormalities to avoid false errors and ease the work of the medical experts. The summary of data provided by MIAS database is presented in Table 3.1.

Table 3.1. Summary of breast cases in MIAS database.

Breast Case	Types of Abnormality	Number of Data
Normal	-	207
Benign	Architectural distortion	9
	Asymmetry	6
	Calcification	15
	Well-defined/ Circumscribed mass	21
	Ill-defined mass	7
	Spiculated mass	11
Malignant	Architectural distortion	10
	Asymmetry	9
	Calcification	15
	Well-defined/ Circumscribed mass	4
	Ill-defined mass	8
	Spiculated mass	8

3.2 Stage 1: Brightness Improvement

An early intervention of breast cancer is very crucial to reduce the death toll as well as improving the treatment plan. Due to the problems with original mammogram images having low image contrast, blurred image, and other lacking, this will give a negative impact to the diagnosis process. Therefore, image enhancement is needed to increase the image quality so that the calcifications will appear clearer and brighter to the eyes of the observer, thus reducing false analysis. The role of image enhancement in image processing is to produce a better-quality output image by eliminating the noise, preserving the brightness, enhancing the image contrast, filtering the image, and maintaining the important details on the image.

Detail structure on mammogram image is significant for analysis purpose, thus losing any information will tremendously affect diagnosis results. As mentioned in Chapter 2, HE-based method is chosen for its simplicity and flexibility, plus it is widely used in many areas and applications especially in medical imaging. The flowchart simplifying the proposed algorithm for brightness improvement stage is shown in Figure 3.4.

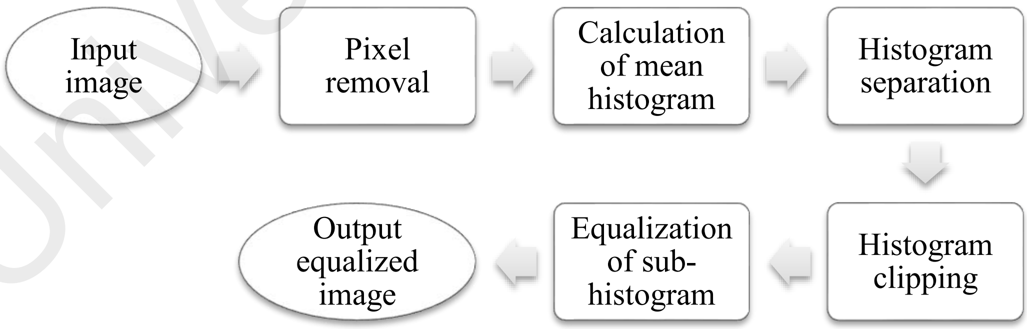
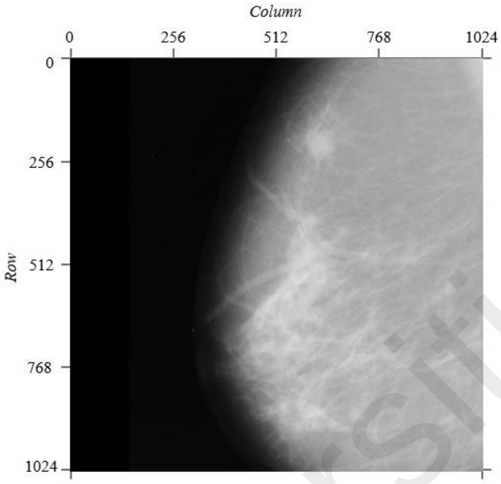


Figure 3.4: Flowchart of proposed algorithm for stage 1: brightness improvement

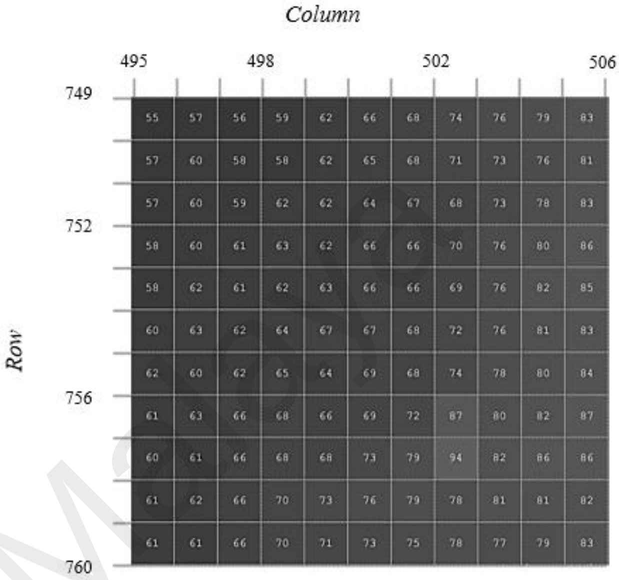
3.2.1 Removal of Unwanted Pixels

The algorithm started from the selection of input mammogram image from the MIAS database. Generally, all images are made up of pixels, or also known as picture element.

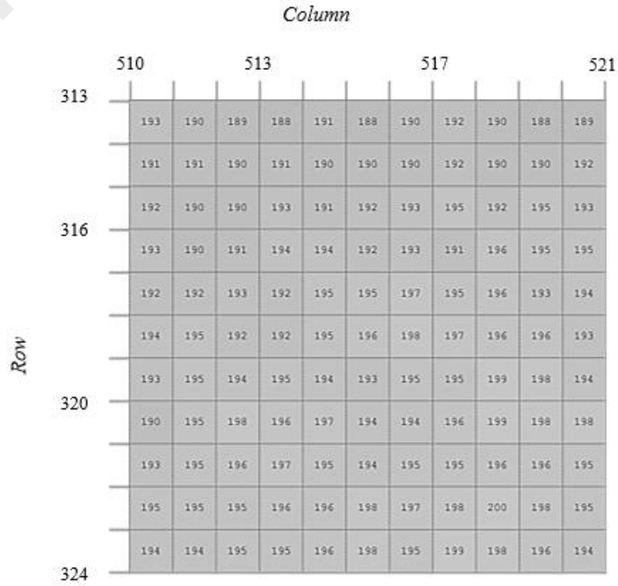
By definition, a pixel is an image component, also recognized as the smallest unit of a digital image that can be depicted by square building blocks on a digital display, combined to form a complete image. All pixels have its own unique logical address and geometric coordinates (Eck, 2016).



(a) Mammogram image digital structure



(b) Pixels of dark region



(c)) Pixels of bright region

Figure 3.5: (a) Digital image structure of mammogram. Represented by pixels where the image array is 1024 rows by 1024 columns, with pixel values from 0 to 255. (b) The dark regions have lower pixel value, while (c) The bright region has higher pixel values.

Figure 3.5 shows the example of pixels distribution in greyscale mammogram image. After the input image is selected, the histogram of the selected input greyscale mammogram image is computed. Image histogram is the graphical representation of pixel intensities, where it plots the number of pixels against pixel intensities that range from 0 (dark) to 255 (bright). By observing the image histogram, the entire distribution of pixels can be determined at a glance. For a typical greyscale mammogram image, it consists of two different regions, labelled as bright region and dark region, which the dark region is usually the black background. Figure 3.6 shows an example of a greyscale mammogram image and its histogram, where the region highlighted by red circle is the dark region (background) and the region highlighted by green circle is the bright region (breast image).

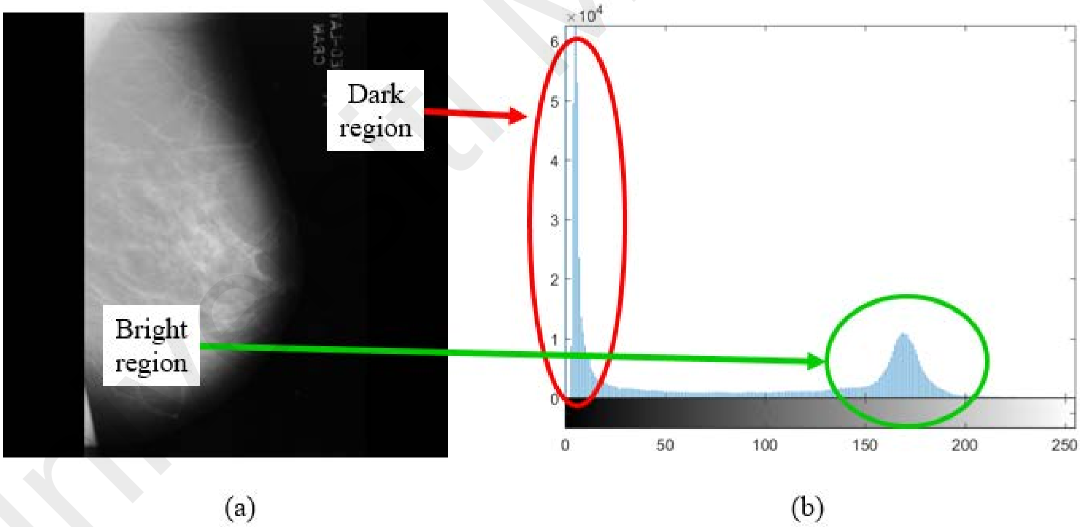


Figure 3.6: Example of (a) mammogram greyscale image and (b) its histogram image

As seen in Figure 3.6, the number of pixels for dark region is high due to the presence of the black background obtained from mammogram itself, while the number of bright regions is moderate, reflecting the image of breast pectoral muscle and breast tissues. The region of interest focuses on the area of breast pectoral muscle, where the presence of lesion can be detected. Thus, eliminating the unwanted pixels of the dark background will improve the efficiency of computation process. The dark background is not significant for the next step, which is the calculation of mean histogram as this research only focus on the bright breast region for lesion detection. A simulation is conducted on 322 breast images from MIAS database to find the suitable pixel threshold value for elimination. Upon simulation, it is found out that the pixel value of 100 is the most suitable pick for threshold value. This can also be seen in Figure 3.5, where bright regions have a pixel value more than 100 and the dark regions have pixel values less than 100. Therefore, all pixels with grey level values less than 100 are removed, and all pixels that exists after 100 are selected for further computation.

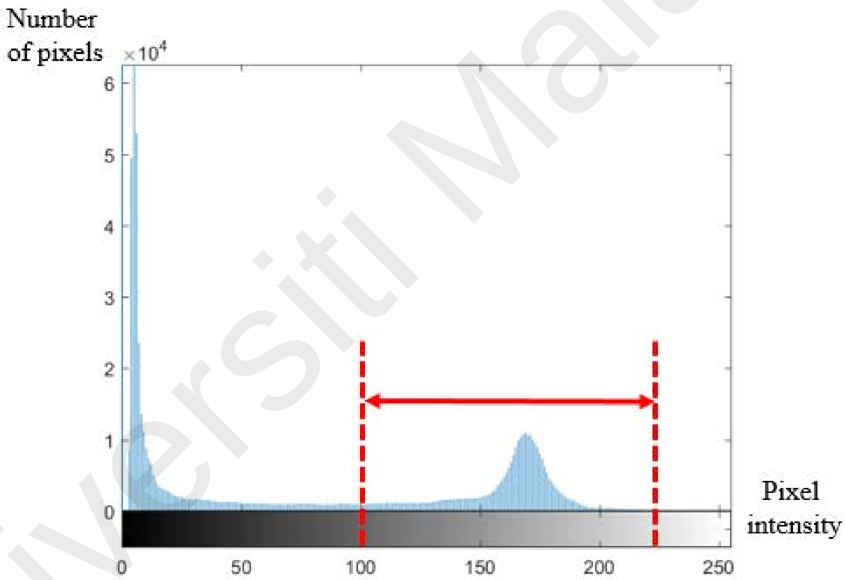


Figure 3.7: The selected pixel intensity region

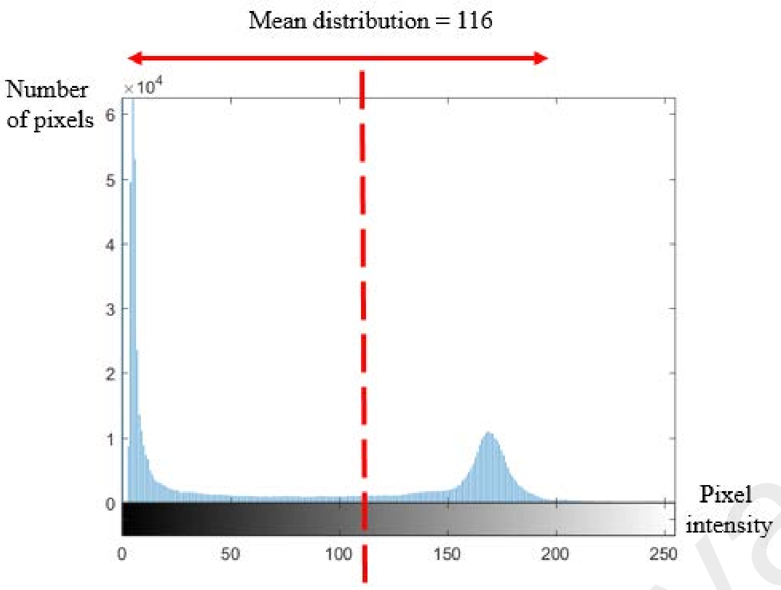
Figure 3.7 shows an example of image histogram where the pixel values more than 100 are selected, indicating the bright breast region. In this example, the maximum pixel intensity value exists at approximately 220, however each mammogram image has different maximum intensity value, and thus the algorithm will automatically choose the intensity value from 100 until its maximum intensity. This value is set as a threshold for the entire dataset of 322 mammogram images.

3.2.2 Mean Histogram Calculation

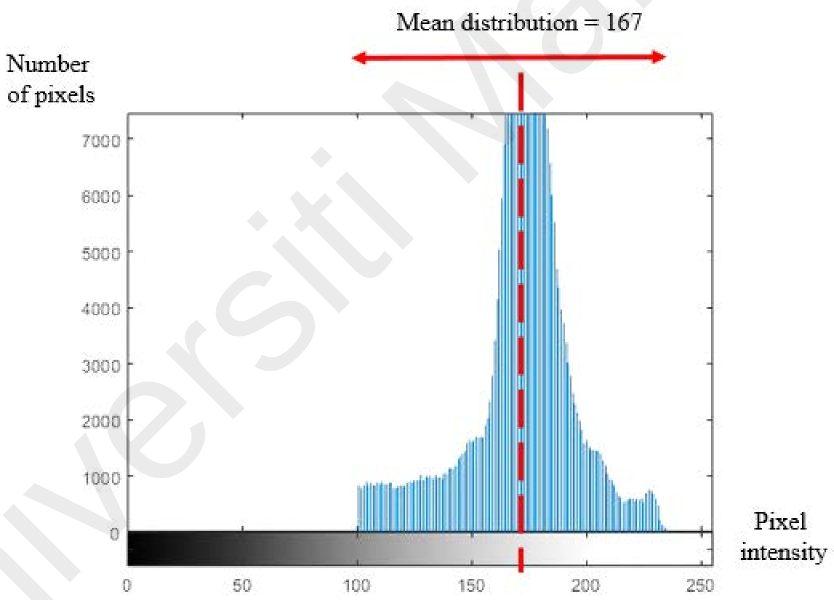
Once the pixel intensity values are selected from previous step, the computation of mean intensity for the image histogram is conducted. The removal of unwanted pixel is significant for the calculation of mean histogram as it will greatly affect the end value for mean. Mean histogram is defined as the average distribution of the pixels in the image histogram. The mean value will be used as the separation point for histogram separation in next step. Say that the input image is given as I, and the histogram for intensity is assumed as *x,* hence the mean intensity denoted by I_m is calculated using the following equation:

$$\boldsymbol{I_m} = \frac{\sum_{\mathbf{101}}^{I_{max}} \boldsymbol{P(x)}}{\boldsymbol{N}} \tag{3.1}$$

where *P(x)* is the pixel intensity, *N* is the total pixel number with intensity values within the range of 101 to the maximum intensity of the input image, I_{max}. Hence, an image histogram is generated with new mean distribution value. Figure 3.8 (a) shows the mean histogram distribution before the removal of unwanted pixel, and Figure 3.8 (b) portrayed the new mean histogram value computed after the removal of unwanted pixel. As observed in Figure 3.8 (a), the image histogram has a poor intensity distribution, where the image histogram appeared to be skewed. Upon removal of the dark unwanted pixels, a bell-shaped image histogram is obtained as portrayed in Figure 3.8 (b) where it is the region of interest for this research. In this example, a mean value of 167 is marked as the separation point between darker and brighter region (Figure 3.8(b)).



(a)



(b)

Figure 3.8: (a) mean histogram distribution BEFORE the removal of unwanted pixel, and (b) new mean histogram distribution AFTER the removal of unwanted pixel.

The calculation of mean distribution of histogram image is conducted on 322 MIAS database mammogram images and the average result is displayed in Figure 3.9. The MIAS database images can be classified into three cases; normal, benign and malignant. The data in Figure 3.9 is presented according to the breast condition, where 207 cases of normal breast have an average mean value of 168.10, 69 cases of benign breast have an average mean value of 168.37, and 54 cases of malignant breast have an average mean value of 168.96. In a nutshell, it can be concluded that the average value for mean distribution obtained range from 167 to 169 for the three breast cases in MIAS database.

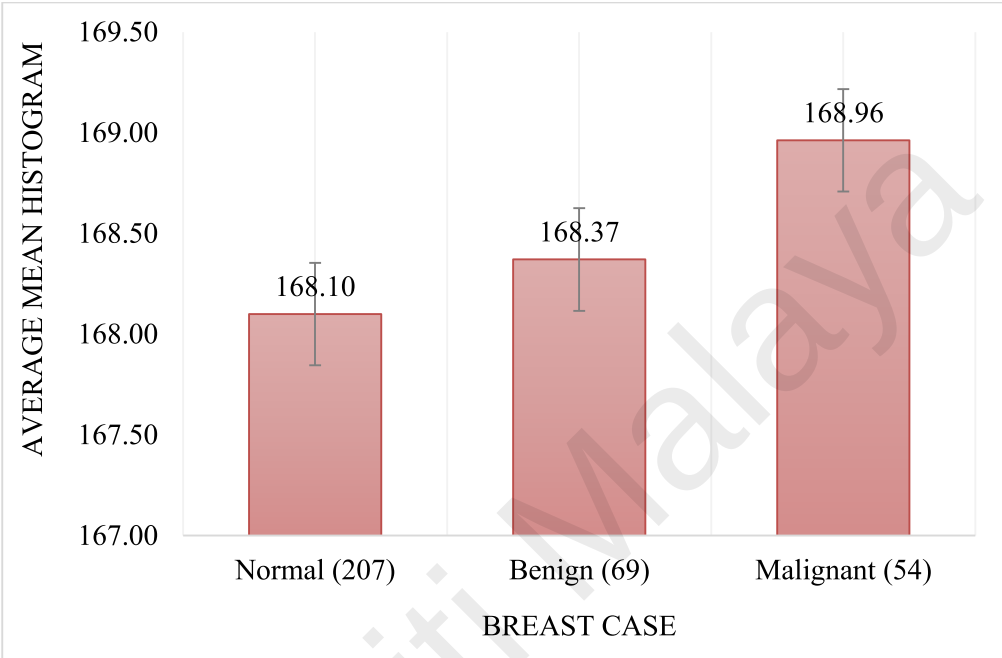


Figure 3.9. The average mean histogram obtained from 322 MIAS database images

3.2.3 Histogram Separation, Histogram Clipping, and Sub-histogram Equalization

Once the new mean histogram distribution is obtained, the histogram is separated into two sub-histograms, which is referred to as high sub (S_H) and low sub (S_L), based on the mean value obtained, I_m. The equation is represented as following:

$$\boldsymbol{I(x) = S_L \cup S_H} \tag{3.2}$$

where $S_L = \{I(x,y)|I(x,y) \leq I_m, \forall\, I(x,y) \in I\}$

and $S_H = \{I(x,y)|I(x,y) > I_m, \forall\, I(x,y) \in I\}$.

The sub-histogram S_L represents the darker regions while sub-histogram S_H represents the brighter regions. The two partition is labelled as in Figure 3.10:

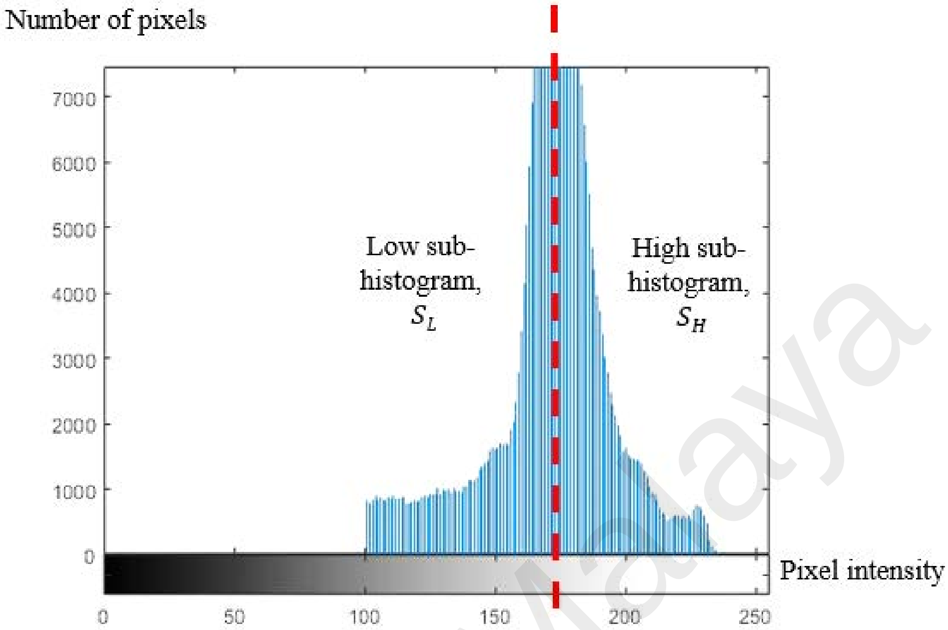


Figure 3.10: The separation of histogram into high and low sub-histogram

In consequence, the plateau limit is calculated for both S_L and S_H, to which eventually it will produce six histogram partition, and the histogram's bin is quantized into their corresponding plateau limit. Plateau limit is the threshold value for each partition in high and low sub-histogram. It is computed by the following equation, where I_w represents the width of input image, I_h is the height of the input image, p_1, p_2, and p_3 are the intensities set to value 0.25, 0.50 and 0.75 respectively (C. H. Ooi et al., 2010).

$$\boldsymbol{p_1 = 0.25 \times \{I_w \times I_h\}} \tag{3.3}$$

$$\boldsymbol{p_2 = 0.50 \times \{I_w \times I_h\}} \tag{3.4}$$

$$\boldsymbol{p_3 = 0.75 \times \{I_w \times I_h\}} \tag{3.5}$$

Figure 3.11 shows an illustration of image histogram that undergoes separation into six different histogram partition. The purpose of histogram partition is to allow the sub-histograms section to be equalized independently and to preserve its brightness (C. H. Ooi et al., 2010).

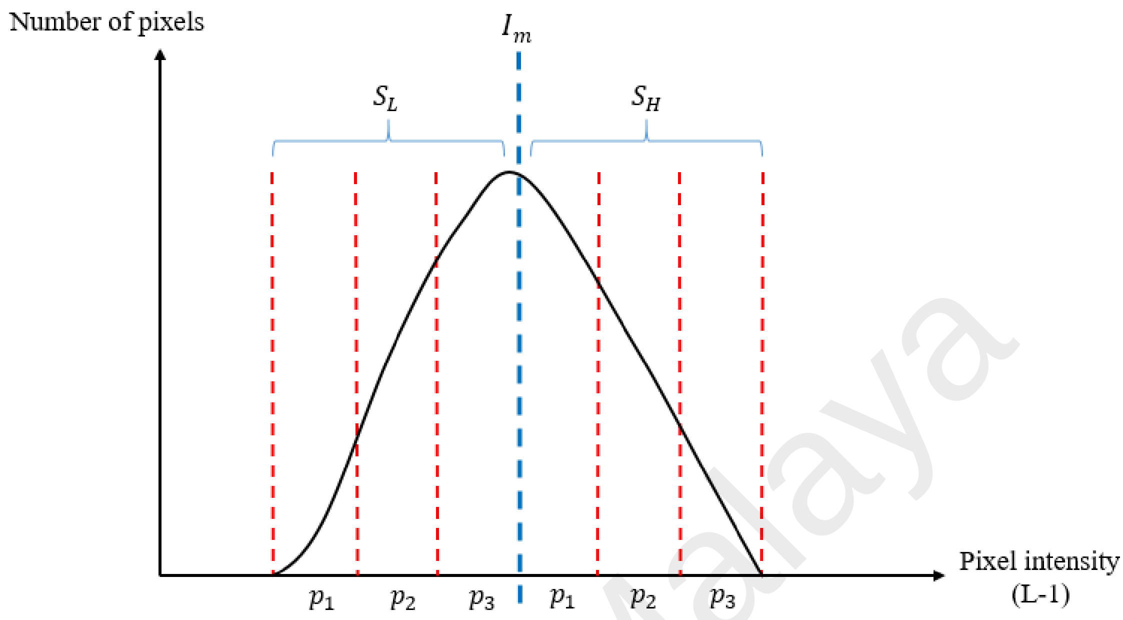
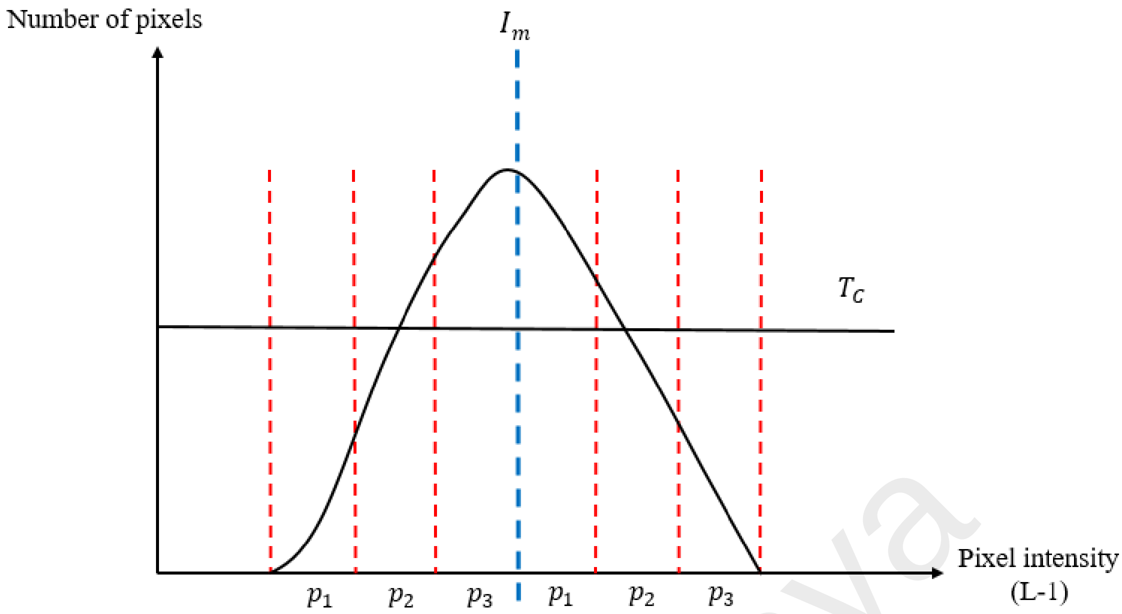
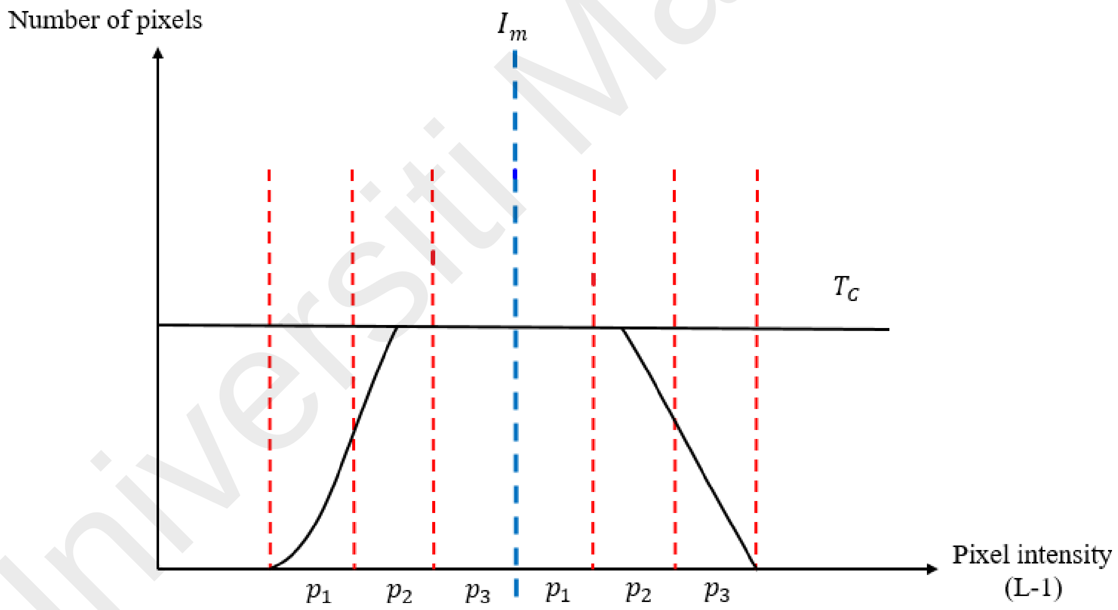


Figure 3.11: Separation of histogram into six partition

Consequently, the histogram clipping process is carried out for both high and low sub-histograms. This process is significant in histogram modification for the purpose of controlling the HE enhancement rate and to avoid saturation, hence the problems with over-enhanced image and unnatural-looking image can be prevented (T. Kim et al., 2008). To limit the enhancement rate, it is necessary to limit the histogram first derivative or the histogram itself. Therefore, the histogram is clipped at the value of T_C, where T_C is the average number of pixels. Next, the bins with higher value than the threshold value are replaced by the threshold value itself. An illustration for the mentioned processes are depicted in Figure 3.12(a) and Figure 3.12(b).



(a)



(b)

Figure 3.12: (a) The threshold is applied for histogram clipping (b) After histogram clipping process.

The next step involved the equalization of all sub-histograms independently, where histogram equalization process is conducted. Here, the calculation of probability density function (PDF) and cumulative distribution function (CDF) in high and low sub-histograms are included.

In image processing, PDF is the probability that the brightness chosen for the area is less than or equal to the specified brightness value. Assuming that the grey level input of the greyscale input image, I is [101, L-1], where L is the greyscale number, the PDF of the processed image, $PDF(x)$ is expressed as:

$$\boldsymbol{PDF\ (x) = \frac{F(x)}{N}} \tag{3.6}$$

where $F(x)$ is the total pixel number of which its grey value is equal to x, and $N = \sum_{x=101}^{L-1} F(x)$

The CDF of the processed image is calculated by the following equation:

$$\boldsymbol{CDF(x) = \sum_{101}^{L-1} PDF(x)} \tag{3.7}$$

Eventually, the sub-images that have been enhanced are then integrated together to form a complete image. Assuming that the i-th histogram is allocated from range [i_{start} i_{end}], then the output of histogram equalization, $K(x)$ of the partition can be computed based on transfer mapping function:

$$\boldsymbol{K(x) = (i_{start} - i_{end}) \times CDF(x) + i_{start}} \tag{3.8}$$

where CDF is the cumulative density function in the sub-histogram. In equation 3.8, a general histogram equalization equation is being utilized, with $i_{start}$and i_{end} replacing the minimum and maximum intensities in the output range respectively. This will produce an output enhanced image with improved brightness features.

3.3 Stage 2: Contrast Preservation

Stage 2: contrast preservation is where the process of local contrast enhancement is carried out to highlight the details in input mammogram image. This stage is important to enhance the local contrast at the region of interest, by smoothing the details or increasing it, while the strong edges are being kept unaltered. Specifically for mammogram images, the local and fine details such as lesions and microcalcifications is more significant than the global details such as the foreground image for detection and identification of cancer cells. It is best to avoid over-saturated and over-enhanced image in the output to prevent false analysis (Sundaram et al., 2011).

In the stage 2, the proposed method starts with the output enhanced image from stage 1: brightness improvement, where it is addressed as input enhanced image in this stage. To preserve the local contrast and image details, Laplacian filtering process is applied where Laplacian pyramids is used to characterize the edges found in the image using a simple threshold, based on the pixels values. Paris et al. (2015) developed an improvement for this technique where it can adaptively generate the edge threshold to allow us to differentiate the small-scale details and the large-scale edges. Paris et. al. mentioned that the Laplacian technique possess the advantage of flexibility and simplicity, other than its achievement in edge-preserving smoothing along with improvement in details enhancement.

The image is convolved with Gaussian kernel to produce Gaussian pyramid image. Gaussian pyramid image is a group of images (G_l) that represents the image with lower resolution version, which is generated by computing the Laplacian pyramid whose level, L_l represents the information at distinct spatial scales, decomposing the image into different frequency bands. In this technique, the Laplacian pyramid, $L[I']$ is formed one coefficient at one time at the output. The flow chart of local Laplacian filtering technique is portrayed in Figure 3.13.

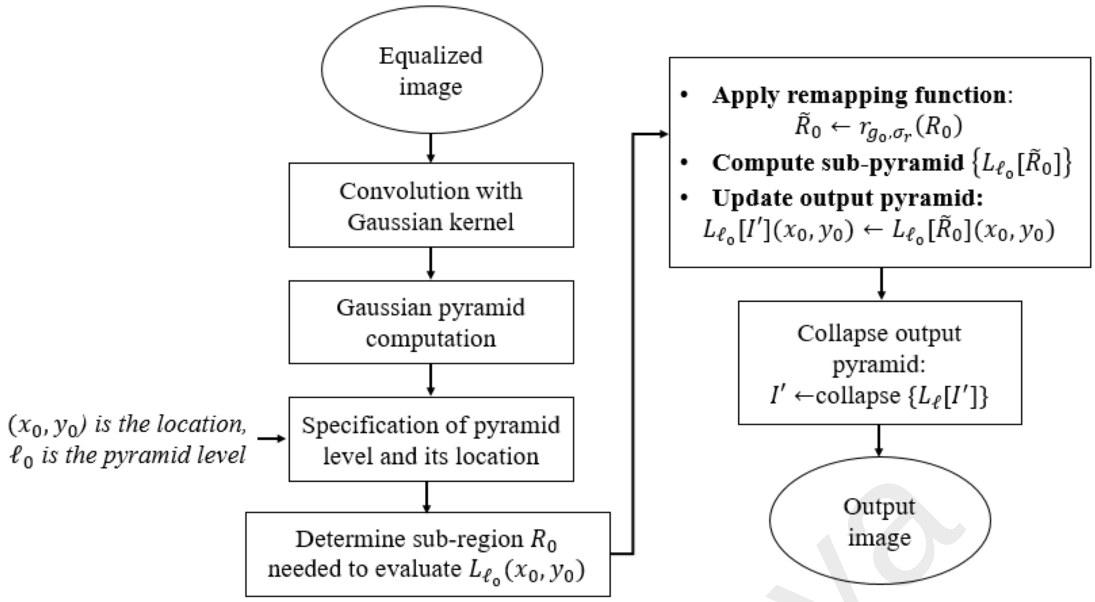


Figure 3.13: Flow chart of local Laplacian filtering technique (adapted from Paris et al., 2015)

Based on Figure 3.13, for each of the coefficients (x_0, y_0, ℓ_0), an intermediate image $\tilde{I}$ is generated by applying the remapping function $r_{g_0,\sigma_r}(R_0)$ to the input image. The remapping function depends on the value of local image which obtained from the Gaussian pyramid $g_0 = G_{\ell_0}(x_0, y_0)$. The edge threshold, σ_r is utilized to differentiate the edges from other details in the image. Consequently, the output pyramid is collapsed to gain the processed image once the calculation is completed. For this stage, there are two main parameters needed to be determined, which are the threshold value, σ_r and the edge smoothing value. The edge threshold value, σ_r is significant to highlight the fine details in the output equalized image from stage 1. An algorithm is developed to obtain the optimized value of σ_r using image quality index, IQ as the main parameter for quality check (Al-Najjar et al., 2012). In image processing, image quality index is known to be one of the most common method used for evaluation of image quality. The measurement of IQ parameter involved three factors; luminance, structure and contrast. IQ value is computed by modelling the image distortion in a combination of luminance distortion, correlation loss, and contrast distortion as shown in the equations below. The original input mammogram image and output enhanced image from stage 1 are set as $I = \{I_x | x = 1,2 \dots Z\}$ and $K = \{K_x | x = 1,2 \dots Z\}$ where I_x and K_x are level of intensity for the original and enhanced image respectively. IQ represents the image quality value, therefore higher value of IQ indicates better image quality where best value achieved is 1. The value of 1 can be achieved when $I_x = K_x$. IQ can be computed by the following equation:

$$IQ = \frac{\omega_{IK}}{\omega_I \omega_K} \cdot \frac{2\bar{I}(\overline{K})}{(\bar{I})^2 + (K)^2} \cdot \frac{2\tau_I \tau_K}{\tau_I^2 + \tau_K^2} \tag{3.9}$$

where

$$\omega_{IK} = \frac{1}{Z-1} \sum_{x=1}^{Z} (I_x - \bar{I})(K_x - \overline{K})$$

$$\bar{I} = \frac{1}{Z} \sum_{x=1}^{Z} I_x$$

$$\overline{K} = \frac{1}{Z} \sum_{x=1}^{Z} K_x$$

$$\tau_I^2 = \frac{1}{Z-1} \sum_{x=1}^{Z} (I_x - \bar{I})^2$$

$$\tau_K^2 = \frac{1}{Z-1} \sum_{x=1}^{Z} (K_x - \overline{K})^2$$

Figure 3.14 shows the flow chart of the process to obtain the optimum value for edge threshold needed for the edge optimization. This process allows the fine details in the enhanced image from stage 1 to be highlighted to distinguish the breast tissue from the actual tumor. On the other hand, the edge smoothing value are in the range of [-1, 1], where -1 value will strongly smoothen the edge details of the input image, while 0 value will leave the input image unaffected. Next, the value 1 will robustly enhance the local contrast of the input image. A simulation is conducted to find the best edge smoothing value where each values range from -1 to 1 are tested on the 322 images. From the result of the simulation, 0.8 is chosen as the best edge smoothing value utilized to highlight the fine details without producing over-saturated and over-enhanced image. The edge smoothing function acts as an assistant to the edge threshold where it helps to smoothen the noise and texture while keeping the sharp edges intact.

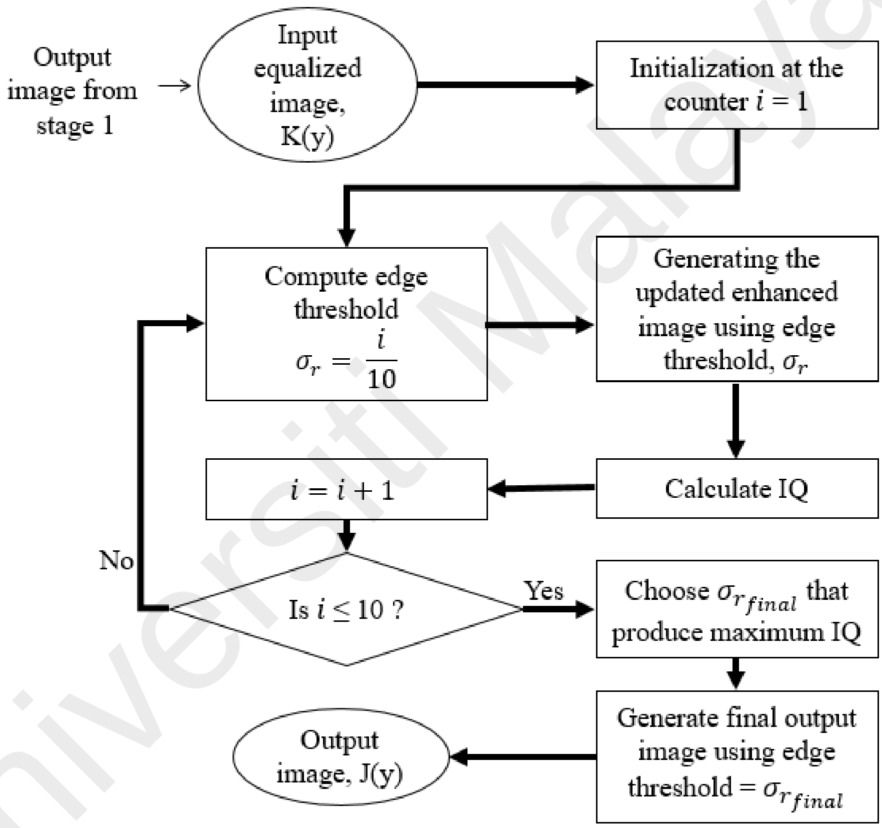
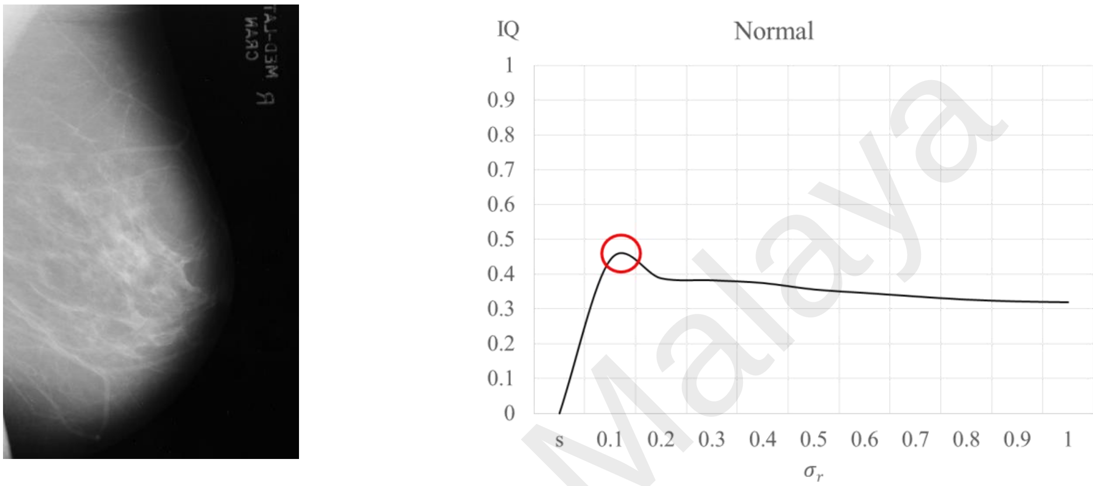
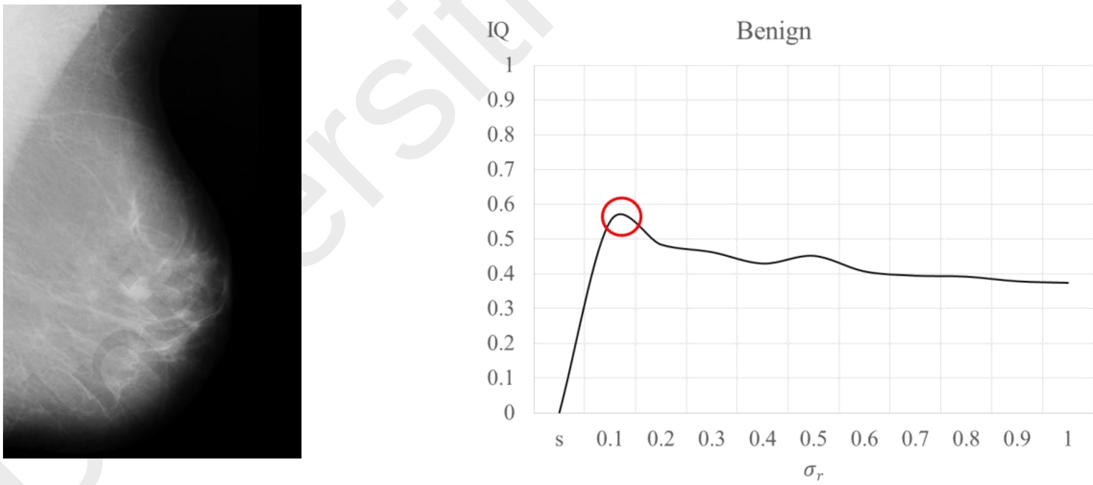


Figure 3.14: The flow chart of the proposed algorithm for optimization of local contrast function

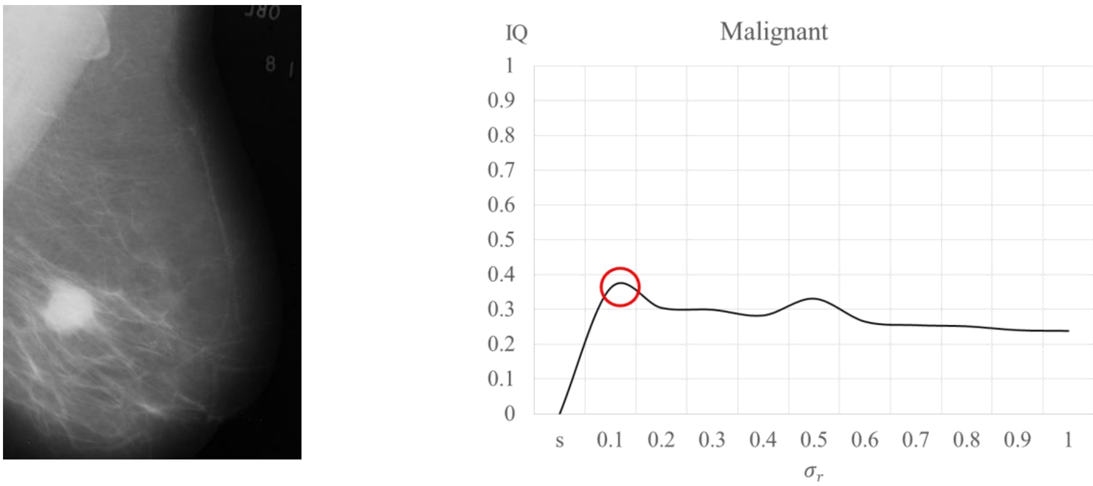
Example of IQ value optimization for three breast cases; normal, benign and malignant are shown in Figure 3.15. The plots of IQ in Figure 3.15 (a), (b) and (c) illustrates the changes in value of IQ as the σ_r is varied from 0.1 to 1.0. For each mammogram image, the σ_r value is chosen based on the maximum IQ value obtained from the simulation. For normal breast case in Figure 3.15 (a), there is a peak where the highest IQ value is attained, which the σ_r value is 0.1 and IQ value is between 0.40 and 0.50. On the other hand, for benign and malignant breast case in Figure 3.15 (b) and (c) respectively, it can be observed that there is two peak for IQ value, but the highest IQ value lies at σ_r having value of 0.1, with IQ value of 0.50 to 0.60 and 0.35 to 0.40 for benign and malignant breast case respectively.



(a)



(b)



(c)

Figure 3.15. Optimization graphs of IQ for; (a) normal case (b) benign case (c) malignant case.

3.4 Image Analysis

The performance of the proposed algorithm is evaluated using two different parameters, which is through qualitative analysis and quantitative analysis. It is quite challenging to establish an effective and precise measurement to quantify the enhanced image quality. The algorithm is expected to improve the quality of the mammogram image, specifically in its brightness and contrast as well as details preservation. As the brightness improve, the lesion should be more visible to the eyes of the observer. In image processing, an image should has an appropriate brightness and contrast to ease the viewing process from the eyes of the observer. By definition, brightness is the overall luminosity or darkness of a particular image, while contrast refers to the difference in brightness between an object and background (Smith, 1997)

Qualitative analysis refers to the subjective judgment and evaluation to analyze a non-numeric information such as video, audio records and images. For qualitative data analysis, there is no specific and universally applicable techniques that can be adapted to generate findings. In this research, human visual system is utilized to determine the output image quality by observing the presence of lesion or microcalcification before and after the enhancement process. An example of bad and good enhanced image is shown in Figure 3.16(a) and Figure 3.16(b) respectively.

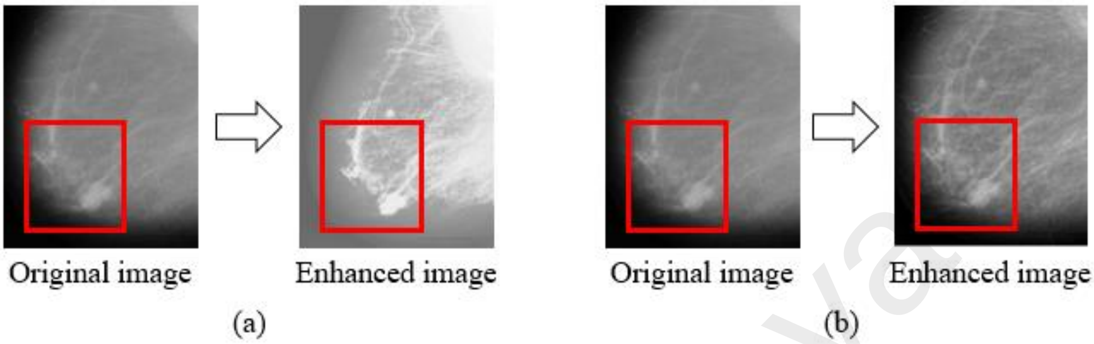


Figure 3.16: (a) example of low quality image after enhancement (b) example of good quality image after enhancement

Figure 3.16(a) shows a low-quality image obtained after enhancement. The output image seems to be over-enhanced, a condition where the image appears too bright due to high exposure, and the contrast is also high. Over-enhancement is a major problem in image enhancement algorithms, which it causes loss of edges, change in image texture or image details, impairment of fine details, and it also leads to unnatural look of the output image, as shown in Figure 3.16(a). A good enhanced image should not alter the original image, preserve its brightness and contrast, preserve the fine details, and improve the selected region of interest, which in this case, the area where lesion or microcalcification are detected.

On the other hand, quantitative analysis refers to the utilization of mathematical modelling, statistical data, parameter measurement, and research to understand the behavior and pattern of the experiment. It is used in many fields and a very useful evaluation tool to get a better picture of the algorithm's performance (Kenton, 2020). For this experiment, the quantitative measurement analysis is performed by using parameters such as average contrast (AC), average entropy (AE), peak signal-to-noise ratio (PSNR), and structural similarity index measurement (SSIM). The mentioned parameters are measured and compared with few other state-of-the-art techniques.

Average contrast (AC) refers to the measurement of average contrast of the 322 sample mammogram images. Image contrast is a representation of the difference in brightness or greyscale of a particular image, which can be used to differentiate between an object and its background. In common situation, high AC is an indication for higher degree of greyscale variation in an image. Generally, the contrast value is maximum at the intersections of regions with different type. Ironically, extremely high AC will lead to over-enhancement condition, which will cause damage to the output image. Contrast value can be calculated using the following equation:

$$\boldsymbol{C} = \sqrt{\sum_{y=0}^{L-1} (\boldsymbol{K_x} - \overline{\boldsymbol{K}}) \times \boldsymbol{p}(\boldsymbol{K_x})} \tag{3.10}$$

where K_x is the intensity of enhanced image, $\overline{K}$ is the mean intensity of enhanced image, and $p(K_x)$ is the histogram of enhanced image. The value of contrast for each 322 MIAS database mammogram images are computed and the average contrast value is determined.

On the other hand, entropy is known as a statistical measure of randomness that can be used to characterize the richness of the input image. It can also be used to quantify the details obtained from the enhanced image. Average entropy (AE) is the average value of entropy for the whole sample of images. The AE value of input image and output image is calculated and compared later for analysis. Since AE deals with the richness of the image, higher AE value for the image output indicates better richness of image and it shows that the image contains more information on the image details. The entropy value can be computed using the following formula:

$$\boldsymbol{entropy}, \boldsymbol{E} = -\sum_x \boldsymbol{p_x} \times \log_2(\boldsymbol{p_x}) \tag{3.11}$$

where *x* is the grey level number and p_x is the probability that associates with *x*.

Another parameter used for quantitative analysis in this research is peak signal-to-noise-ratio (PSNR). PSNR is useful in assessing the quality of an image and it is widely used as a quantitative analysis for image enhancement algorithm. PSNR is defined as the ratio between maximum power a particular signal to the power of distorting noise which the image quality has negative effect. A high PSNR value is needed to achieve a good quality image, as the enhancement method should not amplify the noise level significantly. The average PSNR value for 322 samples images are obtained for analysis and the equation of PSNR can be represented as following:

$$\boldsymbol{PSNR = \frac{10\ \log_{10}(L-1)^2}{MSE}} \tag{3.12}$$

where

$$\boldsymbol{MSE = \frac{\sum_x \sum_y |I(x,y) - K(x,y)|^2}{N}} \tag{3.13}$$

which $I(x, y)$ is the input image, $K(x, y)$ is the output enhanced image, L is the number of intensity values, and N is the total number of pixels in the input.

Structural similarity index measurement (SSIM) is commonly used to search for the similarity of structures between the original input image and the enhanced output image, as the name implies. The degree of similarity is determined between the range of [-1, 1], and as the value closer to 1, it shows that the enhanced image is of better quality. The metric of image quality is being assessed based on the visual impact of three different factors, which are the luminance, structure and contrast. SSIM can be equated using the following equation:

$$\boldsymbol{SSIM(x,y) = \frac{(2\mu_I\mu_K + C_1)\ (2\sigma_I\sigma_K + C_2)}{(\mu_I^2 + \mu_K^2 + C_1)(\sigma_I^2 + \sigma_K^2 + C_2)}} \tag{3.14}$$

where

μ_I and μ_K is the mean intensity of *I(x)* and *K(x)* respectively, σ_I and σ_K is the standard deviation of *I(x)* and *K(x)* respectively, $C_1 = (K_1L)^2$, $C_2 = (K_2L)^2$, L is pixel intensity, K_1 and $K_2 \leq 1$.

3.5 Summary

This chapter presented the proposed methodology for improved brightness of mammogram image with contrast and details preservation. The proposed algorithms are performed right after data acquisition process of the input image, which the algorithm includes two main stages namely Stage 1: Brightness Improvement and Stage 2: Contrast Preserving. Stage 1 process includes the removal of unwanted pixel, i.e. the dark pixel of the background image, calculation of new mean histogram of the mammogram image, followed by histogram separation, histogram clipping, and sub-histogram equalization. On the other hand, Stage 2 of the proposed algorithm includes Laplacian filtering process and the optimization of local contrast factor that utilized image quality index as the parameter for quality check.

For assessment of quality of the output image from the proposed algorithm, a qualitative and quantitative measurements have been performed. Qualitative analysis involves the subjective judgment by human visual and observation. The image quality is being assessed in terms of the overall image brightness, specific brightness at the lesion, image contrast and preservation of image details. For quantitative analysis of the image, four parameters have been chosen for quantitative measurement check, which are average contrast (AC), average entropy (AE), average peak signal-to-noise ratio (PSNR), and average structural similarity index measurement (SSIM). The results of the mentioned parameters are recorded and compared for further analysis.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the results of the proposed image enhancement techniques described in Chapter 3. The new brightness enhancement and contrast preserving technique have been proposed and discussed thoroughly. In this chapter, the results obtained from the experiment conducted utilizing the proposed algorithm is recorded and compared with several existing techniques, which are Histogram Equalization (HE), Contrast-Limited Adaptive Histogram Equalization (CLAHE), Detail Preserving Plateau Limit Histogram Equalization (DPPLHE), Brightness Preserving Plateau Limits Histogram Equalization (BPPLHE) and Quantized Plateau Limits Bi-Histogram Equalization (QPLBHE). These methods were further explained in chapter 2 subsection 2.4.3. The mentioned techniques were chosen because they also implemented histogram-based enhancement algorithm for the purpose of fair comparison.

The comparison of the results based on qualitative analysis is performed in Section 4.2, where the output image obtained from the proposed algorithm is compared with other different techniques based on observation on the overall image brightness, specific brightness at the lesion, image contrast and preservation of image details. Section 4.3 presented the results of quantitative analysis of the images obtained based on four different performance metrics as discussed in Chapter 3 which are average contrast (AC), average entropy (AE), average peak signal-to-noise ratio (PSNR), and average structural similarity index measurement (SSIM). The mentioned performance metrics are measured, recorded and compared with few other techniques. On the other hand, the research contributions are discussed in Section 4.4 and the summary of this chapter is presented in Section 4.5.

4.2 Qualitative Analysis

As mentioned in previous chapter, qualitative analysis refers to the human visual judgment and observation on the output images obtained from the experiment. A good enhancement technique will not produce an output image with problems of under-enhancement on the dark region or over-enhancement of the bright region to maintain the original mammogram image in its natural appearance and keeping its original information.

The mammogram images from MIAS database can be classified into three cases; normal, benign, and malignant cases. Most of the original mammogram images are in low contrast condition where the lesion appears to be similar as the breast tissues or muscles. In this section, the cases of normal, benign and malignant are presented in Figure 4.1, Figure 4.2, and Figure 4.3 respectively, where improvement can be observed at the area highlighted in the red box. The original image is placed in line with other methods which are HE, CLAHE, DPPLHE, BPPLHE, and QPLBHE to ease the observation and comparison process. In addition, the quantitative measurement performance metrics for each image are included for comparison, which are peak signal-to-noise ratio (PSNR), structural similarity index measurement (SSIM), contrast (C) and entropy (E).

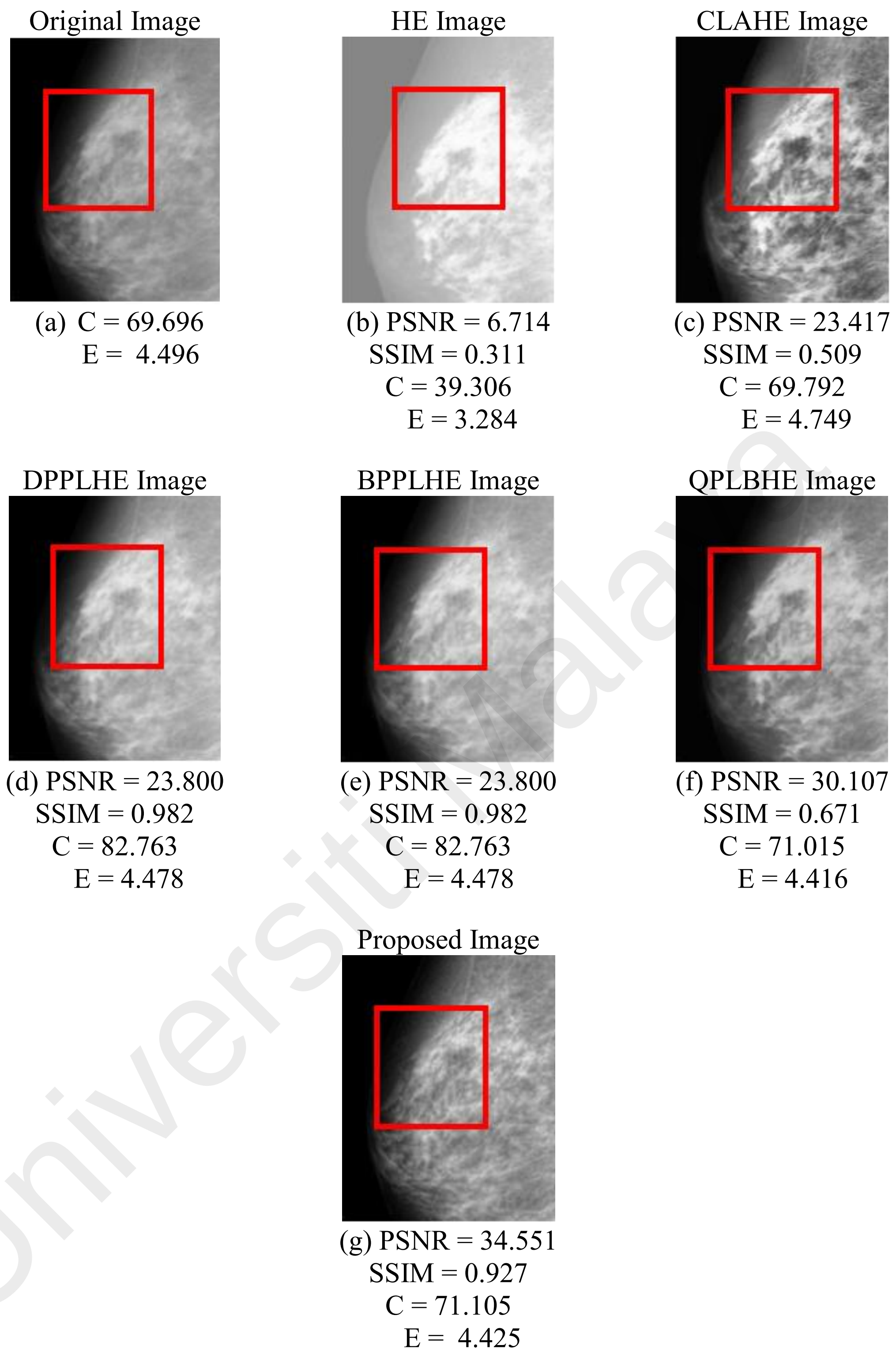


Figure 4.1. The enhancement results when *normal* breast case is used; (a) Original image, (b) HE method, (c) CLAHE method, (d) DPPLHE method, (e) BPPLHE method, (f) QPLBHE method, (g) Proposed method.

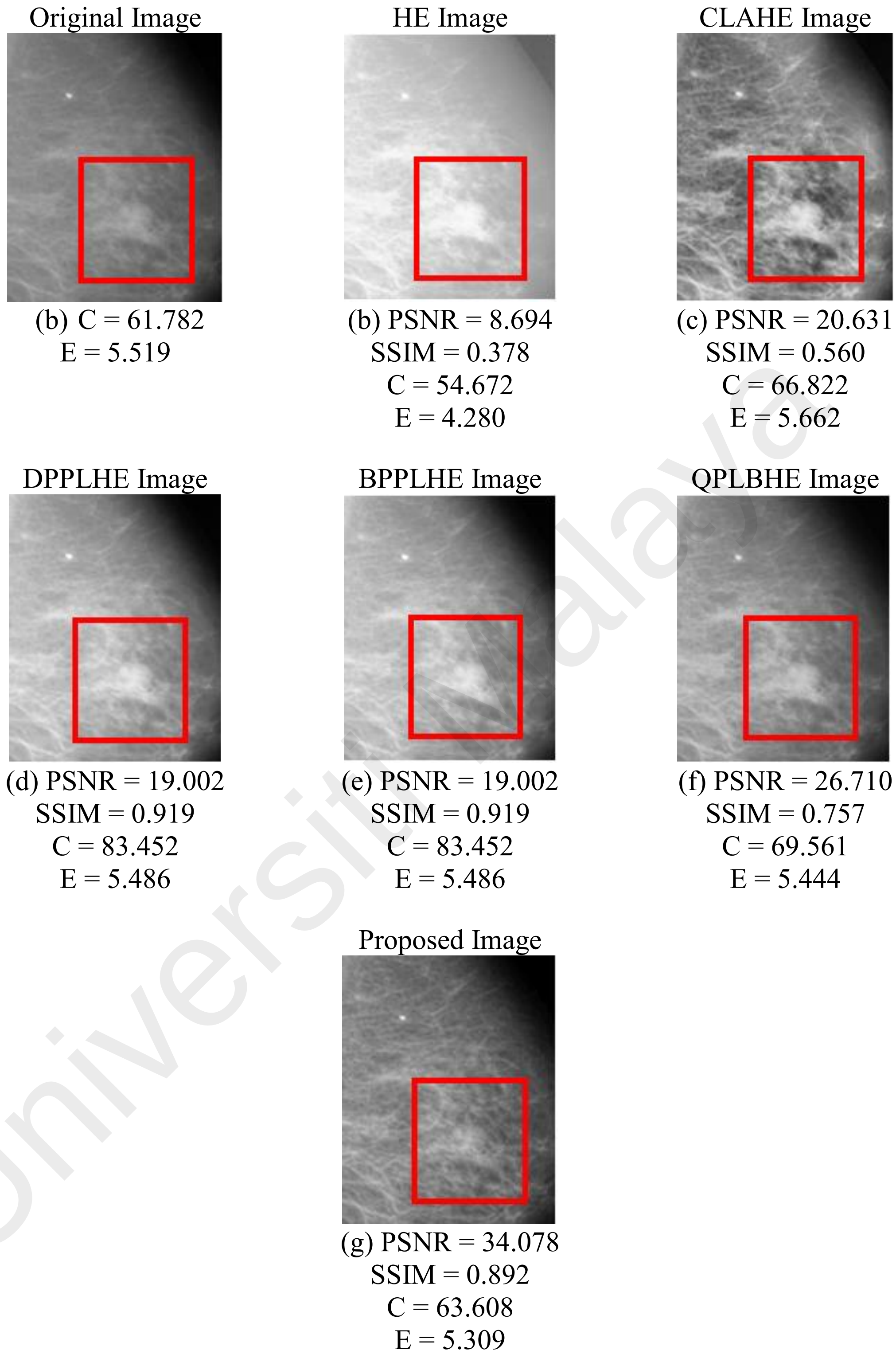


Figure 4.2. The enhancement results when *benign* breast case is used; (a) Original image, (b) HE method, (c) CLAHE method, (d) DPPLHE method, (e) BPPLHE method, (f) QPLBHE method, (g) Proposed method.

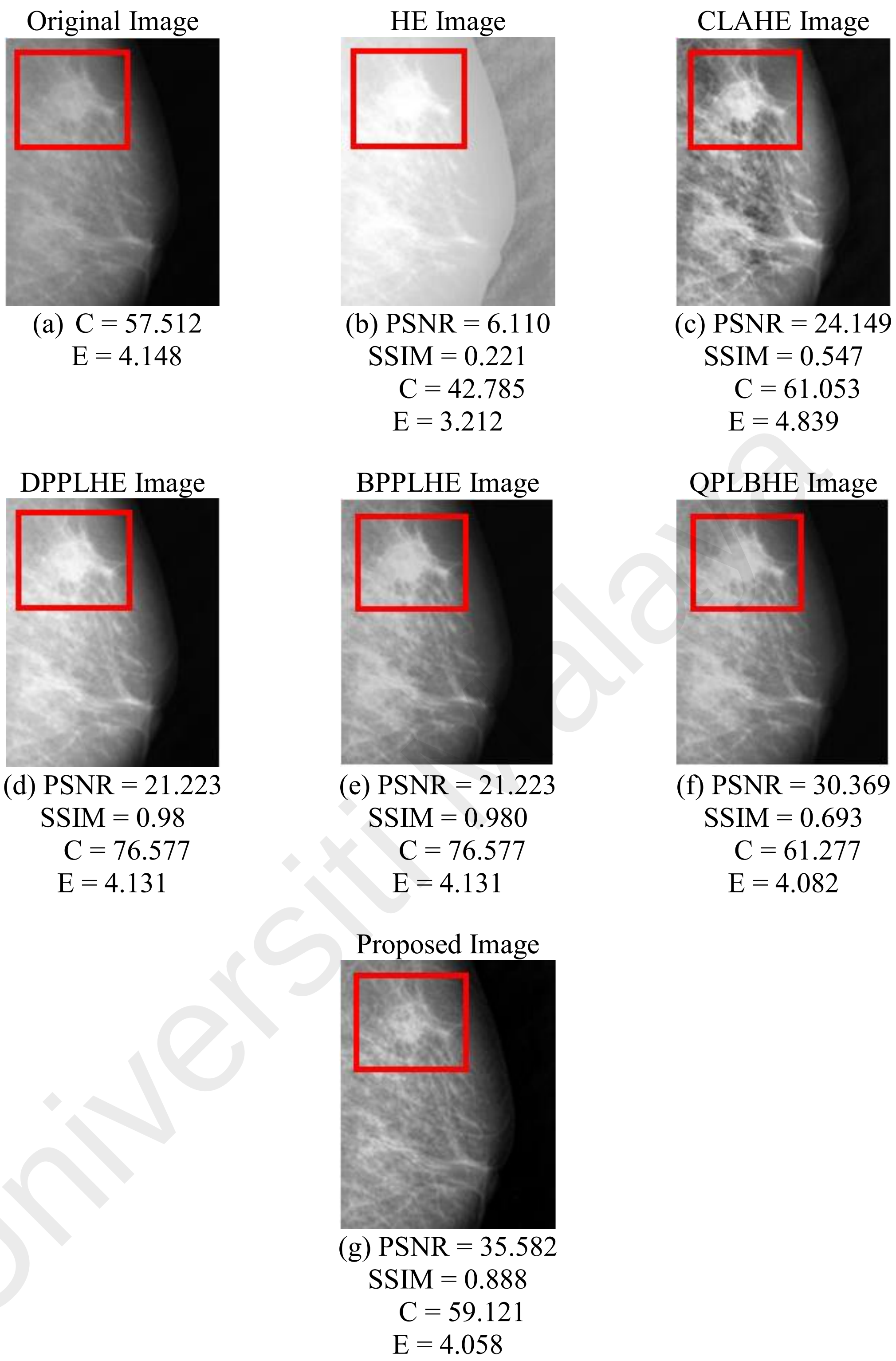
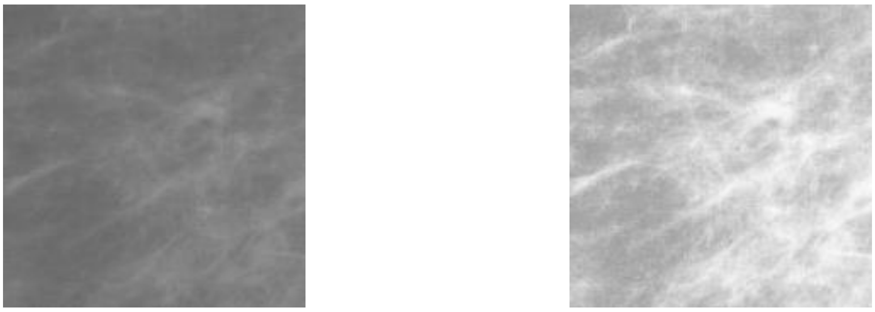


Figure 4.3. The enhancement results when *malignant* breast case is used; (a) Original image, (b) HE method, (c) CLAHE method, (d) DPPLHE method, (e) BPPLHE method, (f) QPLBHE method, (g) Proposed method.

As observed in Figure 4.1, Figure 4.2, and Figure 4.3, HE method produced over-enhanced image when compared with the original image. Over-enhancement is a major drawback of contrast enhancement method where it caused edge loss, change in image texture, impair of fine details and produce unnatural look on the image (Cheng et al., 2012). The over-enhancement is clearly seen in the image as the breast appears too bright and the dark background turns grey-white. This problem leads to loss of visibility of the tiny details such as the breast tissues and muscles. Every details are significant in mammogram image analysis, thus this method is not suitable for mammogram image enhancement. On the other hand, CLAHE method yields a significant increase in brightness at the lesion area and tissues. Ironically, it produced over-saturated image, where the highlighted areas experience strong contrast, causing the image to appear vivid and unnatural. Image saturation is utilized to describe the purity or intensity of color in an image, where it can be modified through image-processing (Plataniotis et al., 2013). Over-saturation is an unwanted condition in image processing as it alters the originality of the real image, therefore, this method is not convenient. Consequently, DPPLHE and BPPLHE method produced almost similar output images. Both algorithms generate an output mammogram image where the whole breast is being highlighted instead of the lesion area. The brightness of the breast is elevating significantly; however, it leads to a condition called over-brightness. The condition of over-brightness leads to loss of originality in the output image. On the other hand, for QPLBHE method the resulting images only provide small differences in terms of brightness without increasing the fine details, hence the visibility of the lesion is not improving. The proposed method produced output mammogram image with increasing fine details of the lesion, where the resulting output image allows the viewer to have clearer view of the lesion without creating over-enhancement, over-saturation or over-brightness problems. The proposed method also preserves the originality of the mammogram input image.

On the other hand, for cases of microcalcification in breast images, the proposed method yielded a significant result in enhancing the region of interest. The presence of microcalcification is very crucial for breast cancer early intervention as it depicts early signs for cancer development. Therefore, detection of microcalcification in early diagnosis can help in preventing the growth of tumor. However, microcalcifications are sometimes hard to be detected at a glance since the size of the calcification is very small, which recorded to be at approximate radius of $10 - 75\mu m$ (Scherer et al., 2016). Furthermore, due to its size, microcalcifications often appeared to be low in contrast and their brightness level are slightly higher than the background tissues. Therefore, enhancement of tiny parts and preservation of details in mammogram images can lead to solve the aforementioned problem.

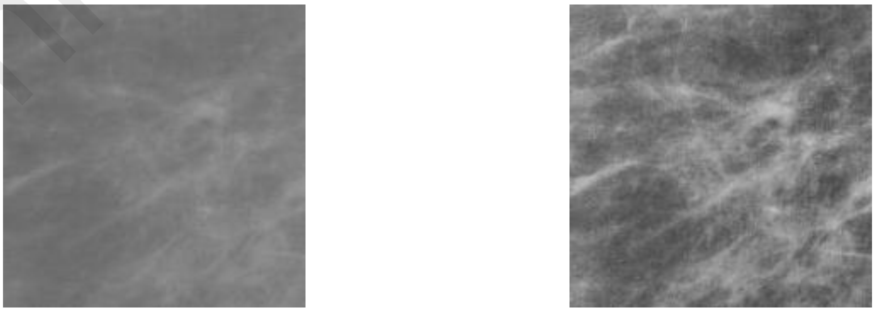
For HE method, the output image produced tend to be over bright, as shown in Figure 4.4 (b). Over brightness problem caused the background to be highlighted as well as the microcalcifications, hence leading to difficulty in distinguishing the microcalcifications from its background, leading to loss of details such as lines and edges. As mentioned, originally, microcalcifications appeared in the shape of dot, slightly brighter than the background. HE method allows the overall image to be highlighted, including the dark background. Therefore, problems arise in lesion detection as this enhancement method does not preserved the original image details and creates unwanted artefacts. In addition, the image produced has unnatural look compared to the original image, which will cause more problem in image interpretation by medical experts.



(a) Original Image (b) HE enhanced image

Figure 4.4. Enhancement of microcalcification. (a) Original image of the microcalcification region, (b) Image obtained after enhancement by the HE method

On the other hand, CLAHE enhancement method produced image with high contrast difference, as shown in Figure 4.5(b). From the comparison with original image, the region of interest for microcalcifications are being highlighted after enhancement is conducted. However, upon observing at the overall output image, it tends to possess an unnatural looking image, compared to the original image in Figure 4.5(a). For mammogram image, it is significant for the enhancement algorithm to retain the natural-looking image to prevent any bewilderment upon diagnosis by the medical expert. In some cases, the CLAHE method produced excessive contrast difference, leading to drawbacks of details loss.



(a) Original Image (b) CLAHE enhanced image

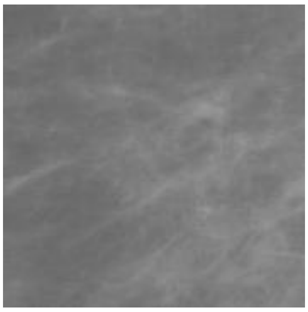
Figure 4.5. Enhancement of microcalcification. (a) Original image of the microcalcification region, (b) Image obtained after enhancement by the CLAHE method

On the contrary, DPPLHE method originally aim to preserve the details of the image with a slight increase in brightness. Upon enhancement of mammogram image, DPPLHE method managed to enhance the overall brightness as shown in Figure 4.6 (b). However, this method fails to preserve the image details. The algorithm calculation includes the dark background during computation, hence affecting the accuracy of the algorithm. The overall output image shows an increase in terms of brightness, but for details preservation, the output image does not show any significant results in enhancing the region of interest for microcalcifications detection.

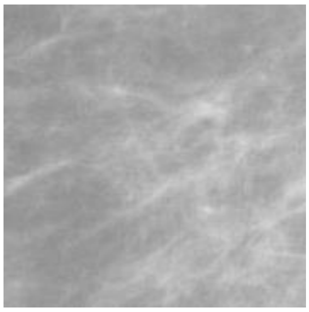
(a) Original Image (b) DPPLHE enhanced image

Figure 4.6. Enhancement of microcalcification. (a) Original image of the microcalcification region, (b) Image obtained after enhancement by the DPPLHE method

For BPPLHE method, the output image shows an increase in its overall brightness. The bright dot-spots can be observed at a glance as shown in Figure 4.7 (b), however upon analyzing the overall image, it only contributes in increasing the overall brightness, including the dark background. The region of interest for microcalcifications are not significantly highlighted due to the increase in overall brightness.



(a) Original Image

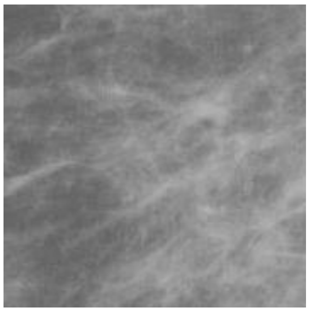


(b) BPPLHE enhanced image

Figure 4.7. Enhancement of microcalcification. (a) Original image of the microcalcification region, (b) Image obtained after enhancement by the BPPLHE method

On the other hand, for QPLBHE method, the output image from the enhancement shows an increase in brightness without altering the natural look of the original image, as shown in Figure 4.8 (b). Although the overall brightness has been elevated without having drawbacks such as over-brightness and over-saturated, the image details including lines and edges are not being preserved. For microcalcification detection, it is important to preserve the edge and line details in contemplation of highlighting the region of interest.

(a) Original Image



(b) QPLBHE enhanced image

Figure 4.8. Enhancement of microcalcification. (a) Original image of the microcalcification region, (b) Image obtained after enhancement by the QPLBHE method

The proposed method carried out stage 1 by optimizing the algorithm to produce an output image with increasing brightness, without altering the natural look of the original image. The removal of unwanted pixels in stage 1 algorithm aids in algorithm computation, allowing the output image to achieve the natural-looking image and preventing problems such as over-brightness and over-saturation. Stage 2 of the proposed method helps in preservation of contrast in the output image. The details and contrast preservation leads to the highlight of edges and lines, which creates an output image with enhanced details. Upon observing Figure 4.9 (b), the natural-look of the original image has been retained with an increase in brightness and also preservation of edges and lines. The region of interest for microcalcifications appeared to be clearer and easy to identify. Therefore, enhancement from the proposed method is practical in enhancing the structure of microcalcifications, improve its visibility from the eyes of the observer, and can aid the medical experts in diagnosis of mammogram image.

(a) Original Image (b) Proposed enhanced image

Figure 4.9. Enhancement of microcalcification. (a) Original image of the microcalcification region, (b) Image obtained after enhancement by the proposed method

4.3 Quantitative Analysis

On the other hand, quantitative analysis are the numbered performance metrics for measurement of image quality. Different from qualitative analysis, quantitative measurements involved numbered data and values obtained using four different performance metrics, which are average peak signal-to-noise ratio (PSNR), structural similarity index measurement (SSIM) contrast (AC), and average entropy (AE). The summary of requirements needed for the quantitative analysis is presented in Table 4.1.

Table 4.1. The description of quantitative analysis performance metrics.

Performance Metrics	**Descriptions**
Peak Signal-to-Noise Ratio (PSNR)	A high PSNR value indicates the output image has achieved a good quality image.
Structural Similarity Index Measurement (SSIM)	Higher SSIM shows that the enhanced image is of better quality.
Average Contrast (AC)	Higher image contrast indicates the enhancement technique is successfully increased the contrast and overall brightness of the image.
Average Entropy (AE)	Higher entropy demonstrates that the image is enhanced while details of the image are preserved.

The values obtained from the quantitative measurements are presented in Table 4.2. The table column represents the quantitative measurement performance metrics while the row represents the values obtained for the four different methods.

Table 4.2. The results of quantitative performance metrics obtained from 322 MIAS database image.

Method	Average PSNR	Average SSIM	Average AC difference (%)	Average AE difference (%)
HE	7.545 ± 2.845	0.311 ± 0.110	0.398 ± 0.491	0.245 ± 0.106
CLAHE	23.431 ± 1.855	0.386 ± 0.071	0.017 ± 0.278	0.071 ± 0.030
DPPLHE	25.883 ± 3.955	0.937 ± 0.084	0.151 ± 0.147	0.008 ± 0.016
BPPLHE	25.992 ± 3.962	0.938 ± 0.083	0.150 ± 0.146	0.008 ± 0.017
QPLBHE	31.546 ± 2.588	0.697 ± 0.077	0.004 ± 0.165	0.015 ± 0.008
Proposed Method	32.676 ± 2.812	0.908 ± 0.042	0.043 ± 0.041	0.012 ± 0.164

PSNR is defined as the ratio between maximum power a particular signal to the power of distorting noise which the image quality has negative effect. A high PSNR value is needed to achieve a good quality image, as the enhancement method should not amplify the noise level significantly. As highlighted in bold, the proposed method achieved the highest value of PSNR compared to other methods, which is 32.676. Higher PSNR value indicates less amplification of significant noise level in the output enhanced image, thus the image quality produced is superior. QPLBHE produced the second-best value of PSNR value while DPPLHE, BPPLHE, CLAHE and HE provide lower value of PSNR.

SSIM is used to search for the similarity of structures between the original input image and the enhanced output image, as the name implies. The degree of similarity is determined between the range of [-1, 1], and as the value closer to 1, it shows that the enhanced image is of better quality. Here, it is perceived that the SSIM value for HE is the lowest among other methods which is 0.311. Since higher SSIM indicates a closer resemblance of enhanced image with the original image, QPLBHE, HE and CLAHE produced an image that has the least structural similarity with the original image. On the other hand, DPPLHE and BPPLHE method yield almost the same SSIM value which are 0.937 and 0.938 respectively. Although the proposed method obtained lower SSIM value than DPPLHE and BPPLHE which is 0.908, the value is still close to 1 and based on visual analysis, the result is acceptable.

Average contrast (AC) is the representation of difference in brightness or greyscale of an image, which can be used to distinguish between an object and its background. In common situation, high AC is an indication for higher degree of greyscale variation in an image. In this experiment, HE method produced high difference in AC value, which normally is a sign of better image quality. However, in this case, based on visual analysis for both method, the enhancement algorithm does not only highlight the tumor, but it highlighted all parts of the breast. In short, the enhancement does not provide advantage for lesion detection. Meanwhile, QPLBHE produced very low AC value which is an indication that only small enhancement process was performed. The proposed method produced AC difference of 0.043%, which is considered as an acceptable contrast difference value as from visual analysis, the algorithm does not over-enhance the input greyscale image.

Entropy is the measure of randomness that can be used to characterize the richness of the input image. Since it deals with the richness of an image, higher AE value for the image output indicates better richness of image and it shows that the image contains more information on the image details. The entropy produced should not be lower than the original image as it indicates that the details and information are lost in the enhanced image. HE and CLAHE has shown a high entropy value, however during qualitative observation, the image appeared to be over-enhanced. Meanwhile, the proposed method provides higher entropy in the processed image output, and the details of the original mammogram image are also preserved.

On the other hand, a comparison is made between quantitative analysis of results from Stage 1 and Stage 2 output images. Table 4.3 presented the quantitative results obtained with their standard deviations.

Table 4.3. Comparison of quantitative performance metrics values between stage 1 and stage 2 of the proposed method.

	STAGE 1: Brightness Improvement	STAGE 2: Contrast Preservation
Average PSNR	36.262 ± 2.425	32.676 ± 2.812
Average SSIM	0.703 ± 0.078	0.908 ± 0.042
Average AC Difference (%)	0.010 ± 0.018	0.043 ± 0.041
Average AE Difference (%)	0.004 ± 0.009	0.012 ± 0.164

From Table 4.3, the result for average PSNR shows that output image from stage 1 produced higher PSNR than stage 2. However, in terms of average SSIM, average AC difference and average AE difference, the output image from stage 2 shows better result than stage 1. The results indicate that stage 2 algorithm helps in increasing the image quality in terms of the image structure, contrast and entropy.

4.4 Research Contributions

Based on the qualitative and quantitative measurement results provided in the previous section, the proposed algorithm has shown the capability to produce good enhancement results, which is also comparable with the conventional method and other state-of-the-art techniques. Based on the analysis, it can be deduced that the proposed algorithm has provided the following contributions:

- *Removal of Unwanted Pixels (Dark background)*

In image enhancement, histogram equalization is one of the conventional techniques that are still utilized until now. In addition, various research and development have been conducted to improve this conventional technique. The state-of-the-art techniques used in this experiment, (i.e. DPPLHE, BPPLHE, and QPLBHE) are working fine for other standard images, however for cases of mammogram images, they suffer from drawbacks of non-uniform illumination. Therefore, by focusing the region of interest at the breast area, removing the unnecessary background with dark pixel will help to improve the computational process and elevate the overall performance for its brightness improvement. Through this approach, the unwanted dark background is excluded for the calculation of new mean histogram in Stage 1, thus the value generated will only focus at the bright area where the lesion is presented.

- *Local contrast function optimization*

The luminance, structure, and contrast of mammogram image in the proposed algorithm are ensured to be in optimum value without existing noise amplification. The optimization process is conducted to select the best value for edge threshold which produced the best image quality index, as well as maintaining the original details of the input mammogram image. It is very significant to preserve the image original details during pre-processing, as the details will be used during the next process such as segmentation and classification of the breast lesions. Having an accurate pre-processing procedure where significant details are enhanced, and brightness is improved without causing over-saturation will lead to increase in accuracy of segmenting the breast lesion process. Therefore, optimization of edge threshold for local contrast function using the IQ value in the second stage aids in elevating the quality of output processed image to its optimum value, resulting to better visualization of edge contrast than the original input image.

To add, the results of image enhancement from the proposed algorithm helps to better visualize the image of microcalcification in breast with high layer of fats and dense glandular tissues. Microcalcification is a small deposited calcium found in breast tissues, which it is tiny in size and a common indicator for pre-cancerous cells. As mentioned, detection of microcalcifications can help the medical experts during early diagnosis. Figure 4.10 depicts the images obtained when the proposed method is experimented on breast with dense tissue, where the appearance of microcalcification is blurry in the original image.

Optimization of local contrast function allows the edges in the mammogram image to appear brighter without causing over-enhancement in the image, leading to clearer visualization of microcalcification. In Figure 4.10, the red circle indicates the location of microcalcification, and it can be seen that the original image appears blurry. The proposed method managed to exhibit a clearer image of the microcalcification with increased in edge details. For image diagnosis, the final output image from the proposed algorithm is preferable as it visualizes better tiny details without causing over-enhancement to the original image and the microcalcification appointed by the red circle is clearer from the eyes of the observer compared to the other methods.

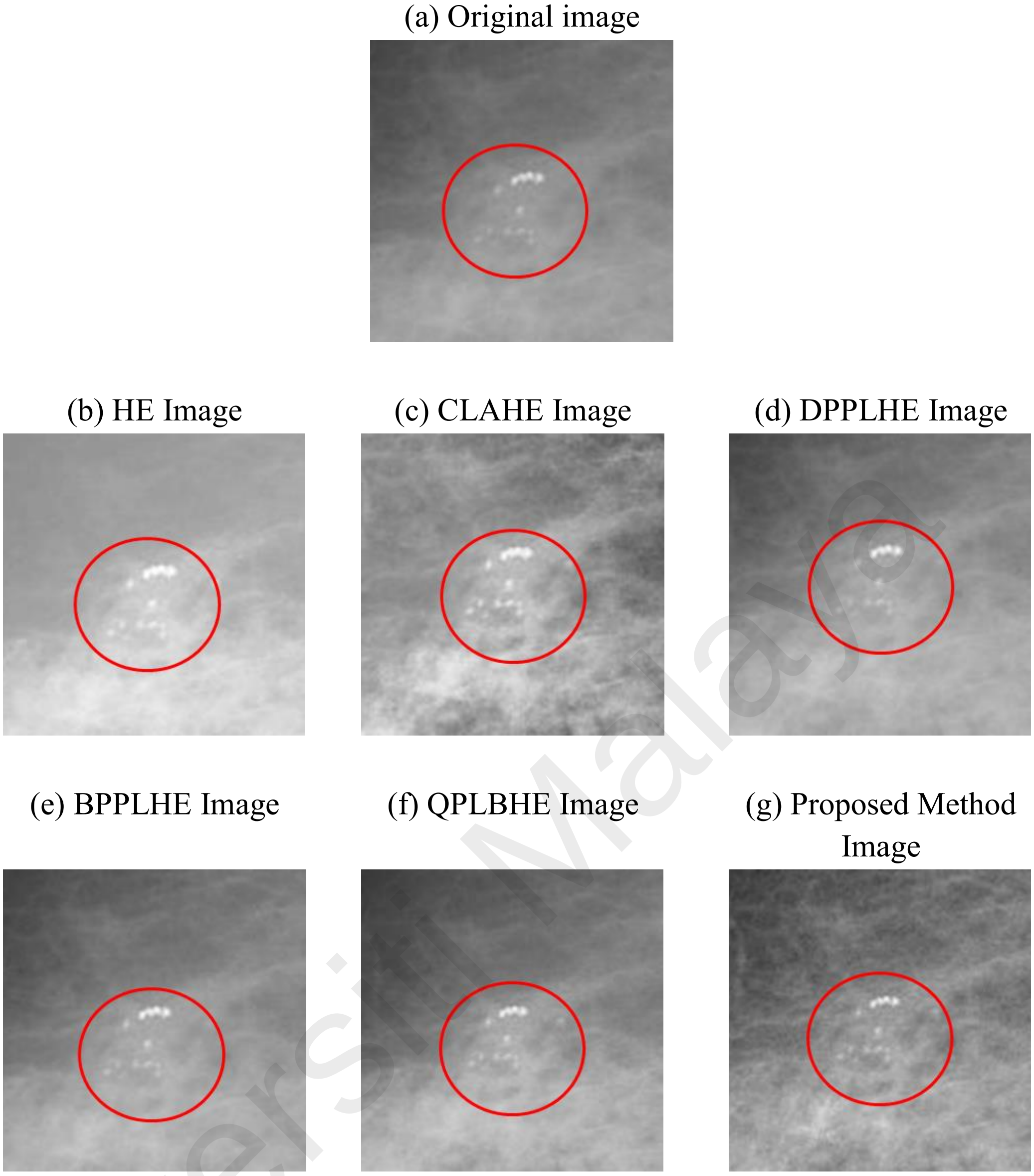


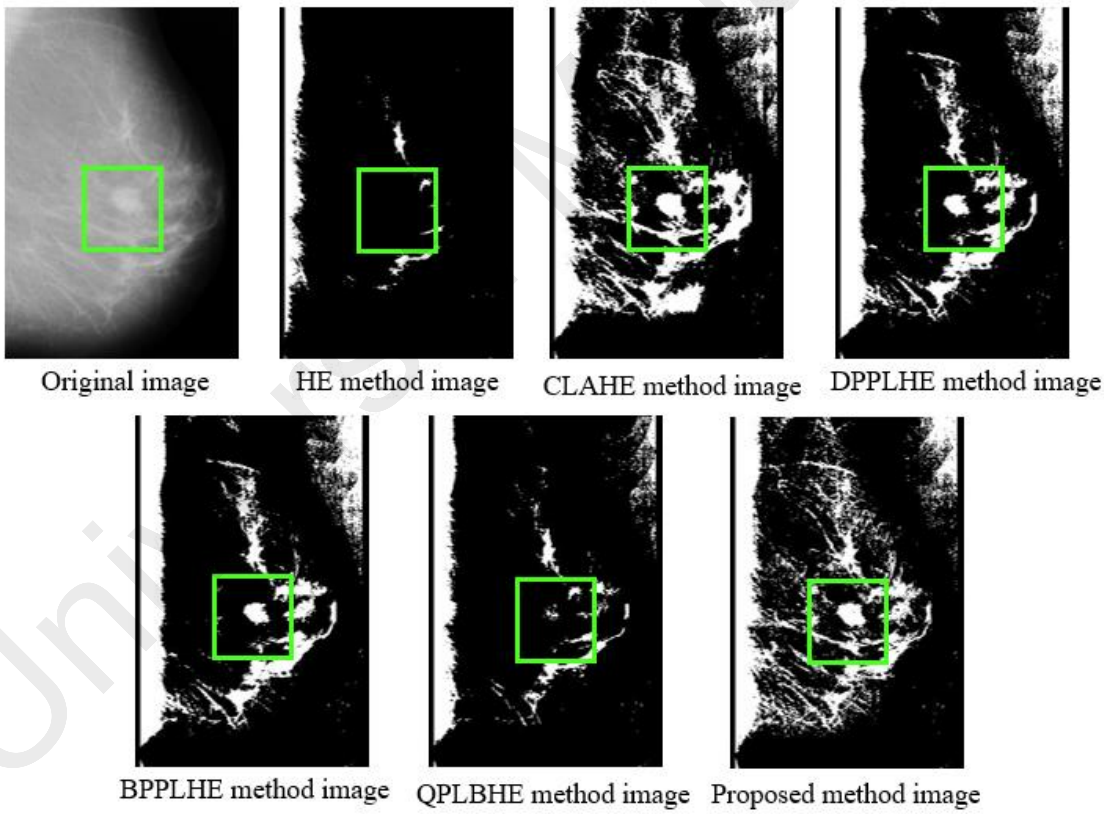
Figure 4.10. The comparison of qualitative results in enhancement for microcalcifications case; (a) Original image, (b) HE image, (c) CLAHE image, (d) DPPLHE image, (e) BPPLHE image, (f) QPLBHE image, and (g) Proposed method image

- *Image enhancement without amplification of the existing noise*

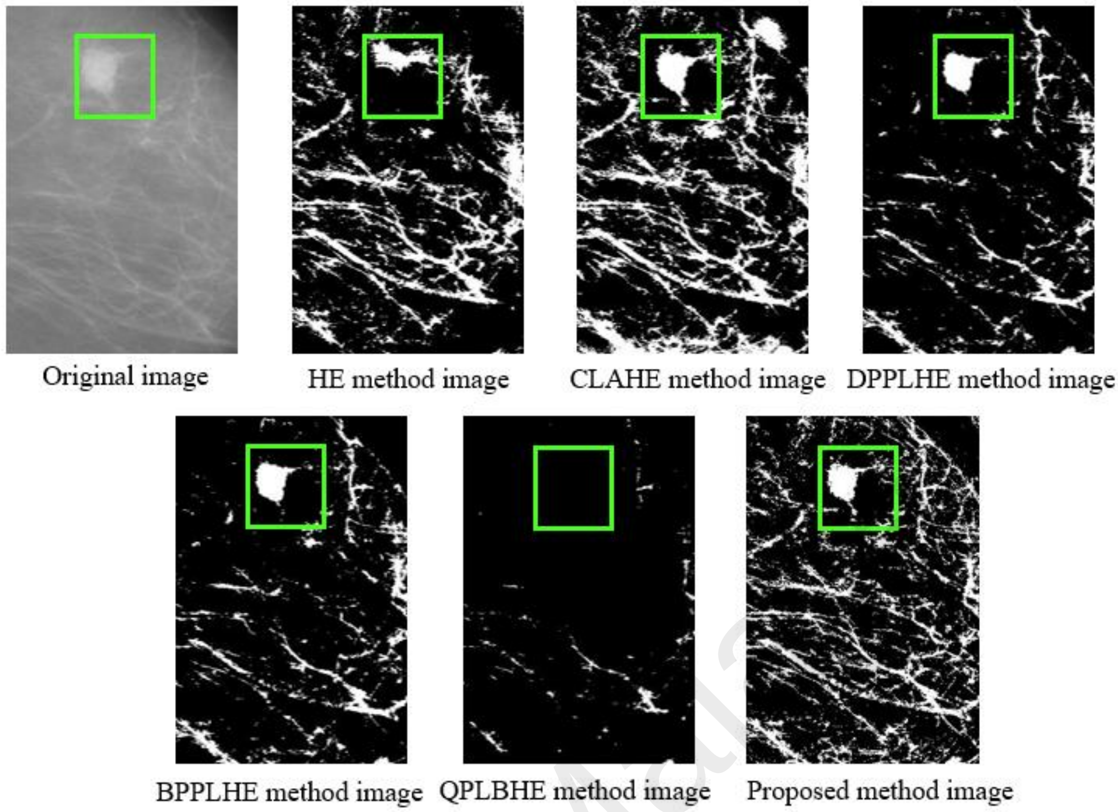
The proposed algorithm managed to achieve good and comparable results as other techniques. Analysis on the PSNR value shows the proposed algorithm achieved the highest and best value compared to other method, which indicates that the existing noise in the original input mammogram image is found to be the least amplified despite all the process that it goes through. The efficiency of the proposed algorithm is proven when the noise amplification is the lowest value.

- *Improved Segmentation of Breast Lesion*

The optimization of local contrast function in stage 2 of the proposed algorithm allows better segmentation of breast lesion. Figure 4.11 shows an example of images produced when segmentation of mammogram image is performed on breast with benign and malignant cases for post-processing.



(a) Segmentation of breast with *benign* lesion on different methods



(b) Segmentation of breast with *malignant* lesion on different methods

Figure 4.11. The image segmentation result for (a) Benign breast case, and (b) Malignant breast case

The breast lesions are highlighted in the green box in Figure 4.11(a) – (b). The proposed method can produce smoother lesion image from the segmentation process as the details of the lesion has been increased during the enhancement process. For both cases of benign and malignant, CLAHE method has falsely segmented a non-lesion area, which creates a false result for diagnosis. The segmentation process has proven that the proposed method gives out better information than the other methods. In addition, segmentation process is conducted on the algorithm without local contrast optimization to compare it with the algorithm that have undergo the process of local contrast optimization. Figure 4.12 below shows the results of the outcome.

(a) Segmentation without the optimization of local contrast

(b) Segmentation when optimization of local contrast is conducted

Figure 4.12. The outcome of breast segmentation when (a) optimization of local contrast is not conducted, (b) optimization of local contrast is conducted

As seen in Figure 4.12 (a), the breast segmentation process is conducted without optimizing the edge threshold value, and the produced binary image does not meet the requirement for segmentation accuracy, as the lesion is seen to be attached to the breast tissues. Meanwhile, when the optimization of edge threshold is performed in stage 2, the image in Figure 4.12 (b) is obtained where the breast lesion is well segmented without having any breast tissues attached to it. This is due to the improvement of edge details, creating better shape of the lesion, leading to better segmentation outcome. The summary of this research novelty and contributions are presented in Table 4.4.

Table 4.4. Summary of research novelty and contributions

Contributions	Explanation
Removal of unwanted pixels in stage 1 for optimization of algorithm computation	Focusing the region of interest at the bright area where lesions are presented, removing the unnecessary background with dark pixel will help to improve the computational process and elevate the overall performance for brightness improvement.

Optimization of local contrast function	Optimization process is conducted to select the best value for edge threshold which produced the best image quality index, as well as maintaining the original details of the input mammogram image.
Image enhancement without amplification of the existing noise	The existing noise in the original input mammogram image is found to be the least amplified in the proposed method based on the PSNR value obtained.
Improved Segmentation of Breast Lesion	Due to the improvement of image brightness and edge details, better shape of the lesions are produced, leading to better segmentation process.

4.5 Summary

In this chapter, the results obtained from the new enhancement and contrast preserving method is presented, compared and discussed. The proposed method is tested on the 322 MIAS database mammogram images from cases of normal, benign and malignant. The results for benign and malignant cases are presented in Section 4.2 for easy viewing on the performance of the algorithm, as this research focused on the enhancement of the lesion and fine details. Each enhancement method is evaluated based on their qualitative and quantitative performance metrics. Section 4.2 presented the qualitative analysis results, where it shows that the proposed method provides better enhancement without altering the originality of the input image and at the same time, the fine details of the image are improved and highlighted. Section 4.3 describes all the quantitative performance metrics which are the average peak-to-signal noise ratio (PSNR), average structural similarity index (SSIM), average contrast (AC) and average entropy (AE) value. Based on the outcome, the proposed method produced a superior result in terms of PSNR, AC and AE, whereas for SSIM, BPPLHE method yields a better result. However, the SSIM value for the proposed method is acceptable to be used as it does not produce any drawbacks of over-enhancement upon analyzing the output image qualitatively. Consequently, the advantages of the proposed method is discussed in Section 4.4, where this technique allows removal of unwanted background which is the dark pixel, optimization of local contrast function, enhancement of image without amplifying the existing noise, and improved the segmentation of breast lesion in post processing of the image.

CHAPTER 5: CONCLUSION

5.1 Conclusions

Mammogram image enhancement during pre-processing is very important as it can aid the medical experts for early diagnosis. An adaptive and optimized local contrast factor method with brightness improvement for mammogram images has been developed in this research. This chapter summarizes the important findings previously presented to apprehend the contributions of the results achieved during the course of this research.

Generally, due to poor contrast, non-uniform illumination and low visibility of dense tissue and breast lesion, the mammogram image obtained from mammography screening tools often deteriorated. This problem creates difficulties for the radiologists to interpret the mammogram image and to diagnose breast cancer, to which it leads to the condition of false positive, where the lesion appears to be there but it actually absent, or the condition of false negative, where the lesion appears to be absent but it actually presents. Therefore, a new enhancement method is developed to solve the aforementioned problems.

The proposed method is divided into two stages, named Stage 1: Brightness Improvement and Stage 2: Contrast Preservation. An experiment was conducted using 322 mammogram images obtained from MIAS database, where the algorithms developed in stage 1 and stage 2 are incorporated. Stage 1 process started with removal of the unwanted pixel, which is the dark background. The aim of the pixel removal is to ease the calculation of mean histogram in the next step. Consequently, the mean histogram of image with removed unwanted pixel is computed, and separated into two different partitions namely low-sub histogram and high-sub histogram. Then, the plateau limit is calculated for sub-histograms, to which eventually it will produce six histogram partitions, and the histogram's bin is quantized into their corresponding plateau limit. The purpose of histogram partition is to allow the sub-histograms section to be equalized independently and to preserve its brightness. Next, the histogram clipping process is conducted for both sub-histograms. This process is significant to control the HE enhancement rate and to avoid saturation, hence the problems with over-enhanced image and unnatural-looking image can be prevented. Eventually, equalization of all sub-histograms independently is carried out for the final step in stage 1.

For stage 2, optimization of local contrast function was performed where image quality index, IQ is utilized to find the optimum edge threshold. This stage is important to enhance the local contrast at the region of interest, by smoothing the details or increasing it, while the strong edges are being kept unaltered. Laplacian filtering process is applied first, and the image is then convolved with Gaussian kernel to produce Gaussian pyramid image. The optimization of edge threshold, σ_r value is performed to highlight the fine details in the output equalized image from stage 1. For stage 2, there are two main parameters that need to be determined, which are the edge threshold, σ_r and edge smoothing value. To obtain the best σ_r value, the image quality index, IQ is utilized as the main parameter for image quality check. Measurement of IQ involve three factors, which are luminance, structure and contrast, and the σ_r value will influence the image enhancement desired. IQ represents the value for image quality, thus higher value of IQ indicates better quality image, and the highest value attained is 1. For edge smoothing value, a simulation is performed and it is found out that 0.8 is the best value that can produce fine details without having drawbacks of over-saturation and over-enhancement on the mammogram image.

The performance of the proposed method is evaluated by using qualitative and quantitative analysis. Qualitative analysis is the judgment of the image quality from the eye of the observer, whereas quantitative analysis is the numbered parameters for measurement of image quality. Quantitative measurements involved four different parameters, which are average contrast (AC), average entropy (AE), peak signal-to-noise ratio (PSNR), and structural similarity index measurement (SSIM). From the outcomes, the proposed algorithm yields the best results when compared with other method in terms of PSNR, SSIM, AE, and AC.

On the other hand, the proposed method are able to provide various advantages, such as it allows removal of unwanted pixel (the dark background), optimization of local contrast function, enhancement of image without amplifying the existing noise, and improved the segmentation of breast lesion in post processing of the image. It can be concluded that the optimization of local contrast function increased the edge details in the image, which significantly improves the image fine details, leading to better segmentation of lesion. This can ease the process of post-processing such as segmentation and classification of breast lesion for diagnosis of mammogram image. The novelty for this research study is highlighted in stage 1 and stage 2 algorithm. In conclusion, this research study has successfully achieved its objectives and purpose.

5.2 Study Limitations

There are a few limitations exists for this research study. For instance, the proposed method is only applicable for greyscale image enhancement and not suitable for colored image. This is because the algorithm in stage 1 is set to remove the dark background specifically for greyscale images with dark background. The aim for stage 1 is to increase brightness at the region with bright pixels, thus removing the unwanted pixels can aid in optimization of the algorithm. Therefore, this algorithm is not suitable to be applied to colored images.

On the other hand, this algorithm has limitation in terms of computation time. Upon analyzing the processing time, it is discovered that the average processing time to complete both stages of the proposed method in one mammogram image is approximately 68 seconds. Accordingly, longer time is needed to complete the images with larger scale.

5.3 Future Works

The proposed method for mammogram image analysis has successfully produced a promising result for brightness improvement at region of interest and preserve the image contrast and its fine details. Nevertheless, there are few possible future works that can be considered as following:

- The algorithm requires a long processing time for 322 mammographic images. Therefore, optimization of algorithm can be conducted to improve the computational efficiency, at the same time reducing the computational and processing time. In addition, the complexity of the algorithm can be reduced by conducting algorithm optimization.
- For stage 2 algorithm, the smoothing edge value is chosen based on manual simulation on 322 images. An automated system to select the best edge smoothing value can be developed to ease the computational process and increase the accuracy of the algorithm.
- The algorithm can be developed to have an automated classification of breast structure at the early stage to differentiate the breast types. This is because different breast structures will result differently for enhancement. The current proposed method is set to have the same threshold for every breast cases. Therefore, in future research, the threshold value can be set automatically according to the breast structures.

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Journal

1. N.H. Chan, K. Hasikin, N.A. Kadri, M. Azizan, and M. Jusoh, “Optimization of Local Contrast Factor with Adaptive Brightness Improvement: Impact on Mammogram Image Analysis”, Journal of Medical Imaging and Health Informatics, 2020, vol 11, pp 1-14.

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1. N. H. Chan, K. Hasikin and N. A. Kadri, "Evaluation of Feature Descriptor on D-Saddle Keypoint Detection in Retinal Image Registration," 2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA), Penang, Malaysia, 2019, pp. 178-181, doi: 10.1109/CSPA.2019.8696015.
2. N. H. Chan, K. Hasikin and N. A. Kadri, "An Improved Enhancement Technique for Mammogram Image Analysis: A Fuzzy Rule-Based Approach of Contrast Enhancement," 2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA), Penang, Malaysia, 2019, pp. 202-206, doi: 10.1109/CSPA.2019.8696016.