MBHE Technique: Contrast Enhancement On Mammograms

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT
FOR THE AWARD OF DEGREE
OF

MASTER OF TECHNOLOGY
IN
SOFTWARE ENGINEERING

Submitted By
POOJA KUMARI
2K18/SWE/10

Under the supervision of

Mrs. SONIKA DAHIYA
Assistant Professor
Department of Computer Science and Engineering
Delhi Technological University

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(FORMERLY DELHI COLLEGE OF ENGINEERING)
SHAHABAD, DAULATPUR, BAWANA ROAD, DELHI – 110042

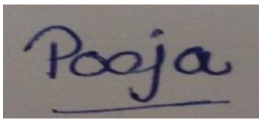
JUNE 2020

M. Tech (Software Engineering) **POOJA KUMARI** **2020**

Department of Computer Science and Engineering
Delhi Technological University
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CANDIDATE'S DECLARATION

I, Pooja Kumari, 2K18/SWE/10, student of Master of Technology (Software Engineering), hereby declare that the Major Project-II Dissertation titled **"MBHE Technique: Contrast Enhancement on Mammograms"** which is submitted by me to the Department of Computer Science and Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master Of Technology (Software Engineering) is original and not copied from any source without proper citation. This work has not been previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship, or other similar title or recognition.



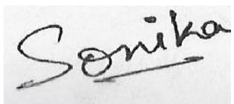
Place: Delhi **POOJA KUMARI**

Date: 30th June 2020 **2K18/SWE/10**

Department of Computer Science and Engineering
Delhi Technological University
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CERTIFICATE

I hereby certify that the Project Dissertation titled **"MBHE Technique: Contrast Enhancement on Mammograms"** which is submitted by Pooja Kumari, (2K18/SWE/10) to the Department of Computer Science and Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology is a record of project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.



Place: Delhi

Date: 30th June 2020

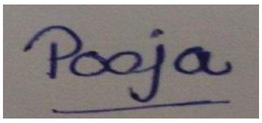
Mrs. SONIKA DAHIYA
(Supervisor)
Assistant Professor
CSE Department
Delhi Technological University
(Formerly Delhi College of Engineering)
Shahbad, Daulatpur, Bawana Road, Delhi- 110042

ACKNOWLEDGEMENT

The successful completion of any task would be incomplete without accomplishing the people who made it all possible and whose constant guidance and encouragement secured us the success.

First of all, I would like to thank the Almighty, who has always guided me to follow the right path of life. My greatest thanks are to my parents who bestowed the ability and strength in me to complete this work.

My thanks are addressed to my mentor **Mrs. Sonika Dahiya**, Department of Computer Science and Engineering who gave me this opportunity to work in a project under her supervision. It was her enigmatic supervision, unwavering support, and expert guidance which has allowed me to complete this work in due time. I humbly take this opportunity to express my deepest gratitude to her.



Date: 30th June 2020

Pooja Kumari

M.Tech (SWE)-4th Sem

2K18/SWE/10

ABSTRACT

Contrast enhancement is significant for medical images like mammograms. Contrast enhancements techniques are broadly of two types: Direct and Indirect contrast enhancement technique. The most popular indirect contrast enhancement techniques are Histogram equalization (HE), Contrast limited adapted histogram equalization(CLAHE), Brightness preserving bi-histogram equalization technique(BBHE) and Recursive mean separate histogram equalization(RMSHE). Some popular direct contrast enhancement techniques are contrast stretching enhancement technique and adaptive fuzzy logic contrast enhancement technique. In this work, we have proposed a new technique for the enhancement of contrast named median-based brightness conserving bi-histogram equalization (MBHE). The experiment is conducted on standard mammogram images from the mammographic Image Analysis Society (MIAS) dataset. MIAS is a standard organization of the UK that researches mammogram images. On the basis of understanding of the mammogram image, it generates a dataset of mammogram images knows as the MIAS dataset. This dataset contains 322 files. An experimental comparison of the proposed technique is done with the most popular direct and indirect contrast enhancement. A qualitative comparison is done using metrics mean square error (MSE), signal to noise ratio (SNR), and peak signal to noise ratio (PSNR). It is observed that the proposed technique outperforms the other techniques HE, RMSHE, CLAHE, adaptive fuzzy logic contrast enhancement technique, BBHE, and contrast stretching. Along with this work, a pre-processing model for mammogram images is also proposed. This model contains two steps first is filtering and the second is contrast enhancement. In this model, first we compare all the filtering techniques. After that different contrast enhancement, techniques are compared. These experiments conducted on images from the MIMA dataset. After comparison, the best filtering and best contrast enhancement technique are proposed for the mammogram images. Here, we also proposed a new contrast enhancement technique for mammogram images named as recursive median-based histogram equalization technique (RBMHE). Qualitative comparison of all these techniques is done using three quality parameters MSE, PSNR, SNR. These results show that the proposed contrast enhancement technique gives the best result among all the contrast enhancement technique and proposed model give the best result for the pre-processing of mammogram images.

Pre-processing is very efficient. It is used to increase the quality of the mammogram images. Pre-processing is the first step in the process of enhancing the quality of mammogram images.

Pre-processing is helpful in noise removal, contrast enhancement, and many other mathematical operations.

The first main two-step for pre-processing is noise removal and contrast enhancement. For Noise removal from the images, several filters are developed. There are mainly five filters for noise removals such as mean filter, median filter, Gaussian filter, wiener filter, and Gaussian filter. Contrast enhancement of mammogram images is done using contrast enhancement technique for example histogram equalization (HE), contrast limited adaptive histogram equalization (CLAHE), brightness preserving bi-histogram equalization technique (BBHE) and recursive mean separate histogram equalization technique (RMSHE) and contrast stretching. In this paper, we proposed a model for the pre-processing of mammogram images. For this, a comparison of all filters is performed on different noises such as salt & pepper noise, speckle noise, and Gaussian noise. After comparison, the best filter is proposed for mammogram images. Different contrast enhancement techniques are also compared and the best contrast enhancement technique is proposed in this model. Along with the proposed model, a new contrast enhancement technique named as a recursive median-based histogram equalization technique (RMBHE) is proposed. The experiment is conducted on standard mammogram images from the mammographic Image Analysis Society (MIAS) dataset. MIAS is a standard organization of the UK that researches mammogram images. This dataset contains 322 files. Experimental comparison of this proposed technique is done with the most popular direct and indirect contrast enhancement techniques such as CLAHE, BBHE, RMSHE, CONTRAST STRETCHING, ADAPTIVE FUZZY ENHANCEMENT TECHNIQUE, and HE. A qualitative comparison is done using metrics mean square error (MSE), signal to noise ratio (SNR), and peak signal to noise ratio (PSNR). It is observed that the median filter give the best noise removal for mammogram images compare to other filters such as median filter, Gaussian filter, wiener filter, and adaptive median filter and the CLAHE technique give the best contrast enhancement compared to other contrast enhancement techniques such as HE, RMSHE, BBHE, and contrast stretching. Here we observe that the proposed technique RMSHE technique outperforms all other contrast enhancement techniques such as HE, RMSHE, CLAHE, BBHE, and contrast stretching.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

BBHE	:	Brightness Preserving Bi-Histogram Equalization
MBHE	:	Median based brightness conserving bi-histogram equalization technique
CLAHE	:	Contrast limited adaptive histogram equalization
RMSHE	:	Recursive Mean-Separate Histogram Equalization
HE	:	Histogram equalization
MIAS	:	Mammographic Image Analysis Society
RMBHE	:	Recursive median-based histogram equalization
MSE	:	Mean square error
PSNR	:	Peak signal to noise ratio
SNR	:	Signal to noise ratio

CHAPTER-1

INTRODUCTION

The most common disease in women after lung cancer is breast cancer [9]. Detection and treatment of this in the early phase may enhance the chances of successful removal of disease. To detect breast cancer in the early phase, mostly screen mammogram technique is used [34]. It is used to check abnormalities [33]. The decrement in the mortality rate is recorded with the help of a breast cancer-screening program [29]. The annual death rate has been decreased from 32.69 in 1991 to 24 in 2005 [2]. The decrement in mortality rate has been occurred because of technological enhancement in early detection and treatment.

1.1 Overview

1.1.1 Mammogram Image

It is defined as an X-ray image. Mammogram gives images that have soft-tissue, and have a beneficial demonstration. It has a multi-lobular contour. It contains irregular outlines [2]. Mammogram images generally used in screen mammography. Screen mammography is used for the early detection of breast cancer in women.

1.1.2 Contrast Enhancement

Screen mammography is generally used to early detect disease in mammogram images. However, mammogram images have attenuated malignant tissue if the contrast of an image is low [19]. This malignant part is mainly present in the area of the image that has high intensity. Therefore, to identify its contrast of the image should be efficient. A malignant tumor is normally rounded in the shape. The difference in the contrast of malignant tissue and normal tissue is very low and human eyes cannot observe it normally, so it may be present but humans cannot detect it [9]. Doctors need a pre-processed image to identify breast cancer at an early stage [10].

It is used to enhance the contrast of the images. Different human has a different interpretation for the image because of its low contrast resolution. At first, the HE technique is developed for contrast enhancement [31]. HE technique just increases the intensity of the image. It does not give good results for mammogram images. After this CLAHE technique is developed, this technique gives shows a clear image concerning the background of the image [4]. It gives much better results than HE does. A different type of technique is developed named BBHE. This technique bifurcates the image-using mean and then do histogram equalization [12]. This technique gives better results then HE but worse than CLAHE. After this an enhanced version of BBHE is developed named RMSHE, this technique bifurcates the image using mean and does histogram equalization. This process is repeated recursively [14]. This technique gives better results than BBHE but worse than HE does. After these techniques, an adaptive fuzzy logic contrast enhancement technique is developed that uses fuzzification for enhancement. This technique gives better results than just HE does.

After this one more contrast enhancement technique is developed named as contrast stretching, this technique enhances the range of intensity. It gives better results than CLAHE. Here, in this work, we proposed a new technique for contrast enhancement named as median-based brightness conserving bi-histogram technique is proposed for the enhancement of the contrast of an image. This technique gives a better contrast-enhanced image compare to the previous technique. The proposed technique uses the median intensity of the original image for performing contrast enhancement.

1.1.3 Pre-processing of Mammogram Images

Early identification of cancer is done using the mammogram technique. These images have a very low contrast. Noise may be present in these images. Therefore, before using mammogram images to detect cancer we need to enhance their quality. Pre-processing is the initial move to enhance quality. Pre-processing is very important in image processing [5]. Pre-processing includes noise removal, contrast enhancement, mathematics operation. Pre-processing of images contains two steps first is Noise removal and second is contrast enhancement.

To remove noise from mammogram images, several filers are developed. For noise removal from mammogram images first of all mean filter is developed. In the mean filter, the value of every pixel is replaced with the mean value of neighborhood pixels. Mean filter use mean value, which can generate blurring in the image. To overcome its Median filter is developed. In the median filter, the value of every pixel is replaced with the median value of neighborhood. This filter gives a better result for mammogram images compare to the mean filter. After a Median filter, an adaptive median filter is developed. This first selects a filter with impulse error and then replace it with the median pixel value. This filter is very effective for Gaussian noise.

After this Gaussian filter is developed. It applies the Gaussian function to remove noise. Gaussian filter is mainly effective for speckle noise. This technique gives a better result than the adaptive median filter technique. After this wiener filter is developed. Wiener filter first performs inversing filtering and then do smoothening of noise. Wiener filter is most effective for Gaussian noise. After noise removal from mammogram images, contrast enhancement of mammogram images should be done for pre-processing. Different human has a different interpretation for the image because of its low contrast resolution. For contrast enhancement of mammogram images first HE technique is developed [31].

HE technique just increases the brightness. It displays the worst output for mammogram images. After this CLAHE technique is developed, this technique gives shows a clear image concerning the background of the image [4]. It gives much better results than HE does. A different type of technique is developed named BBHE. This technique bifurcates the image-using mean and then do histogram equalization [12]. This technique gives better results then HE but worse than CLAHE. After this an enhanced version of BBHE is developed named RMSHE, this technique bifurcates the image using mean and does histogram equalization.

This process is repeated recursively [14]. This technique gives better results than BBHE but worse than HE does. After that contrast stretching enhancement technique is developed. This technique enhances the intensity range of the image. This technique gives a better result than RMSHE. In this work, we proposed another contrast enhancement technique named as recursive median-based histogram equalization technique(RMBHE). This technique first divides the image using the median and then perform histogram equalization on sub-images. This process is done recursively. This technique gives better results than other contrast enhancement techniques. After noise removal and contrast enhancement, a pre-processed image is obtained.

1.2 Motivation

Breast cancer is the most common disease in the world. In her complete life women has a 5% chance of getting breast cancer. A five-year study estimate was around 50% in Malaysia and about 90% in Australia, Canada, and the United States with the difference connected to a combined process of early identification, access to therapy.
If breast cancer identified in early-stage than the possibility of recovery and becoming a healthy increase. Due to early detection of breast cancer, treatment therapy become effective and efficient. It is done at the time of screening mammograms. If we have an effectively designed cancer tumor screening application, then the breast cancer mortality rate can be decreased worldwide.

The death rate has reduced to 24.00% in 2005 from 32.69% in 1991. This decrement is recorded per 100,000 people. This decrement is with the improvement in early detection. Some published report states that a majority of women are at the last stage of cancer in Malaysia. It is defined as an X-ray image. Mammogram gives images that have soft-tissue, and have a beneficial demonstration. However, mammogram images have attenuated malignant tissue if the contrast of an image is low [11]. This malignant part is mainly present in the area of the image that has high intensity. Therefore, to identify its contrast of the image should be efficient. A malignant tumor is normally rounded in the shape.

It has a multi-lobular contour. It contains irregular outlines. The difference in the contrast of malignant tissue and normal tissue is very low and human eyes cannot observe it normally, so it may be present but humans cannot detect it. Different human has a different interpretation for the image because of its low contrast resolution. To solve this problem in this work we have proposed a new contrast enhancement technique MBHE. This technique gives the best contrast enhancement for mammogram images. Due to contrast enhancement, malignant tissue that is present in high contrast areas can be easily detected.

Except for contrast mammograms, some noise or any other speckles can effect images resolution. To enhance the quality of mammogram images and remove noise pre-processing is done. Pre-processing has two main steps first is noise removal and second is contrast enhancement. In this work, we have proposed a pre-processing model for mammogram images to enhance their quality. For noise removal, many filters are developed.

After applying the different filters and performing analysis of all these filters best filter is proposed. Same for the second step we apply different existing contrast enhancement techniques and performed analysis. After that best contrast enhancement technique is presented for the best contrast-enhanced image. In this work, a new contrast enhancement technique RMBHE is also proposed that gives the best result among all the contrast enhancement techniques. Therefore, this proposed model gives the best pre-processes image that can help in the early detection of breast cancer.

1.3 Problem Statement

Contrast enhancement is very significant for medical images like mammograms. Contrast is generally the variation from the highest and smallest intensity values in the image. The contrast is affected by noise, brindle, light, darkness. This technique enhances the visual observation of the image's attribute. The contrast enhancement technique enhances all the attributes of an image for better visualization of humans. Contrast enhancement is considered as a pre-processing step. It highlights important attributes in image, Machinery, pattern identification, and other programs. Medical images are used generally to detect the abnormal condition of the human body.

Therefore, attribute enhancement of medical images is a basic step. In breast cancer, mammogram images are used to identify the unusual condition of the breast. For lesser quality images present in the research area, It has a dominant role for example in medical image identification and distant observe analysis. In this report, mammogram images are enhanced to enable better treatment and analysis of breast cancer in women. So here, for the enhancement of mammogram images, a new technique is proposed. This technique is named as MBHE. This technique divides an image into two sub-images. After bifurcating into two images histogram equalization of these images is performed.

This technique is compared with other contrast enhancement techniques such as HE, BBHE, CLAHE, RMSHE, adaptive fuzzy logic contrast enhancement technique, and contrast stretching technique. After comparison, we find out that the proposed technique gives the best contrast enhancement technique for mammogram images. This enhanced image will be helpful for early identification.

Contrast enhancement is a pre-processing step. Pre-processing of images is used to enhance the quality of the image. It is a necessary step. Medical images also contain a different type of noise, poor contrast, and weak boundaries. These things determine the quality of the image. Noise can reduce this quality. Noise removal is important to increase the quality. Various organs may present at different depths in the body that may produce some inaccuracies in the report and the diagnosis of disease.

Pre-processing mainly contains noise removal, contrast enhancement, and some mathematics operation for increasing quality. Noise can be defined as a variation in the intensity of the image. Some conditions can affect image sensors in the camera. Noise can be defined as a light photon effect. Noise can be introduced in the mammogram image at the time of image capturing. Removal of noise is also an important task because at the time of noise removal some important features can be affected. Therefore, noise removal is done using taking care of its feature. There are mainly three types of such as salt and pepper noise, Gaussian noise, and speckle noise. The mathematical formula for Noise is:

$$N(a, b)=o(a, b)+e(a, b) \tag{1}$$

Here o(a, b) is the natural image, e(a, b) denotes error, and N(a, b) denotes the noisy image. Many filters are developed for noise removal from mammogram images. In this report, we proposed a model for the pre-processing of mammogram images. In this, model different filters such as median filter, mean filter, Gaussian filtering, and wiener filter and adaptive median filter are compared. After comparison, the best filter is proposed so that noise of the mammogram image can be removed without affecting its feature.

Contrast enhancement is the second step in pre-processing. Poor contrast affects the visual representation of the image. Malignant tissue in the mammogram images is present in the high contrast part of the image. For identifying tissue, we need high contrast image. In contrast, enhancement of different contrast enhancement techniques is proposed. In the proposed model, we compare different existing techniques such as HE, BBHE, RMSHE, CLAHE, adaptive fuzzy logic contrast enhancement technique, and contrast stretching.

After comparison, the best contrast enhancement technique is proposed. In this report, we proposed a new contrast enhancement technique RMBHE and compare it with existing techniques. We find that this technique gives the best result for the mammogram image. Therefore, this proposed model gives the best-pre-processed image, which helps for a better diagnosis.

1.4 Organization of the Dissertation

Mammogram images are used for the detection of cancer. Mammography is the best technique for the early detection of mammogram images. Mammogram images have low contrast. We need to enhance the contrast of the image so that malignant tissue can be identified easily. For this, we proposed a new contrast enhancement technique is proposed which give the best contrast enhancement of the mammogram images.

Pre-processing is useful for enhancing quality. It contains two important steps one is filtering and the second is contrast enhancement. Here best filtering technique is proposed and the best contrast enhancement technique is proposed. This proposed model gives the best-processed mammogram image. Along with this, one another contrast, enhancement technique is also proposed which gives the best contrast enhancement for mammogram images. The current chapter describes the overview behind carrying out this study and also the motivation and problem statement for doing this study.

Chapter 2 describes the literature review behind this study.

Chapter 3 describes the Median based brightness preserving bi-histogram equalization technique (MBHE) and pre-processing model for mammogram image.

Chapter 4 provides an explanation of the implementation and the results that were obtained in the report.

Chapter 5 contains an explanation of the conclusion and the future scope of this study.

CHAPTER-2

LITERATURE REVIEW

This model discusses the work, which is conducted by various researchers in the fields of mammogram images. In the area of contrast enhancement of mammogram images, many scientists have researched in the area of "contrast enhancement technique". In the area of pre-processing of mammogram images, different scientists have researched in the area of "filtering" and "contrast enhancement". It also discusses the work of different researchers to know about filtering and contrast enhancement in depth.

2.1 Application of X-Ray in the Medical Image:

Willian roentgen found out X-rays in 1895. X-Rays were founded at the time of experimenting on cathode radiation. X-rays used for detecting the disease in patients. X-rays are very useful in the medical field. Along with the detection of disease, X-rays are also used in the treatment of patients. X-rays are used in the various analysis in determining disease-using images.

X-rays images are generally used in general radiography, angiography, fluoroscopy, computed tomography, and bone mineral densitometry. X-rays images make the detection and treatment of diseases easy and effective.

2.2 Screen Film Mammography:

Mammogram screening is the finest technique to detect cancer. In this, we have two x-ray pictures. One image is captured from the boundary and another image is captured from the top for every breast. In mammogram screening X-rays are exposed to the mammogram. These are of mammographic energy. After this X-rays are communicated and dispersed across breast tissue which is shown in Figure 2.1.

Mammogram screening has been appeared to decrease the death rate by almost 18% to 30% in the last decade [17]. Mammogram screening gives a high standard image, the death rate has been decreased by using these images in medical. Mammogram screening is known as the best technique for the analysis of breast cancer. But almost 10% to 20% cases which can be identified by self-analysis or substantial study are not detected by screen-film mammography.

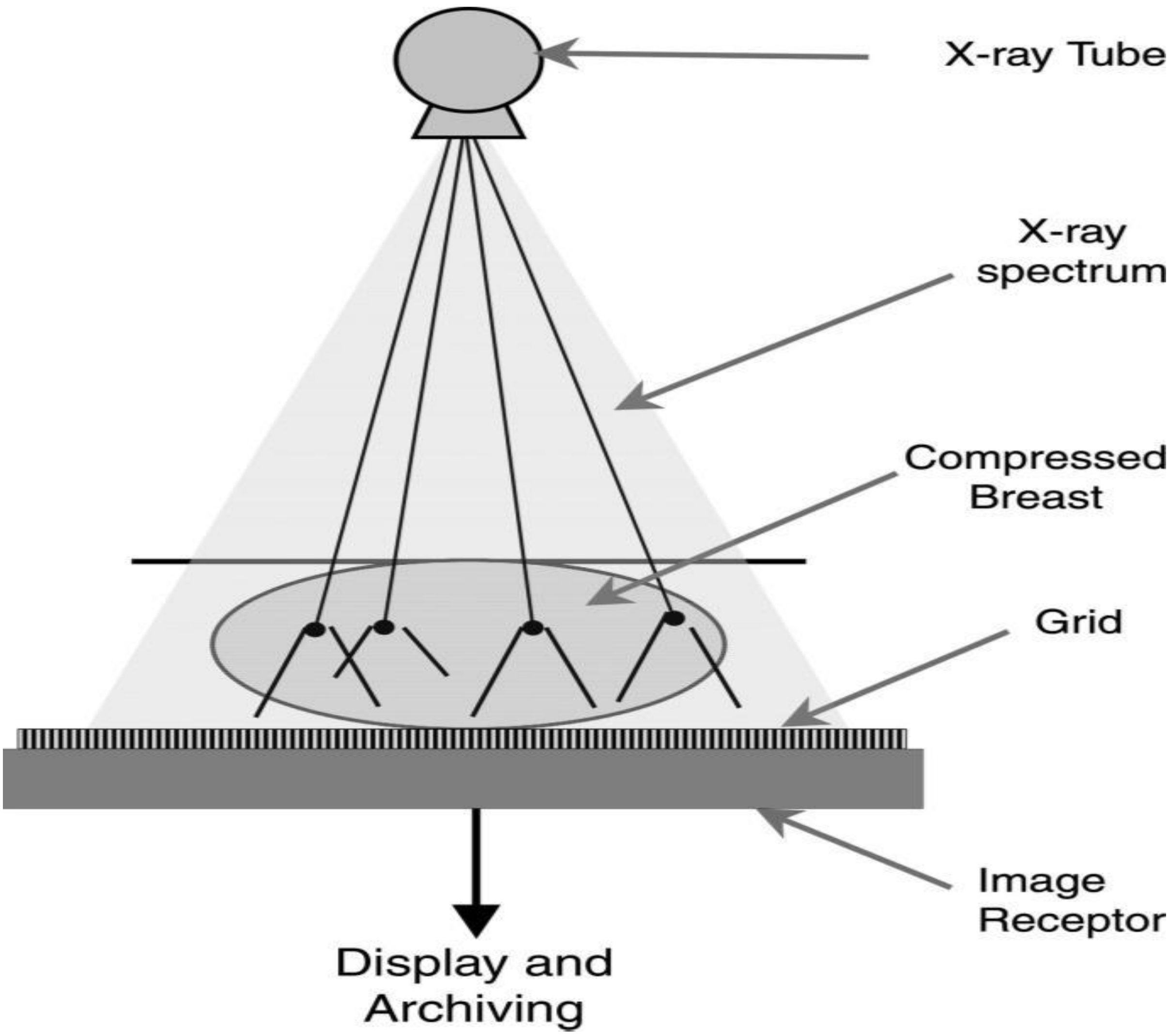


Figure 2.1: Procedure of mammogram screening [17]

Only 5%-40% cases out of the total detected cases by screen-film mammography are correct [7]. This shows that this technique also gives false positive. False-positive cases can produce useless biopsies and mental pressure on patients.

Captured x-ray photons pass across the framework and link with the image receiver. His photons are now analyzed as a hidden picture in the film. After preparing, the film is projected for analysis. This complete process is taken, projected, and stored using one medium that is the film. SFM technology has several advantages such as:

1. The high resolution which is almost 20 row per millimeter, can illustrate good speculum and microcalcification.
2. It shows a high contrast image that permits the evasion of precise differences in the breast soft tissues [7].
3. Use of high range brightness view boxes that upgrade visualization of dense tissue.

4. Projection, arrangement, hiding of film at the time of analysis is very easy. It permits simultaneous projection at the time of screening analysis and addition projection of previous pictures on several panel illuminators.
5. Use of several picture receptor sizes that allow picturing breast of distinct sizes.
6. The film works as a structured medium to store at a low cost for a long time.

SFM has several disadvantages with a number of advantages. The most important disadvantage of SFM is a bounded dynamic range, which is expressed in Figure 2.2. There is noise because of film roughness and the trade-off between resolution and efficiency. In SFM technology, Film is the only medium to capture, project, and store pictures. Any trivial condition of pace can affect picture quality in the process. This can affect and degrade performances of the whole mammography process. Figure 2.3 shows the limitation of SFM which is because of the large variety of tissues.

It can be explained in Figure 2.3 that, our system is efficient for the dense area of the breast but main tissues are present in the film screen result curve. Because of this, it is not possible to visualize other tissue.

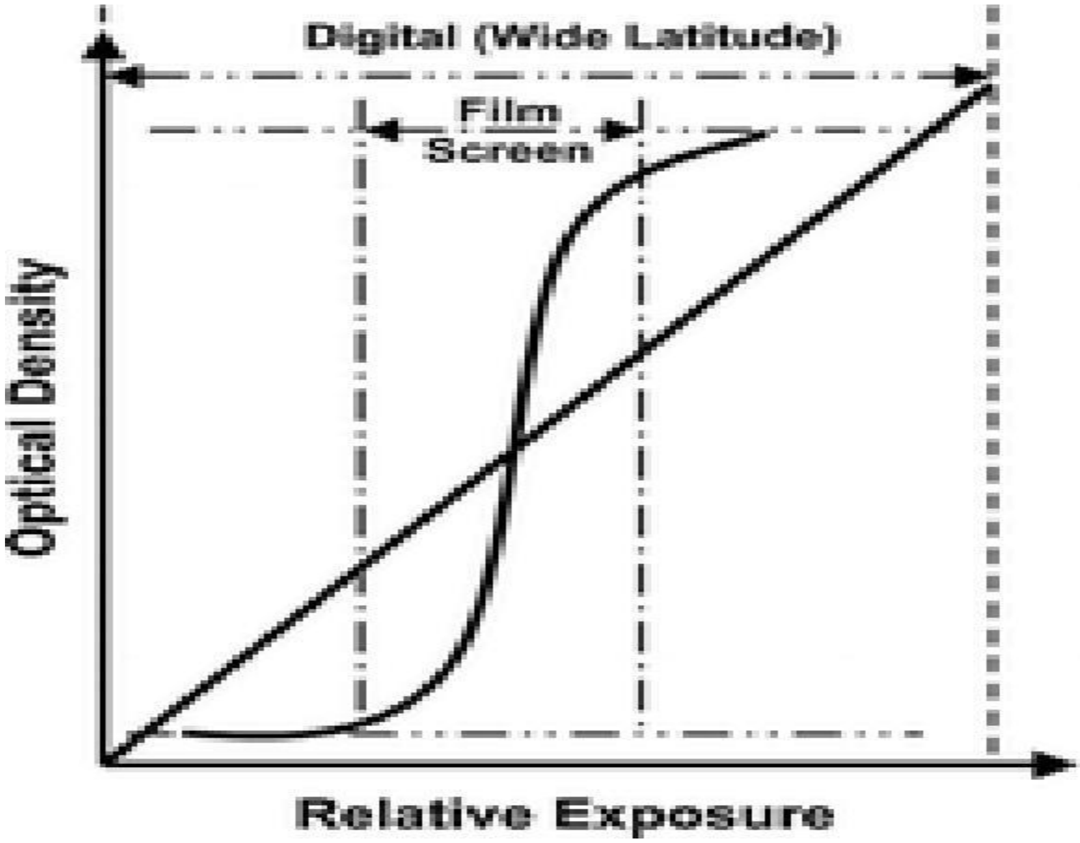


Figure 2.2: Comparison of dynamic range between SFM and digital mammography [17]

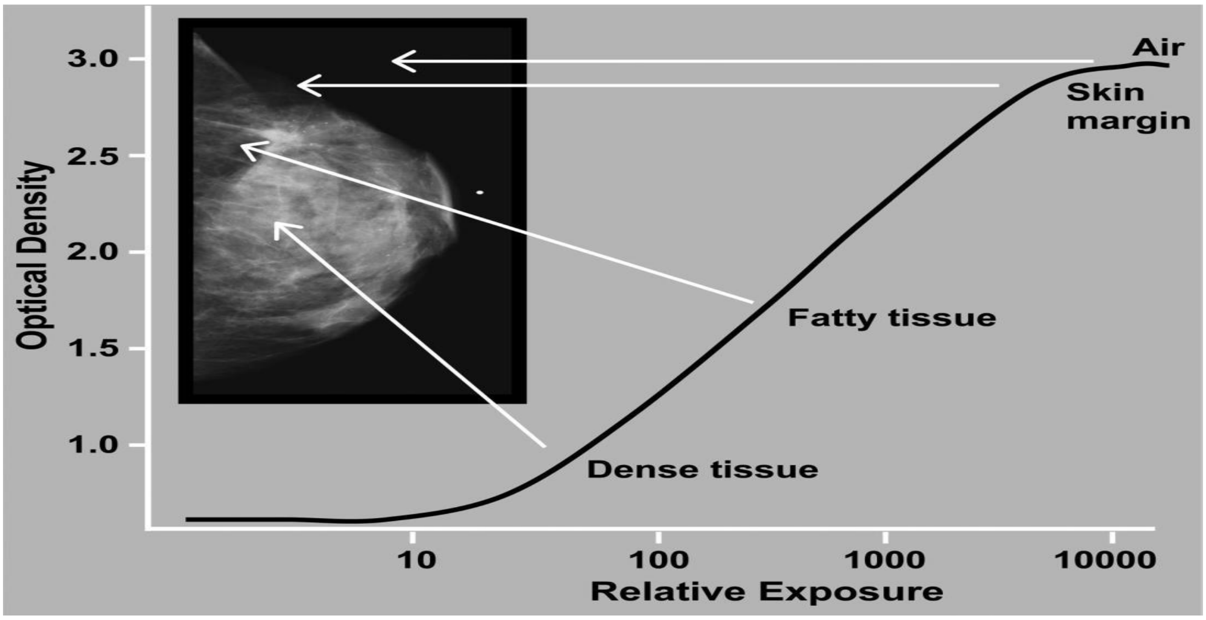


Figure 2.3: Different regions of the breast image are represented according to the Characteristic response of a typical mammographic film [17]

SFM has limitations for example film transmission, development, and picture ratification. To overcome the drawback of SFM, digital mammography is developed. It detects breast cancer at an early stage.

2.3. Digital Mammography

Mammograms can be captured digitally in two different ways [17]. First is by converting conventional images obtained by screen-film mammography into a digital picture. The second way is directly capturing a digital image, which is named a full filed digital mammogram (FFDM). Different images are produced in both ways. FFDM is of two types; Direct system and Indirect system.

The indirect system takes two-step in capturing the digital image. At first, the same as SFM a scintillator captivate the X-rays and produce a light scintillation. In the second step detection of the scintillator is done using photodiodes. In a direct system, photoconductor directly acquire X-rays photons. These X-rays photons are changed in the digital signal. At the time of the direct acquisition, spatial resolution is bounded by the size of the pixel not the width of the photoconductor.

The process of X-ray picture capturing is explained using an easy model of a breast having an only interesting part. An interesting part could be tissue, microcalcification, breast tumor. Several X-rays are sent with path “X” across the normal breast tissue.

$$X_{\mathbf{B}} = X_0 e^{-\mu Y} \quad (1)$$

Here X_0 denotes X-rays, which are projected on breast, Y denotes width. Here µ denotes tissue's attenuation coefficient. We suppose that X-rays do not get scatter form a point and no radiation arrives at the picture plane. So now, several of these rays that are sent with path 'B' that is shown in Figure 2.4. These are going across the interesting part of the breast. X-ray attenuation coefficient, u' is:

$$X_C=X_0e^{-\mu(Y-b)-\mu' b} \quad (2)$$

Here b denotes the width of a part in the direction where X-rays move.

Due to the appearance of the structure some variation in the signal are generated:

$$SV=X_B-X_C \quad (3)$$

The contrast of the radiation is as follows:

$$CO_{rd}= X_B-X_C / (X_B+X_C) \quad (4)$$

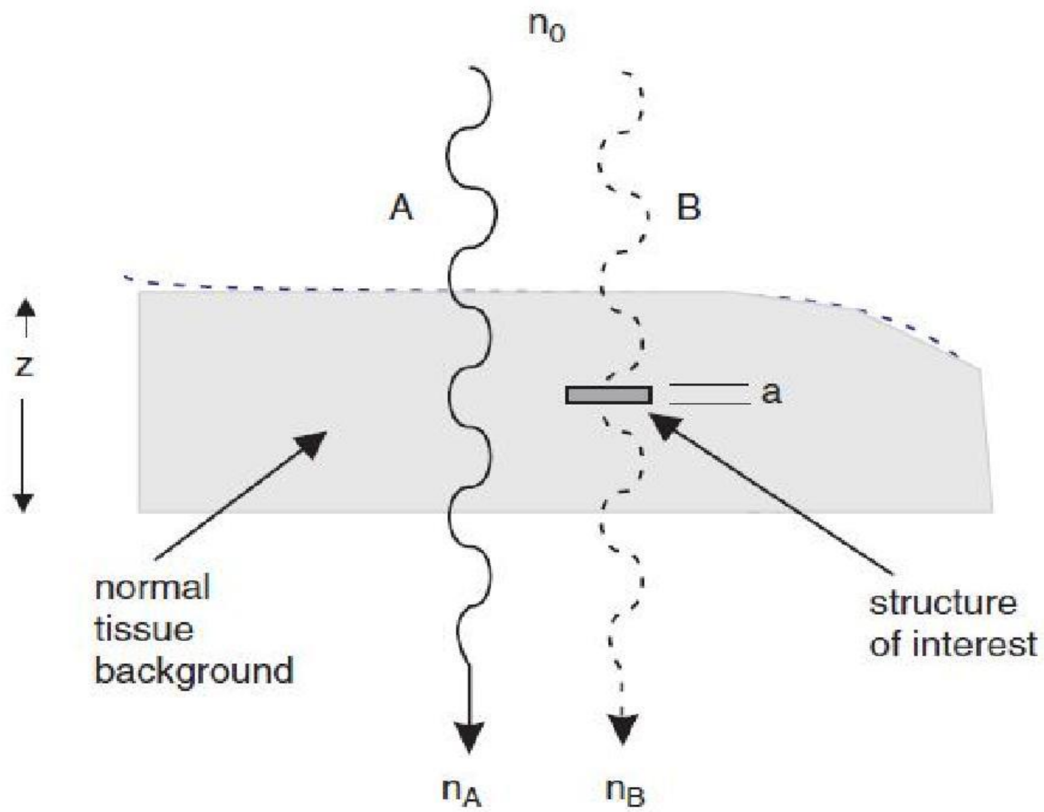


Figure 2.4: Differences in x-ray transmission between path A and path B

By using equation (1) and (2) and replacing these in equation (4) we get:

$$Co_{rad}= 1-e^{-(\mu-\mu')b} / 1+e^{-(\mu-\mu')b} \quad (5)$$

Advantages of digital mammography:

Digital mammography does an efficient fascination with occurring x-rays photons. Due to this, some improvement in digital identification gives better detection.

The main advantage of the digital detector is that it give a straight response for a large range of x-rays brightness and poor noise system. The procedure of picture capturing, projecting, and storing is decoupled that gives a chance to make every process optimal independently. Digital mammography has a large dynamic range in comparison to SFM. Due to this, it can modify a dynamic image and can postprocessor it. This will generate improvement in the visualization of the image. An optimal digital mammography process has the following advantages:

1. Highly effective acquisition of x-rays for the mammogram due to:
    - Here the width of the detector can be increased to get several x-rays communicated form the breast.
    - Speckle noise must be removed.
    - The diffusion amount should be decreased.
2. The picture information is acquired in numeric form.
3. Projection intensity and contrast can be handled.
4. Here pictures can be adjusted to fit the eye visualization and some boundation of projection device can be overcome.
5. It can remove other noises.

2.4 Noise Removal of Digital Mammography

The purpose of noise is to remove noise from the mammogram picture. It is a step of the pre-processing of mammogram images. It is essential to increase the quality of further steps. Mammogram images are very complex for analysis but results for mammogram images must be perfect. To enhance the quality of the picture and to make the outcome of results perfect some pre-processing is essential.

Noise can be initiated in the images at the time of acquisition. Noise can affect the results. Eliminating noise from the medical picture is a very important and difficult process in medical image processing. In medical fiend, doctors need a noise-free image to analyze diseases. There is a large number of filters to remove noise.

Noise:

Noise generally denotes an imbalance in the brightness of the image that may be generated while capturing images. Noise can produce some unwanted effect on the acquired image and image can lose its original content. There are mainly three types of noise such as salt and pepper noise, Gaussian noise, and speckle noise that can influence mammogram pictures, which can affect fine diagnosis and correct description of the mammogram image generated from digital mammography. Due to noise, incorrect analytical results can be produced. Noise present in the mammogram can influence the complete procedure of mammogram images. It is introduced at the start in the image so the effect of it can generate unknown effects in later stages. THEREFORE, the removal of this noise is very essential in mammography. There are mainly three types of noises in a mammogram, which are as follows:

1. **Salt & pepper noise**

   Salt and pepper noise constitute dark pixels in the position of bright pixels and they constitute bright pixels in the position of the dark pixel. It will generate a black and white spot in the picture [15, 35]. The intense and unexpected modification of the picture will generate salt and pepper noise [8]. It introduces alteration. It is also named projection noise and spontaneous noise

2. **Gaussian Noise**

   Gaussian diffusion is followed by this noise. It has a supplement character. This has a Gaussian distribution. It is a normal disrupting density function [11]. This noise has many types. One of the important types is white Gaussian noise. In the white Gaussian noise, value is not dependent. To make computation easy, extra white Gaussian noise is introduced sometimes.

3. **Speckle noise**

   Speckle noise generally influences the radar pictures. This noise generates picture quality Mortification. In a radar system, the light that is reflected from an instance generates random variation in the system [10]. It can lead to rigorous noise. Speckle noise will result in an enhancement of the grey signal in the image. It will introduce some problems for picture explanation in SAR pictures. The consistent processing of the rays that are scattered back from several assigned targets is the important cause of this.

Noise removal is done using different filters. There are mainly five types of filters, which are explained as follows:-

2.4.1 Mean Filter:

This filter is to enhance image quality. It is also named the average filter. In the average filter, each pixel is replaced with the mean intensity value of pixels in neighbourhood mass [24].

The average filter is used to improve the images that are destroyed by compulsive noise. These filters just shatter or weaken the noise not remove it. The mean filter can only cultivate local fluctuation in a picture. Noise is removed and as an outcome the picture cultivated but edges in the picture become a blur. Mean Filter as low pass filters. It means they remove noise at high intensity. Mean filters are the simplest filter among all the filters. Here for average we generally take 3*3 neighborhood mass.

We can use 5*5 neighborhood mass for better smoothening of the image. If S_{xy} is the mass of rectangular shape of size x*y having center pixel at point (x, y). Then noise is removed to get the original image at point (m,n) is explained as:

$$H(a,b)= (1/mn)\sum_{(s,t)\in Smn} g(S,t) \tag{6}$$

Here g(m,n) denotes the noisy image. H(a,b) is the filtered image using the mean filter. In the mean filter in place of arithmetic mean geometric mean value is also used sometimes to remove noise. It gives good results for salt noise. In this, each pixel is replaced with the geometric mean of its neighborhood pixels. Harmonic mean can also be used in place of arithmetic mean to remove noise. Here pixel value is replaced with the harmonic mean of its neighborhood pixel. This does not perform well for salt and pepper noise.

Advantage of mean filter:

- This filter is the simplest. It can be easily understood.
- The implementation is very easy.
- Mean filter gives the best result for short disturbance for example uniform noise and Gaussian sorted noise. It distributes this type of noise effectively.

Disadvantages of mean filter:

- Mean filter uses mean to remove noise in the picture. The mean value is affected by very high or very low-intensity values present in the picture. A pixel with very high intensity can increase median to a large extent and a pixel with very low-intensity value can reduce the mean intensity to a very small value.
- At the time of mean filtering when the pixel value of edge pixel is replaced with the mean intensity of its neighborhood pixel. It will introduce blurring in the edge.

2.4.2 Median Filter

Order static filters generally perform ordering of the pixels present in the neighborhood mass. A median filter is also a type of order static filters. This is mainly to abolish the drawback of mean filters. This is used to eliminate noise from the images. It performs well to remove salt and pepper noise [26]. In this, each pixel is substituted with the median brightness value of pixels in neighbourhood mass. Neighbourhood mass is generally of size 3*3 [28]. This filter has one main advantage that is it preserves edge sharpness of the image.

Median is more stable as compared to mean. The mean value of neighbourhood pixels can be affected by the lowest and highest pixel value of any neighbour and it can affect the sharpness of edges. This filter can connect images because here edges are not affected. This generally removes impulse noise.

This removes noise without producing blurring in the picture. nonlinear. Median filter does not affect the edge and preserves its smoothness. The size of neighbourhood mask in the median filter affects its performance. If we take a small neighbourhood mask than it, conserve the attribute of the image but it can reduce the noise regression.

If we take large, size of neighborhood mask than it will give high noise regression but picture features are less preserved. At the edges, neighbourhood mask size must be small so that each value in the window can be taken. Due to enhancement in median filters, some new types of median filters developed which are weighted median filter, adaptive median filter, threshold median filter, rank order median filter, and some more advanced filters. It is a non-linear filter. The filter is mathematically formulated as:

$$X\,(m, n) = \mathrm{med}_{(s,\,t)\,\in S_{mn}} \{g(s, t)\} \tag{7}$$

Here g(s, t) denotes noisy image, and X (m, n) is the filtered images of the size m*n.

Advantages of median filter:

- The median value is better than mean because the median value is not affected by a very high pixel intensity or a very low pixel intensity value in the neighborhood mask. This uses the median.
- The median value uses the value of one of the neighborhood pixels for replacement, so it does not create an unexpected or unreal value for replacement.
- The median filter does not affect edges' sharpness. This filter does not introduce

blurring in the edges and preserves sharp edges.

Disadvantages of median filter:

- It uses the median for replacement so there must be a good median finding algorithm so the best result can be obtained. After finding the median value it is not checked that whether the median pixel is noisy or not.
- In the case of a large image having several pixels, it is difficult to decide where to end the median selection process and the process becomes complex.

2.4.3 Adaptive Median Filter

It is a modified form of the median filter. This is an order static filter. It is used to improve the non-repulsive disturbance produced by any signal. This filter also preserves the sharpness of edges. Adaptive filters take mass in the rectangular neighbourhood [24]. Adaptive median filter does not affect curves, or we can say it does not shrink or widen their limits. It is a non-linear filter. The adaptive median filter uses spatial filtering to find out the pixels with impulse noise in the neighbourhood and then replace the value of only these pixels with a median intensity value of neighbourhood pixels [23].

The threshold of impulse noise and neighbourhood size can be changed in adaptive median filtering. This filtering technique has the advantage that it reduces variation in all pixels and just change only the required pixel. In the adaptive median, each pixel is checked if this value is less than the minimum grey level or greater than the maximum intensity of the image that it is a noisy pixel. Then it is substituted with the median of neighbourhood. Therefore, the adaptive median filter does not change an unnoisy pixel. It conserves the originality of the image and grey intensity of the picture.

According to the noise solidity, the size of neighbourhood mask is altered in an adaptive median filter. Here at each level, we can change the neighbourhood mass size. Suppose X_{min} minimum intensity. X_{max} is of maximum intensity. If our pixel value X_a is in between X_{min} and X_{max} than it remains unchanged, otherwise it is replaced with X_{mid}, which denotes the median value of neighbourhood pixels. Denoising the picture, it also decreases changes in the picture.

Advantages of the adaptive median filter:

- This filter does not need any matrix operation or any mean operation.

- This filter only changes noisy pixels in the image so it conserves the naturalness. This keeps it real and does not insert a nonrealistic or unexpected value.
- In the adaptive median filter, neighborhood mask size is not definite, we can change it during the process. Because of this, it works well for nonstationary pictures.

The disadvantage of the adaptive median filter:

- It does not use a fixed value for replacement. To handle different values a stability algorithm is required.
- The adaptive median filter becomes complex at the time of two-dimensional images or multidimensional pictures.
- This filter considers only the nearest impulsive pixel.

2.4.4 Wiener Filter

Wiener filters are upper-level filters. Weiner filter first performs inverse filtering to reduce the additive noise. Inverse filtering can produce some noise in the image. Then to remove this noise smoothing is performed. There is an unknown signal in the image that affects the pixels and produces noise. Weiner filtering is a definite filter. These filters either destroy disorganized parts or rebuild them [18]. Weiner filter does not of the image and it refines clarity.

In this filter, we take pictures and noise as a non-linear variable. Wiener filtering technique combines abasement function and analytical behavior of noise into filtering procedure. $Y^{\wedge}$ is the minimum MSE. The main purpose is finding an approximate function $Y^{\wedge}$ of the filtered picture Y. The equation to find the error is:

$$err= E\{(Y-Y^{\wedge})^2\} \tag{8}$$

Frequency domain $Y^{\wedge}$ is given by:

$$Y^{\wedge}(c, d) = [H^*(c, d)\, S_x(c, d) / \{ S_x(c, d)|\, H(c, d)|^2 + S_n(c, d)\}]\, G(c, d) \tag{9}$$

Wiener filter is a linear type filter. This is for additional noise and blur. The filtered image is defined as:

$$F(c, d)= Wi(c, d)\, U(c, d) \tag{10}$$

U(c, d) is the input image.

Advantages of wiener filter:

- Wiener filter considers and gives importance to the original picture and the noise for measurement.

- This gives the best results for the blurred images or to remove additional noise.
- Wiener filter analyzes both noise and the abasement function.

The disadvantage of the wiener filter:

- Wiener filters generally give point to point estimates. There is not any fixed estimate function. In this, some assumptions need to be made.
- Mean square error does not always give efficient and related information of the image.
- It does not perform well for noises, which are dependent on signal [27].

2.4.5 Gaussian Filter:-

Gaussian filters are invariable filters. These are low pass filters. Gaussian filters are a type of time-domain filter. The Gaussian function uses a Gaussian function. These functions work according to time so the delay does not happen in these. This filter restricts high and low signals form malformation [20]. In Gaussian filters, Gaussian smoothing is performed. Gaussian smoothing is performed on the images using Gaussian capacity. It is a convolution filter. It removes the ingenious element. Gaussian filters perform worse for salt & pepper noise.

The Gaussian filter can be a low pass or high pass. This removes noise and performs smoothing on the picture. The Gaussian filter uses a Gaussian. This can be defined as:

$$N(a)= (1/\sqrt{2\pi\sigma^2})\, e^{-a2/2\sigma 2} \tag{11}$$

Here σ denotes the standard deviation for the image. For picture two dimensional function used which is as follows:

$$N(a, b)= (1/\sqrt{2\pi\sigma^2})\, e^{-a2+b2/2\sigma 2} \tag{12}$$

Gaussian filter use two-dimensional function as the point function for each pixel. For Gaussian filtering, it, twine this two-dimensional function with the picture. The gaussian filters also perform smoothening along with removing noise from images.

Advantage of Gaussian filter:

- This uses a Gaussian function for filtering. This function has just multiplication and addition operation so the Gaussian filter is very fast in performing filtering. It takes very little time compared to other filters.
- The Gaussian function performs smoothing to remove Gaussian noise. Here smoothing

is bounded by σ function.

- Gaussian filter is symmetric and performs work in the same direction. This filter reduces edge blurring in the image.

Disadvantages of Gaussian filter:

- Gaussian smoothing function can introduce noise in the image.
- By using this filter naturalness of the image is not preserved. Gaussian filter decreases the details in the picture.
- Gaussian filters are very complex to use.

2.5 Contrast Enhancement

It is used to increase contrast for the picture concerning the background so that human eyes can see all the details. In digital mammography, we use x-rays and the density of these rays decides the details in the mammogram in the image. Digital mammography has low contrast images. By using these images doctor is not able to identify breast cancer at an early stage. In the later stage, the patient has to suffer a lot of pain, and the chances of his recovery decrease.

Necessary information is present in high contrast area of mammogram while low contrast is contained unnecessary information. Contrast enhancement increases the high contrast of the image and also reduce unnecessary information. Contrast enhancement gives better visualization. Digital mammography uses digital technology to get the image. Therefore, we can use a contrast enhancement technique for these digital pictures. The contrast enhancement technique increases the contrast in the breast parts so that breast cancer can be detected as an early stage.

Contrast enhancement techniques also increase contrast at the edge along with preserving their sharpness. We can get full details of the suspected part clearly after applying contrast enhancement. These are of two types, one is direct contrast enhancement and second is indirect contrast enhancement.

2.5.1 Indirect Contrast Enhancement

The indirect contrast enhancement technique cannot directly increase the contrast. This technique first modifies the histogram. By doing this, these techniques directly increase the contrast of the image. There is five indirect contrast enhancement technique, which is as follows:

2.5.1.1 Histogram Equalization:

Histogram equalization is an indirect contrast enhancement technique. It maps all input levels of the image to one grey level based on the cumulative density of that input level [13, 25]. The probability of all grey levels is uniformly distributed in the output image [21].

Histogram equalization technique is to alter image brightness to increase the contrast of the picture. Histograms are the frequency of various grey levels in the image. Suppose we have an image X which have intensity values from 0 to t-1. The probability density function is explained as:

$$P_{(L\_k)} = n\_g / n \tag{13}$$

Here $P_{(L\_K)}$ denotes probability density function. Here n denotes the total number of having a value from 0 to t-1. L_k denotes g^{th} grey level. Here $n_{\_g}$ denotes total pixel at grey level L_k.

The mathematical formula for histogram equalization is defined as:

$$I_0 = \text{histeq}\,(I_i) \tag{14}$$

I_i is the image obtained after applying HE on the image I_0 . Here ‘histeq’ is the function that performs histogram equalization on the image.

Advantages of histogram equalization

- This technique has simple calculation and it needs less time. HE is the fastest contrast enhancement technique.
- It is a basic technique.

Disadvantages of histogram equalization:

- Histogram equalization allocates one intensity value to two pixels having different intensity. This technique assigns one high-intensity value to every pixel. We can say at all grey levels the same intensity value present. This will erase the appearance of some object in the image having very low-intensity value.
- HE can introduce variation in the intensity of the picture to get a high value of the consistently distributed picture.
- HE technique uses global contrast instead of local contrast. The resulting image looks unnatural and introduces visual artifacts in the picture.

2.5.1.2 Contrast Limited Adaptive Histogram Equalization (CLAHE) Technique:

CLAHE is an indirect technique. It is an advanced form of adaptive histogram equalization [13, 16, 32]. This is generally used for low contrast images. This technique first divides the input image into several disjoint images that do not overlap each other. In this technique slope of the function used for transformation, depending on the height of the histogram. Then all histograms of these disjoint images are clipped to a limit. This clip limit is used to determine the amount of noise, which needs to be smoothened. Clip limit also used to determine contrast, which is to be enhanced.

Clip limit reduces noise amplification, which can be introduced by this technique. Clipping limit is used to bound the upper range of enhancement of every pixel [4]. An average number of pixel is:

$$P_{avg}=P_{CR-X} * P_{CR-Y})/ P_g \qquad (15)$$

Here P_{avg} denotes the average number of pixels. P_g denotes the grey level of the image. P_{CR-X} denotes pixels in the direction X of the contextual region. P_{CR-Y} denotes pixel in direction Y of the contextual region.

Histogram equalization is performed on all the disjoint images. CLAHE technique applied to small sub-images. These images are merged using operation. CLAHE technique enhances both the foreground and background. All the details are very clear concerning the background [22].

$$Img_0 = adapthisteq\ (Img_i) \qquad (16)$$

Where Img_0 is output image and Img_i is the input image. Here 'adapthisteq' is the function used to perform CLAHE. CLAHE technique is complex because the function is performed recursively.

Advantages of the CLAHE technique:

- CLAHE technique is used to reduce noise amplification which is not removed by adaptive histogram equalization.
- Grey level is changed in this. This technique is applied to small sub-images compared to a complete image.
- This technique enhances the contrast till a range.
- CLAHE technique enhances the background with the foreground. So this technique gives an image with a natural look.

Disadvantages of CLAHE technique:

- The CLAHE technique is very expensive.

- This is complex because the recursive operation implemented and the results of the recursive operation are stored.
- CLAHE technique is time-consuming because of sequential recursive operation.

2.5.1.3 Brightness Preserving Bi-Histogram Equalization (BBHE)

It is an indirect contrast enhancement technique. BBHE technique bifurcates the image by using the mean brightness as the base [12, 13]. The first sub-level image contains pixels having intensity value from zero intensity to mean intensity of the original image and the other sub-level images contain pixels having intensity value-form mean intensity to max intensity.

After bifurcating original images, the BBHE technique independently performs histogram equalization on both sub-level images. After histogram equalization of both the images, this technique performs a union of both sub-level images and gives brightness preserved contrast-enhanced image [1].

Suppose Y_mean is the mean intensity of the image Y. Here this image Y can be represented as {Y_0, Y_1, ….., Y_L-1}, where Y_0, Y_1, ….., Y_L-1 are pixel intensity values in non-descending order. Here Y_0 and Y_L-1 are the lowest and highest intensity of the image Y. This bifurcated into Y_S and Y_U. For the formation of two sub-level images transform functions are defined as follows:

$$X_L(Y) = Y\_0 + (Y\_mean - Y\_0)\, C_L(Y) \tag{17}$$

$$X_U(Y) = Y\_mean{+}1 + (Y\_L{-}1 - Y\_mean{+}1)\, C_U(Y) \tag{18}$$

Where $C_L(Y)$ and $C_U(Y)$ are cumulative density functions for Y_S and Y_U respectively [4]. The mathematical formula for cumulative density function is:

$$C(Y)=\sum_{m=0}^{L-1} P(Y\_m) \tag{19}$$

Where Y_m is the image's intensity at different pixel values such as m, which is normalized to [0, 1]. P(Y_m) is the probability density function for Y_m intensity. The equation for probability density function is:

$$P(Y\_m) = t^m / t \tag{20}$$

Here t^m denotes the number of pixels having intensity value Y_j and t denotes the total pixel. The output image of BBHE technique is as follows:

$$\text{outputimg} = X_L(Y\_S) \cup X_U(Y\_U) \tag{21}$$

Here 'outputimg' is the resultant image obtained by applying the BBHE technique. Here we perform union of both sub-level images to get the resultant image. The disadvantage of this method is that it does not preserve brightness. The advantage is that it is simple and it does not perform equalization recursively.

Advantages of BBHE technique:

- This enhancement algorithm preserve brightness of the image along with contrast enhancement.
- This technique takes less time because just average operation needs to perform. Along with this, some multiplication and the additional operation performed that do not take more time.
- BBHE technique is easy to implement. It does not contain any complex operation.

Disadvantages of BBHE technique:

- Brightness preservation is not able to remove some artifacts from the image.
- In this technique for brightness preservation mean brightness is used, mean brightness value can be affected by a very large intensity value of any pixel or very low-intensity value of any pixel. So this value can become very small or very large and can affect the contrast of the image inappropriately.

2.5.1.4 Recursive Mean-Separate Histogram Equalization (RMSHE)

It is an indirect contrast enhancement technique. This technique first separate mean then perform histogram equalization. This technique gives better contrast enhancement for the mammogram images. This technique has better brightness preservation also [1, 14]. RMSHE first bifurcates the original image by using the mean intensity. After separation, this technique performs histogram equalization on both the images.

However, as the BBHE technique, it does not stop here; this technique does mean separation recursively. Every time it does mean separation, it will get a better image. We can say that more mean separation gives a better image. RMSHE technique is the same as the BBHE technique if only one time mean separation is done. When mean separation is done only once then mean is calculated using the formula:

$$R(Y) = (I_M + I_G) / 2 \quad (22)$$

Here R(Y) is the output mean value. I_M denotes middle-intensity value and I_G is the input mean value. However, to get more brightness preservation we divide the mean further. Now Image I is separated into four portions using two median histogram I_{ML} and I_{MU}.

$$I_{ML} = 2 \int_{I0}^{Im} iP(i)di \quad (23)$$

$$I_{MU} = 2 \int_{Im}^{Il-1} iP(i)di \quad (24)$$

Here Io is the minimum intensity value, Im denotes mean intensity value, and I_{l-1} denotes maximum intensity value. After that output means at the second level is calculated with the help of the mathematical formula:

$$R(Y) = ¼ \{R (Y| I<I_{ML}) + R (Y| I_{ML} < I <I_M) + R (Y| I_M < I < I_{MU}) + R (Y| I > I_{MU}) \quad (24)$$

This indicates output mean value at the second level. In the same way, we can further get another mean and divide the image into different sub-images. Perform histogram equalization on these images. After histogram equalization, all images are merged using union operation.

Advantages of RMSHE technique:

- RMSHE technique removes all the artifacts which are not needed and introduces noise in the image.
- RMSHE technique performs natural increment in contrast.
- RMSHE technique increase the contrast up to an efficient limit.

The disadvantage of RMSHE technique:

- This technique is very complex. When one recursion level is increased then the time complexity increase. So it is a very time-consuming process.
- RMSHE technique has uncertain recursive separation. An image can need recursion till level two or till more than two.

2.5.2 Direct Contrast Enhancement:

These techniques directly increase the contrast of the image. These techniques do not use any other function or feature for contrast enhancement. SO here, contrast is modified directly. There is following direct contrast enhancement techniques:

2.5.2.1 Adaptive Fuzzy Logic Contrast enhancement

It is a direct contrast enhancement technique. Nowadays, the fuzzy set theory has been performed on the images for contrast enhancement, removing noise, and spatial filtering. In the fuzzy set theory for fuzzy processing, there are three steps:

- Image Fuzzzification
- Membership modification
- Image defuzzification

First, fuzzification is done. Membership functions are of various types [6]. These for fuzzification is based on brightness, edginess, texture, homogeneity. After that, some fuzzy technique is implemented to modify the plane. According to the requirement, the appropriate technique is chosen. This step is the most important in the fuzzy set theory. After this defuzzification is done. This is the last step. In this step, the modified fuzzy plane is transferred back to the original plan that has modified grey levels [30].

So Fuzzy logic has mainly this three-step. These three-step results in a contrast-enhanced image. The fuzzification algorithm can use different membership functions for enhancement. It has an important role in this technique.

Advantage of adaptive fuzzy logic contrast enhancement technique:

- The Fuzzification technique gives better enhancement for high contrast images.
- This technique uniformly distributes pixels in the histogram of the image.
- It improves the lesion of the breast. This technique performs contrast enhancement on a single threshold for the image

Disadvantages of adaptive fuzzy logic contrast enhancement:

- This technique does not perform well for poor contrast images. This technique will reduce edge information and make them lost.
- This technique is very complex. The selection of the membership function for fuzzification is very confusing and time-consuming.

2.5.2.2 Contrast Stretching Enhancement Technique

It is an indirect contrast enhancement technique. Contrast stretching is a type of normalization. It is a basic and easy image enhancement technique. This technique performs stretching on the range of intensities.

The quality can be improved by stretching the intensity range. This technique replaces each intensity value with the modified value. The contrast stretching technique enhances the brighter portion of the image as well as the darker portion. It enhances the contrast of the complete image. To perform stretching this technique specifies limits of upper pixel value on which normalization is performed, it also specifies limits of lower pixel value for normalization of the image. Suppose s is the lower limit and t is the upper limit. In this technique, we need to find the minimum and maximum pixel. Suppose l is the lowest pixel value and h is the highest pixel value. Then every pixel K is modified using the following equation:

$$K_L = (K_0 - l)\ (t-s/\ h-l) + s \tag{25}$$

K_L is the pixel obtained by scaling input pixel K_0. In this technique, outliers can cause problems. For example, l and h can be affected by very high pixel value or very low pixel value and could result in unreliable scaling. The advantage is that it improves contrast in the image without distorting grey levels.

Advantages of contrast stretching technique:

- Contrast stretching technique is easy to implement and this technique does not consume more time.
- This technique provides an enhancement in the contrast to a great range. It improves the contrast of the image without destroying the grey level.
- This technique provides great contrast enhancement for both high contrast and poor contrast images.

Disadvantages of contrast stretching technique:

- This technique uses the minimum and maximum pixel value for the enhancement, the maximum and minimum pixel value can be affected by an outlying pixel. Then this technique will give unrealistic enhancement.

CHAPTER-3

MBHE CONTRAST ENHANCEMENT TECHNIQUE AND MODEL FOR PREPROCESSING OF MAMMOGRAM IMAGES

This model describes a newly proposed technique named median-based brightness conserving bi-histogram equalization technique. Here one proposed model is also described which is used for pre-processing of mammogram images. After that, one more proposed contrast enhancement technique named recursive median-based brightness preserving bi-histogram equalization technique is explained.

3.1 Median Based Brightness Conserving Bi-histogram Equalization (MBHE) Contrast Enhancement:

It is an indirect contrast enhancement technique motivated by BBHE. The proposed technique bifurcates an image using the median brightness. In high contrast, varying images mean value can change drastically because of very low pixel intensity or very high pixel intensity. Brightness preserving the bi-histogram technique will not give good results for distorted contrast images.

Different low and high values can affect the mean but not median. Median is not affected by the very low and very high value of pixels. Therefore, in the newly proposed technique, the median is used to bifurcate the image such that one sub-level image contains pixels having intensity value from zero intensity to median intensity value. Another sub-level image contains pixels having intensity value-form median intensity to maximum intensity of the original image. After bifurcating the original images, the MBHE technique independently performs histogram equalization on both sub-level images. After histogram equalization of both the images, this technique performs a union of both sub-level images and gives better brightness preserved contrast-enhanced image.

Suppose Y_{mean} is the mean intensity of the image Y. Here this image Y can be represented as $\{Y_0, Y_1, \ldots, Y_{L-1}\}$, where $Y_0, Y_1, \ldots, Y_{L-1}$ are pixel intensity values in non-descending order. Here Y_0 and Y_{L-1} are the minimum and maximum intensity value of the original image Y. The original image is bifurcated into images Y_S and Y_U. For the formation of two sub-level images transform functions are defined as follows:

$$X_L(Y) = Y\_0 + (Y\_mean - Y\_0)\, C_L(Y) \quad (1)$$

$$X_U(Y) = Y\_mean+1 + (Y\_L\text{-}1 - Y\_mean+1)\, C_U(Y) \quad (2)$$

Where $C_L(Y)$ and $C_U(Y)$ are cumulative density functions for Y_S and Y_U respectively [3]. The mathematically formulated for cumulative density function is formulated as:

$$C(I)=\sum_{m=0}^{L-1} P(Y\_m) \quad (3)$$

Where Y_m is the intensity of the image at different pixel values such as j, which is normalized to [0, 1]. P(Y_j) is the probability density function for Y_m intensity. The mathematical formula for probability density function is:

$$P(Y\_j) = n^m / n \quad (4)$$

Here n^m denotes the number of times for which intensity Y_m appears and n denotes the total pixels. The output image of BBHE technique is as follows:

$$outputimg = X_L(Y\_S)\ U\ X_U(Y\_U) \quad (5)$$

Here 'outputimg' is the resultant image of the BBHE technique. It is obtained by performing the Union of two sub-level images. This resultant image shows that all the details in this are very clear. In the experiment and result section table and images are shown to show the result and quality of the proposed work.

3.2 Model for Pre-processing of Mammogram Images:

A proposed model for pre-processing of mammogram images. Pre-processing contains mainly two steps, the first one is Noise and the second is contrast enhancement. First, we apply different filters to remove different noise from different images and perform a comparison of all these filters. After comparison, the best filter of mammogram images is purposed. After that, apply different techniques on different images and perform a comparison of all these techniques. Based on the result of these techniques the best technique for contrast enhancement is purposed. The proposed model is represented in Figure 3.1.

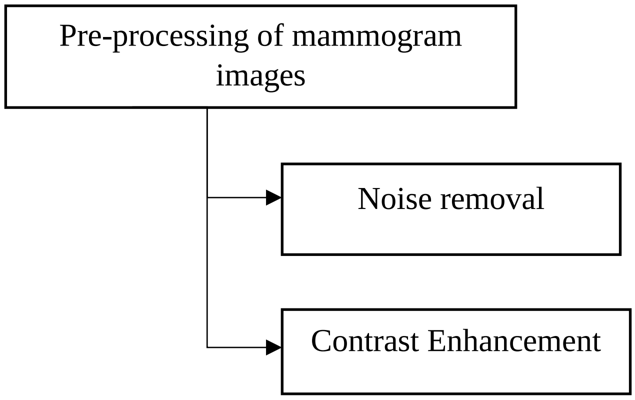


Figure 3.1: Model for pre-processing of Mammogram images

3.2.1 Noise Removal:

For noise removal from mammogram images, several filters are developed. To decide the best filter technique, a comparison of different filters is done to remove three types of noise first one is salt & pepper noise, second is Gaussian noise, and the third is speckle noise.

3.2.1.1 Removal of Salt and Pepper Noise:

Here Comparison of different filters for salt and pepper noise is performed. Salt & pepper noise is introduced to mammogram image mdb021. Figure 3.2(a) represents a mammogram image mdb021 and Figure 3.2(b) represents a noisy image with salt & pepper noise. Different filters are applied to remove noise in the noisy image. At first mean, the filter is applied. Figure 3.3(a) represents a filtered image using the mean filter. This technique removes salt & pepper noise from the image but introduces some blurring.

After that, the median filter is applied. Figure 3.3(b) represents the result of the median filter on the noisy image. This filter removes noise from the edge. It also protects the edges. After that wiener filter is applied to noisy mammogram images. Figure 3.3(c) denotes the result of the Wiener filter. This filter gives less good results than the median filter. After that, the Gaussian filter is applied to the noisy image. Figure 3.3(d) represents a filtered image using the Gaussian filtration technique. The Gaussian filter gives worse results than the median filter but better results than the Wiener filter. At last, the adaptive median filter technique is applied on mammogram images. Figure 3.3(e) represents the result of the adaptive median filter on a noisy image. This technique gives a better result than a wiener filter but less good results than a medianfilter.

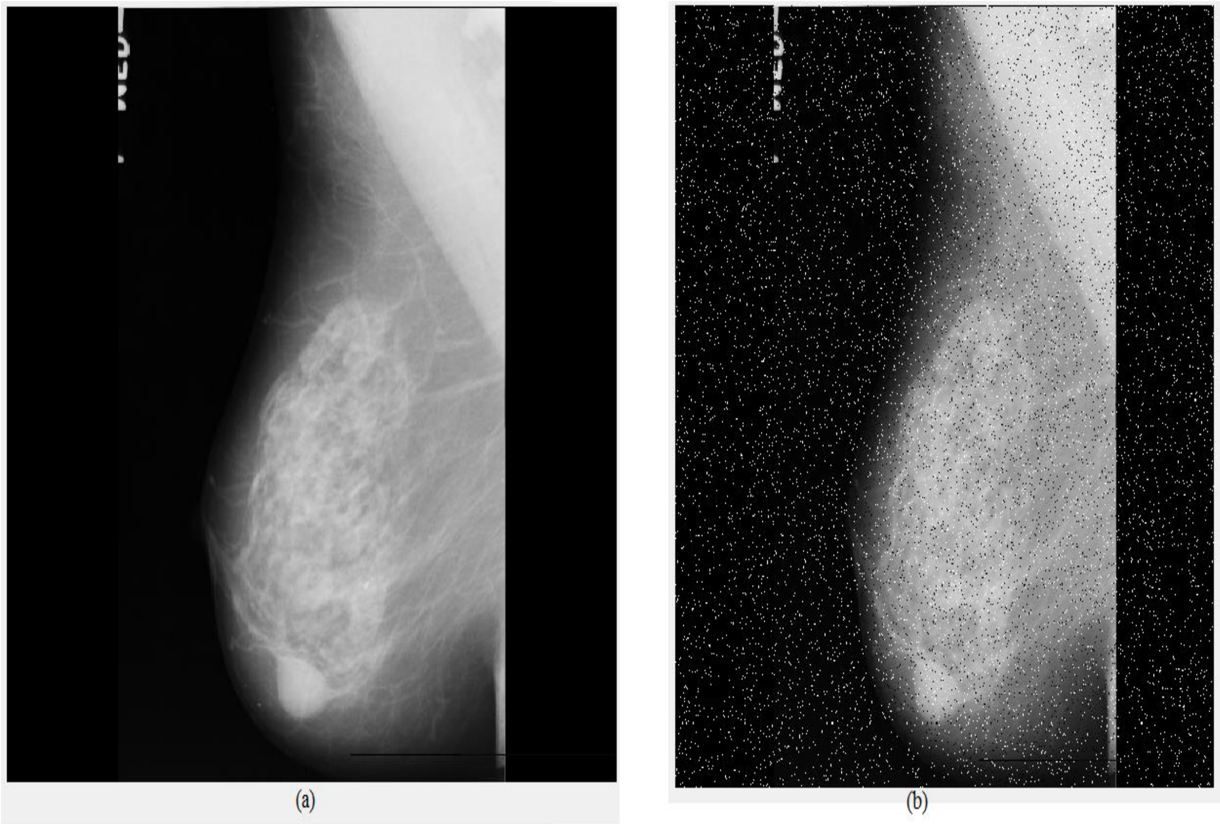


Figure 3.2: (a) Original image (b) Image with Salt & pepper Noise

From Figure 3.3, it can be concluded that the median filter gives the best result for all the images. However, by visual specification complete and specific characterization can not be obtained. Although there is no parameter or method that can give both subjective and objective specialization. For a better analysis of all the techniques, two quality parameters are used such as mean square error (MSE), peak signal to noise ratio (PSNR) to evaluate the performance of different filter techniques. All filters are applied to the number of images and their performance is evaluated using MSE, PSNR.

Mean Square Error (MSE): MSE finds out the average of the squares of the difference of pixel values in both the images. MSE is a risk function also known as mean square deviation. Smaller the value of MSE better the quality of the image and vice versa.

$$\text{err} = \text{immse}(A, B) \tag{6}$$

Here 'immse' is the function used in matlab to find mean square error for the image A and B. we find error between two images by using the following mathematical formula:

n

$$MSE = (1/n) \sum_{i=1} (Ai\text{-}Bi)^2 \tag{7}$$

A_i and B_i denote ith pixel of images A and B. Here n denotes the number of pixels present in the input image.

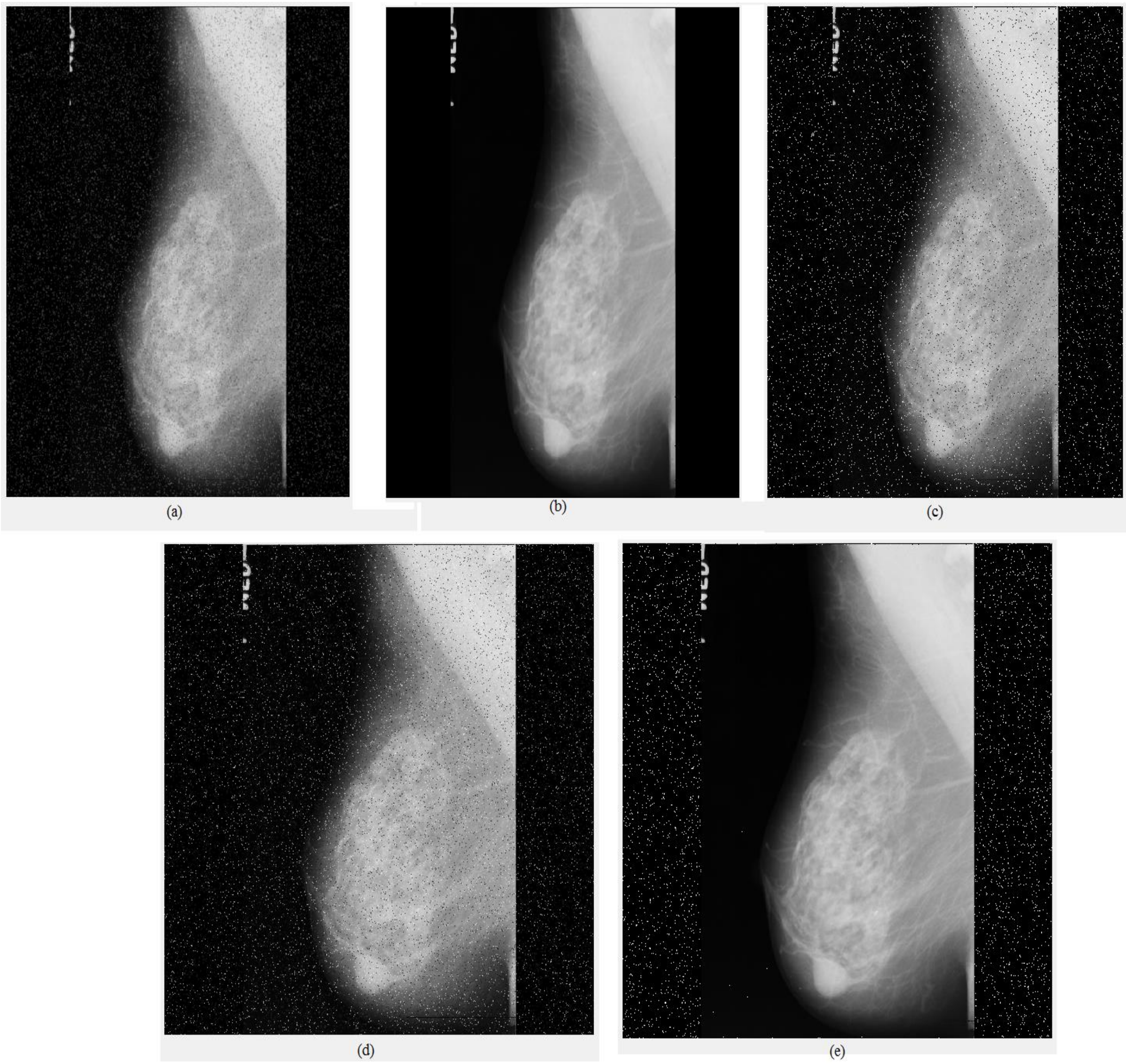


Figure 3.3: (a) Filtered image using a mean filter (b) Filtered Image using a median filter (c) Filtered image using Wiener filter (d) Filtered image using Gaussian filter (e) Filtered image using Adaptive median filter

Peak Signal to noise ratio (PSNR): High value of PSNR shows a smaller contrast amongst original and enhanced images. PSNR quantifies peak error and compares image compression quality. Small PSNR value indicates poor image quality. The high PSNR indicates good image quality.

The equation for calculation of PSNR is:

$$PSNR = 10 \log 10(R^2/M) \quad (8)$$

M is the MSE value in the image. Here *R* denotes the highest fluctuation present in the image or we can say that this is the highest possible pixel value. For images that represent pixel with 8 bits per sample, R is 255. R can be calculates using the formula:

$$R = 2^B - 1 \quad (9)$$

Here B denotes bits value per sample by which pixel of the images is represented.

Table 3.1 Performance of different filtering technique on salt & pepper noise based on MSE

Image	Mean Filter	Median Filter	Wiener Filter	Gaussian Filter	Adaptive median filter
Mdb021	187.6783	10.5368	882.8581	574.8692	607.7793
Mdb002	183.9288	2.3757	908.4810	584.7641	797.9859
Mdb013	187.9867	8.2458	911.2782	587.4212	940.3420
Mdb004	188.1851	2.1882	918.7332	595.6718	723.4214
Mdb005	168.7252	5.3548	790.7730	535.0644	687.0819
Mdb007	186.0374	10.0985	882.0239	576.5872	844.5588
Mdb014	181.4724	1.6647	887.8774	575.4914	840.9739

Table 3.1, Table 3.2 shows the results of all filters for salt and pepper noise. On analyzing table 3.1, it is observed that the median filter gives the least mean square error value for all images among all the filter techniques. After the Median filter, the mean filter and Gaussian filter gives good results for salt and pepper noise.

Similarly, on analyzing Table 3.2, it is observed that the median filter gives the highest PSNR value for all images among every filter. For PSNR, the mean filter and Gaussian filter give good results after the median filter method.

Table 3.2 Performance of different filtering technique on salt & pepper noise based on PSNR

Image	Mean Filter	Median Filter	Wiener Filter	Gaussian filter	Adaptive Median Filter
Mdb021	25.3967	37.9037	18.6719	20.5351	20.2933
Mdb002	25.4843	44.3729	18.5476	20.4610	19.1109
Mdb013	25.3895	38.9685	18.5343	20.4413	18.3973
Mdb004	25.8300	44.7300	18.4989	20.3807	19.5369
Mdb005	25.8590	40.8434	19.1503	20.8467	19.6707
Mdb007	25.4348	38.0882	18.6760	20.5222	18.8645
Mdb014	25.5427	45.9173	18.6473	20.5304	11.1863

Thus, based on the performance analysis of MSE, PSNR it can be concluded that the median filter gives the best-filtered image for salt & pepper noise in comparison to mean filtering, Wiener filtering, Gaussian filtering, and adaptive median filtering.

3.2.1.2 Removal of Gaussian Noise:

Now, different filters are compared for Gaussian noise. It is applied to mammogram image mdb021, which is represented in Figure 3.2(a). Figure 3.4(a) represents the image with Gaussian noise. Different filters are applied to the noisy image to remove the noise. At first mean, the filter is implemented. Figure 3.4(b) represents a filtered image using a mean filter. This removes noise from the image but introduces some blurring.

Then the Median filter is implemented on noisy images. Figure 3.4(c) represents the result of the median filter on the noisy image. As we can see this filter removes noise from the edge and also protect edges of the image. After this, we apply a Wiener filter. Figure 3.4(d) denotes the result of the Wiener filter. This shows that wiener gives less good results than the median filter. Then Gaussian filter is implemented on the noisy image. Figure 3.4(e) represents a filtered image using a Gaussian filter. The Gaussian filter gives less good results than wiener filter and median filter, at last, we apply an adaptive median filter on mammogram images. Figure 3.4(f) represents the result of the adaptive median filter on the noisy images. This technique gives less good results than the median filter and Gaussian filter.

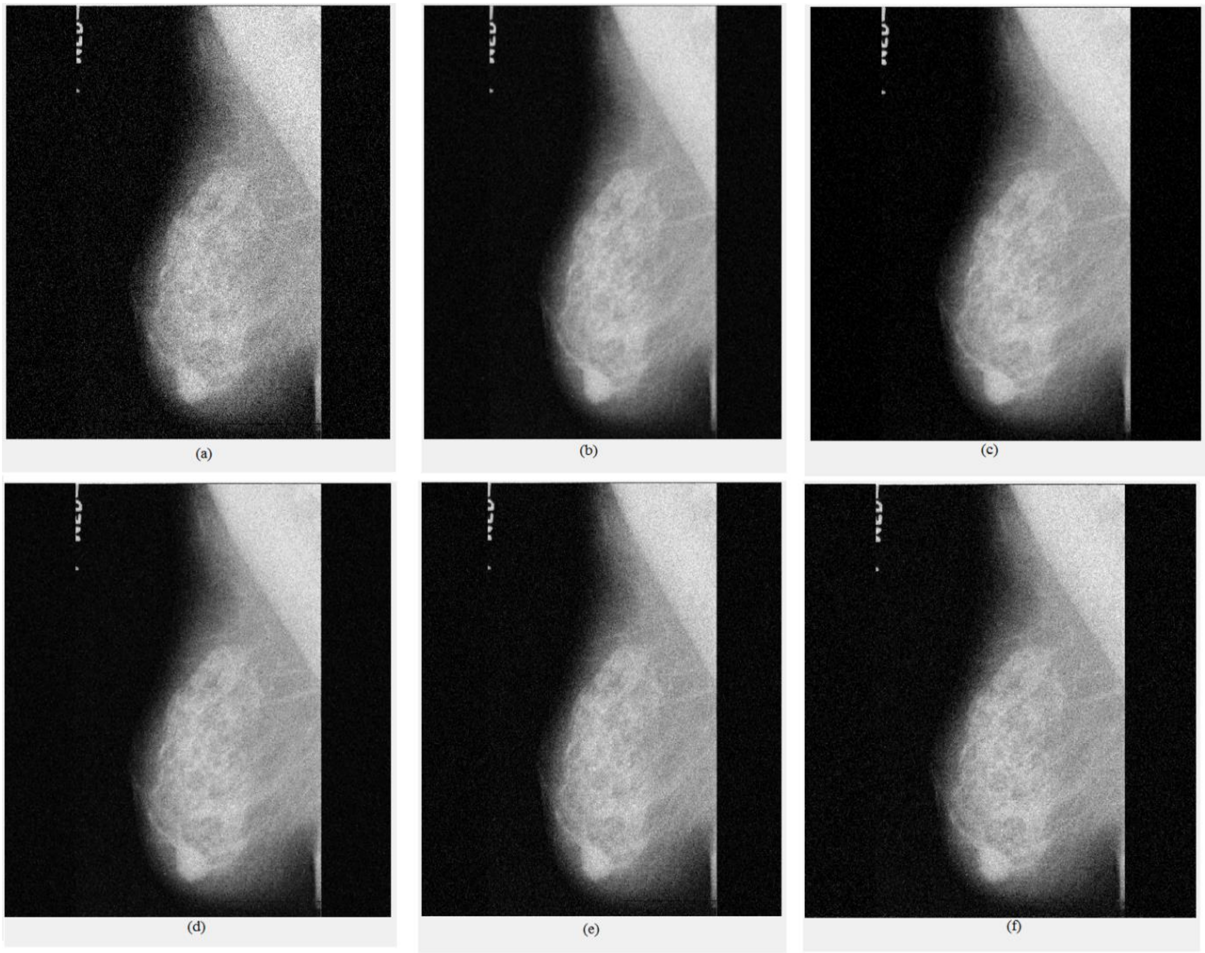


Figure 3.4: (a) Image with Gaussian noise (b) Filtered image using mean filter (c) Filtered image with median filter (d) Filtered image using wiener filter (e) Filtered image using Gaussian filter (f) Filtered image using the adaptive median filter

From Figure 3.4 we can conclude that the median filter gives the best result for all the images. However, by visual specification, we cannot get complete and specific characterization. Although there is no parameter or method that can give both subjective and objective specialization.

Here, for better performance analysis of all the filters we use two quality parameters: mean square error (MSE), peak signal to noise ratio (PSNR) to evaluate the performance of different filters. All filters are applied and their performance is evaluated using MSE, PSNR.

Table 3.3 Performance of different filtering technique on Gaussian noise based on MSE

Image	Mean Filter	Median Filter	Wiener filter	Gaussian filter	Adaptive median filter
Mdb021	111.7452	89.0810	148.0203	219.7880	252.1269
Mdb002	108.5012	79.1623	153.3113	216.1041	251.2762
Mdb013	115.6716	81.2949	157.4583	218.1062	253.7348
Mdb004	108.4977	78.4085	151.6226	216.7949	252.0015
Mdb005	104.4558	88.2655	149.6877	228.4751	262.5559
Mdb007	115.3828	85.0342	155.0982	219.3483	253.4015
Mdb014	110.0627	79.2175	154.5702	221.5587	256.1186

Table 3.4 Performance of different filtering technique on Gaussian noise based on PSNR

Image	Mean filter	Median filter	Wiener filter	Gaussian filter	Adaptive median filter
Mdb021	27.6485	28.6330	26.4276	24.7108	24.1146
Mdb002	27.7765	29.1456	26.2751	24.7842	15.0325
Mdb013	27.4985	29.0302	26.1591	24.7441	24.0870
Mdb004	27.7766	29.1872	26.3232	24.7703	24.1168
Mdb005	27.9415	28.6729	26.3789	24.5424	23.9386
Mdb007	27.5094	28.8349	26.2247	24.7195	24.0927
Mdb014	27.7144	29.1426	26.2395	24.6759	24.0464

Table 3.3, Table 3.4 shows the results of all filters for Gaussian noise. On analyzing Table 3.3, it is observed that the median filter gives the least MSE value for all images among all the filters. After Median filters, the mean filter and wiener filter gives good results for salt and pepper noise. Similarly, on analyzing Table 3.4, it is observed that the median filter gives the highest PSNR value for all images among all the filters. For PSNR, mean filter and Wiener filter, give good results after the median filter method.

Thus, based on performance analysis on MSE, PSNR it can be concluded that the median filter gives the best-filtered image for Gaussian noise in comparison to mean filter, wiener filter, Gaussian filter, and adaptive median filter.

3.2.1.3 Removal of Speckle Noise:

At last, we compare filters for speckle noise. This is introduced in the mammogram picture mdb021, which is represented in Figure 3.2 (a). Figure3.5 (a) represents the image with speckle noise. Now, we apply different filters to the noise image represented in Figure 3.5 (a). First of all, the mean filter is applied. Figure 3.5 (b) represents a filtered image using the mean filter. This shows that this removes noise but introduces some blurring.

Then the median filter is applied. Figure 3.5 (c) represents the result of the median filter. This shows that it removes noise from the image and also protect the edges. After this wiener filter is applied on a mammogram. Figure 3.5 (d) denotes the result of the Wiener filter. This shows that the wiener filter gives less good results than the median filter. After that, the Gaussian filter is applied to the noisy image. Figure 3.5 (e) represents a filtered image using Gaussian filtering. The Gaussian filter gives better results than a wiener filter but not better than the median filter. At last, an adaptive median filter is performed on a mammogram image.

Figure 3.5(f) represents the result of the adaptive median filter on a noisy image. This filter gives better results than a wiener filter but less good results than the median filter and wiener filter. From Figure 3.5 we can conclude that the median filter gives the best result for all the images. However, by visual specification, we cannot get complete and specific characterization. Although there is no parameter or method that can give both subjective and objective specialization.

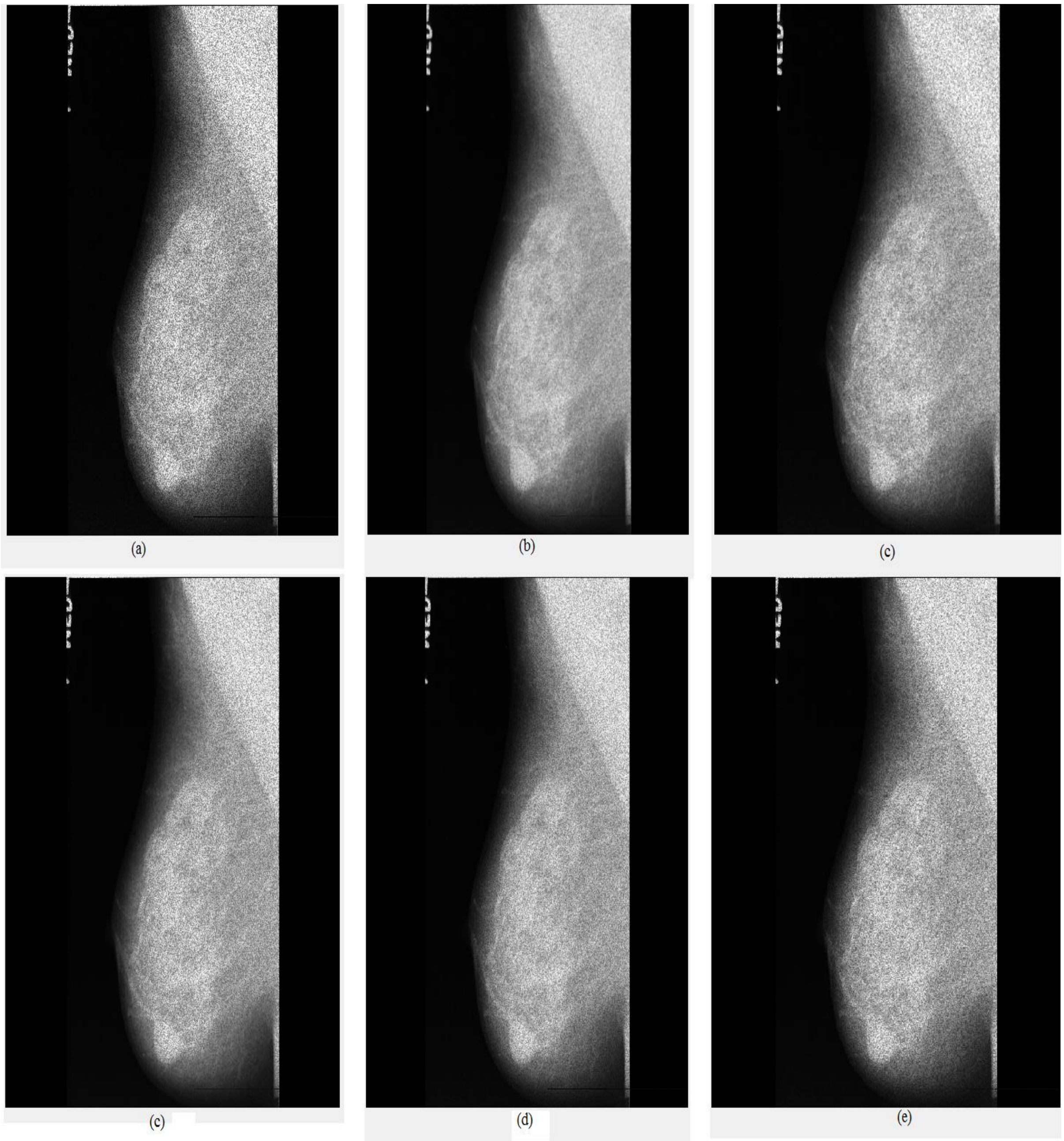


Figure 3.5: (a) Image with speckle noise (b) Filtered image using mean filter (c) Filtered image with median filter (d) Filtered image using wiener filter (e) Filtered image using Gaussian filter (f) Filtered image using an adaptive median filter

For a better analysis of all the techniques, two quality parameters are used such as mean square error (MSE), peak signal to noise ratio (PSNR) to evaluate the performance of different filters. All filters are applied to the number of images and their performance is evaluated using MSE, PSNR.

Table 3.5 Performance of different filtering technique on speckle noise based on MSE

Image	Mean Filter	Median Filter	Wiener filter	Gaussian filter	Adaptive median filter
Mdb021	65.5068	140.9146	227.4485	187.3437	267.8240
Mdb002	48.1167	104.2275	197.7897	145.9037	208.9530
Mdb013	55.6853	120.8313	222.5036	167.7587	240.9830
Mdb004	61.9931	137.3914	238.4056	189.8501	266.3300
Mdb005	59.0596	127.0310	187.6752	184.3029	267.8730
Mdb007	53.6888	109.9177	187.7905	149.4435	217.1317
Mdb014	63.9736	139.9671	243.6532	201.1159	288.8513

Table 3.6 Performance of different filtering technique on speckle noise based on PSNR

Image	Mean Filter	Median Filter	Wiener filter	Gaussian filter	Adaptive median filter
Mdb021	29.9679	26.6412	24.5620	25.4044	23.8523
Mdb002	31.3078	27.9510	25.1688	26.4901	24.9303
Mdb013	30.6734	27.3090	24.6574	25.8840	24.3109
Mdb004	30.2074	26.7512	24.3576	25.3467	23.8766
Mdb005	30.4179	27.0917	25.3967	25.4755	23.8515
Mdb007	30.8320	27.7201	25.3941	26.3860	24.7636
Mdb014	30.0708	26.6705	24.2631	25.0963	23.5241

Table 3.5, Table 3.6 shows the results of all filters for salt and pepper noise. On analyzing Table 3.5, it is observed that the median filter gives the least MSE value for all images among all the filters. After the Median filter, the mean filter and Gaussian filter give good results for salt and pepper noise. Similarly, on analyzing Table 3.6, it is observed that the median filter gives the highest PSNR value for all images among all the filters. For PSNR, the mean filter and Gaussian filter give good results after the median filter method.

Thus, based on performance analysis on MSE, PSNR it can be concluded that the median filter technique gives the best-filtered image for speckle noise in comparison to mean filter, wiener filter, Gaussian filter, and adaptive median filter.

3.2.2 Contrast enhancement:

For contrast enhancement, different contrast enhancement techniques are used. This technique increases the contrast of the image to enhance image quality. A comparison of different contrast enhancement techniques such as HE, CLAHE, BBHE, RMSHE, and contrast stretching on mammogram images is performed. A comparison is performed on standard images from the MIAS dataset. All the contrast enhancement techniques are applied to several mammogram images from the MIAS dataset.

All these techniques are applied to mammogram image mdbo21 which is represented in Figure 3.2(a). The results are projected using Figure 3.6. Figure 3.6(b), Figure 3.6(c), Figure 3.6(d), Figure 3.6(e) shows results of HE, CLAHE, BBHE, RMSHE, and contrast enhancement techniques respectively on the original image, mdb021. It is observed from Figure 3.6 that the HE technique enhances all the pixels to a uniform level, and thus it just shows a brighter image. HE technique gives a non-realistic image. CLAHE technique gives better results for mammogram images compare to other techniques. It shows details in the image relative to the background. This technique uses clip-limit to limit the intensity of the image.

BBHE technique uses median intensity for enhancing the contrast of. BBHE technique gives better results for the image compared to the HE technique. However, the BBHE technique gives worse results compare to the CLAHE technique. RMSHE technique uses a recursive median to increase the contrast. This gives better results compared to the BBHE technique but worse than the CLAHE technique. The contrast stretching technique gives better results for mammogram images after the CLAHE technique. This technique stretch intensity of the image. It can be concluded that the CLAHE technique gives the best contrast enhancement for the mammogram images.

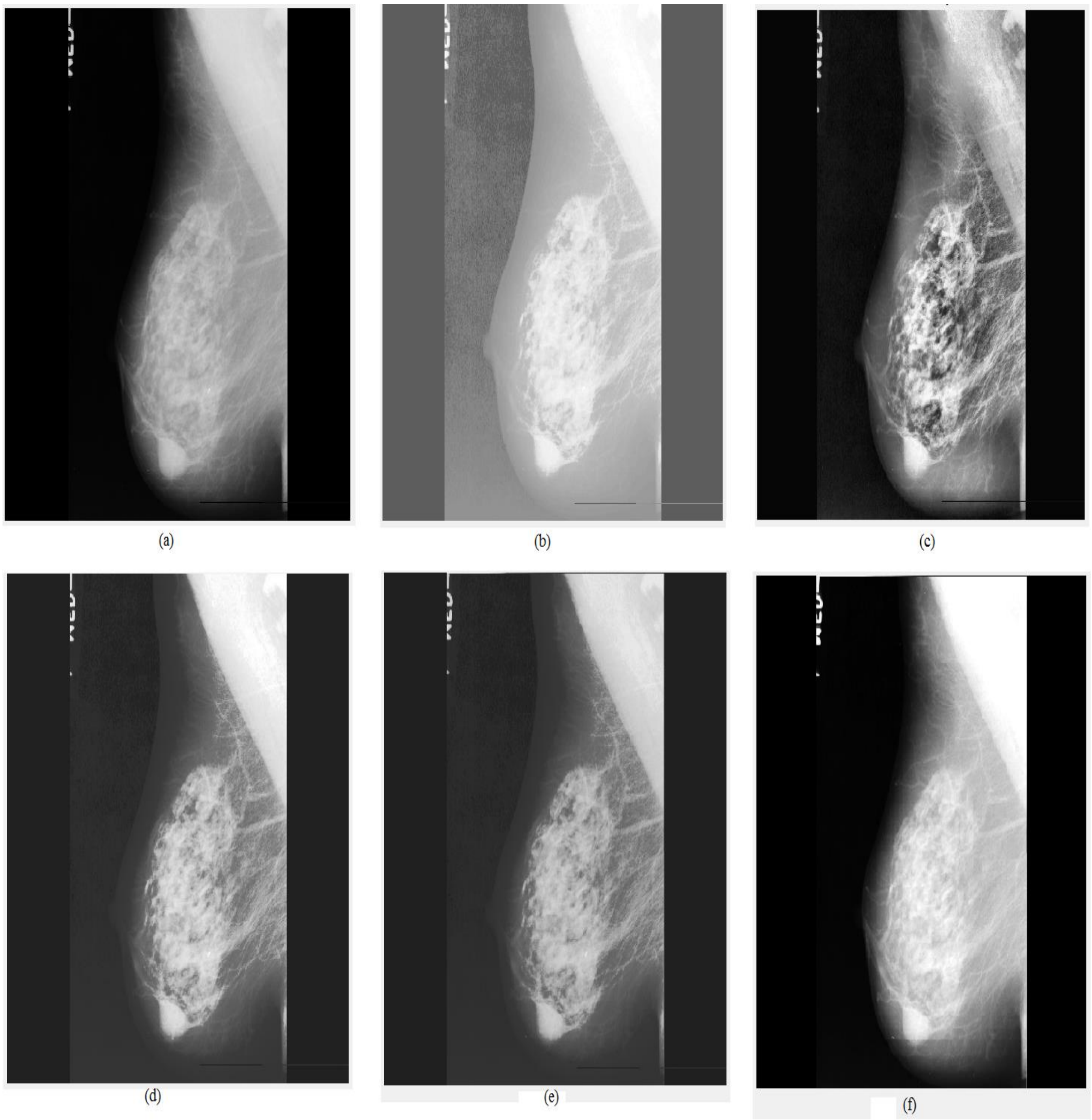


Figure 3.6: (a) - Original image (b) Contrast-enhanced image using HE (c) contrast-enhanced image using CLAHE (d) contrast-enhanced image using BBHE (e) Contrast-enhanced image using RMSHE (f) Contrast-enhanced image using Contrast stretching technique

Contrast enhancement techniques are used for enhancement of the quality of the image. Contrast enhancement gives a processed image that has better contrast than the unprocessed image. We can identify this type of enhancement by visual inspection of the image. However, by visual inspection, we cannot get complete and specific characterization. Although there is no parameter or method that can give both subjective and objective specialization. We have used quality parameters: MSE, PSNR, SNR for the performance evaluation of these techniques.

Signal to noise ratio (SNR):

SNR is defined as the ratio of signal to noise in the image. Higher SNR value indicates high image quality and vice versa. The mathematical formula for SNR is:

$$SNR = P_{signal} / P_{noise} \quad (10)$$

P_{signal} is a signal of power and P_{noise} is the noise of power.

Table 3.7, Table 3.8, Table 3.9 shows results of HE technique, CLAHE technique, BBHE technique, RMSHE technique, contrast stretching technique. On analyzing Table 3.7, it is observed that the CLAHE technique gives the least mean square error value for all images among all the contrast enhancement techniques. Similarly, on analyzing Table 3.8, it is observed that the CLAHE technique gives the highest PSNR value for all images among all the contrast enhancement techniques. In the same way on analyzing on Table 3.9, it is observed that CLAHE technique give the highest SNR value for all images among all the contrast enhancement technique followed by, contrast stretching technique.
Thus, based on performance analysis on MSE, PSNR, and SNR it can be concluded that the CLAHE gives the best-enhanced image in comparison to HE technique, BBHE technique, RMSHE technique, contrast stretching technique.

Table 3.7: Performance of different Enhancement technique based on MSE:

Image	HE	CLAHE	BBHE	RMSHE	Contrast Stretching
mdb021	8126.14	541.4066	958.0308	892.3173	596.1570
Mdb013	15796.721	389.1220	1427.8652	1229.8841	848.5835
Mdb005	7780.204	690.2713	1712.767	1402.126	1257.6404
Mdb007	13857.83	528.7091	1265.621	1080.996	1438.5546
Mdb014	12243.8410	507.6258	1659.9960	1541.3725	789.0313

Table 3.8 Performance of different enhancement technique based on PSNR

Image	HE	CLAHE	BBHE	RMSHE	Contrast Stretching
Mdb021	9.0320	20.7956	18.3170	18.6256	20.1746
Mdb013	6.1451	22.2299	16.589	16.9918	18.8439
Mdb005	9.2209	19.7406	15.7938	16.6629	17.1352
Mdb007	6.7139	20.8986	17.1078	17.7926	16.5515
Mdb014	7.2516	21.0754	15.9297	16.2517	19.1599

Table 3.9 Performance of different enhancement technique based on SNR

Image	HE	CLAHE	BBHE	RMSHE	Contrast Stretching
mdb021	0.7476	12.5112	10.6243	10.2510	11.6568
Mdb013	-2.77449	13.3099	8.4372	8.4593	12.3133
Mdb005	0.6467	11.1665	9.1843	9.5946	11.0996
Mdb007	-2.7584	11.4263	9.0754	9.3392	10.2158
Mdb014	-0.7874	13.0363	8.5398	8.3618	1.2280

3.2.3 Proposed RMBHE Contrast Enhancement Technique:

After a comparison of all contrast enhancement techniques, a new technique is proposed named as recursive median-based histogram equalization technique (RMBHE). This technique is a modified version of the recursive mean separate histogram equalization technique. RMBHE technique bifurcates images using the median intensity. The first image contains pixels having intensity values from zero intensity to median intensity value and the second image contain pixels having intensity values from median intensity value to high-intensity value.

Histogram equalization is performed on both the images separately. After histogram equalization, median-based separation is done recursively. We again find the median for both sub-images. Divide the images using the median. Then the total of four sub-images was formed and histogram equalization is performed on all these images. Median separation before histogram equalization preserves brightness. More median separation gives more brightness to preserve contrast enhancement. Here we use the median instead of mean because the mean intensity of the image is affected by very low pixel intensity value or very high-value pixel intensity value but the Median intensity value does not affect by the high and low-intensity value of any pixel.

Suppose Y_median denotes the median of the image Y. Here the image Y can be represented as {Y_0, Y_1, ….., Y_L-1}, where Y_0, Y_1, ….., Y_L-1, are pixel intensity values in non-descending order. Here Y_0 and Y_L-1 are the lowest and highest intensity value of the image Y. According to the median intensity, Y_median the original image is bifurcated into images Y_L and Y_U.
Y_L is the sub-level image, which contains pixels from the original image with intensity value ranges from Y_0 to Y_median. Similarly, Y_U is another sub-level image, which contains pixels from the original image with pixels intensity ranges from Y_median to Y_L-1. After histogram equalization of Y_L and Y_U, we again bifurcate image Y_S based on the median intensity and image Y_U also. We do this separation recursively. After all these separations, we transform images, after that perform union of all the images, and get the resultant image. For the transformation of sub-level images, transformation functions are formulated as follows:

$$X_L(Y) = Y\_0 + (Y\_median - Y\_0)\, C_S(Y) \qquad (11)$$

$$X_U(Y) = Y\_median+1 + (Y\_L-1 - Y\_median + 1)\, C_U(Y) \qquad (12)$$

Where $X_L(Y)$ and $X_U(Y)$ are the transformation functions for sub-level images Y_L and Y_U. $C_S(Y)$ and $C_U(Y)$ are the cumulative density functions for images Y_L and Y_U respectively. The cumulative density function to transform images is mathematically defined as:

$$C(I)=\sum_{m=0}^{L-1} Pd(Y\_m) \qquad (13)$$

Where Y_m is the image's intensity at different pixel values such as m, which is normalized to [0, 1]. P(Y_m) is the probability density function for Y_m intensity. Probability density function can be defined as:

$$P(Y\_m) = t^m / t \qquad (14)$$

Here t^m denotes the number of pixels having intensity value Y_m in the image and t denotes the total number of pixels in the image. Now again median is calculated for both the images Y_L and Y_U. The median for Y_L is Y_ML median for image Y_U is Y_MU. After that based on these median four sub-images are obtained named Y_L1, Y_L2, Y_U1, and Y_U2. Y_L1 having intensity values from minimum intensity to Y_ML intensity. Y_L2 having intensity values from Y_ML to Y_Ml. Image Y_U1 is having intensity values from Y_median to Y_MU. Image Y_U2 is having intensity values greater than intensity Y_MU. Histogram equalization is performed on these four images. The transformation of these images is done according to the function defined in equation 2 and equation 3 which is defined s follows.

$$X_{L1}(Y) = Y\_0 + (Y\_ML - Y\_0)\, C_{L1}(Y) \tag{15}$$

$$X_{L2}(Y) = Y\_ML+1 + (Ymedian - Y\_ML+1)\, C_{L2}(Y) \tag{16}$$

$$X_{U1}(Y) = Y\_median+1 + (Y\_MU - Y\_median+1)\, C_{U1}(Y) \tag{17}$$

$$X_{U2}(Y) = Y\_MU+1 + (Y\_L-1 - Y\_MU+1)\, C_{U2}(Y) \tag{18}$$

Here $X_{L1}(Y)$, $X_{L2}(Y)$, $X_{U1}(Y)$, $X_{U2}(Y)$ are transformation functions for sub-images Y_L1, Y_L2, Y_U1, Y_U2 respectively. $C_{L1}(Y)$, $C_{L2}(Y)$, $C_{U1}(Y)$, $C_{U2}(Y)$ are cumulative density functions for sub-images Y_L1, Y_L2, Y_U1, Y_U2 respectively. Recursion is performed until level two, our proposed technique performs recursion until level 3. So again median of all four images Y_L1, Y_L2, Y_U1, Y_U2 is calculated. Suppose the median for image Y_L1 is Y_ML1 and for Y_L2 is Y_ML2 and for Y_L3 is Y_MU1 and for Y_L4 is Y_MU2.

Now, these four images are divided into eight sub-images based on the median of these images such as Y_S1, Y_S2, Y_S3, Y_S4, Y_R1, Y_R2, Y_R3, and Y_R4. I_{S1} image contains intensity values form intensity Y_0 to Y_MLl. Image Y_S2 is having intensity values form intensity Y_ML1+1 to Y_ML. Image Y_S3 is having intensity values form intensity Y_Ml+1 to Y_ML2.

Image Y_S4 is having intensity values form intensity Y_ML2+1 to Y_median. Image Y_R1 is having intensity values form intensity Y_median+1 to Y_MU1. Image Y_R2 is having intensity values form intensity Y_Mu1+1 to Y_MU. Image Y_R3 is having intensity values form intensity Y_MU+1 to Y_MU2. Image Y_R4 is having intensity values form intensity Y_MU2+1 to Y_L-1. Now transformation function is performed on these images which are as follows:

$$X_{S1}(Y) = Y\_0 + (Y\_ML1 - Y\_0)\, C_{S1}(Y) \tag{19}$$

$$X_{S2}(Y) = Y\_ML1+1 + (Y\_ML – Y\_ML1+1)\, C_{S2}(Y) \tag{20}$$

$$X_{S3}(Y) = Y\_ML{+}1 + (Y\_ML2 - Y\_ML{+}1)\, C_{S3}(Y) \tag{21}$$

$$X_{S4}(Y) = Y\_ML2{+}1 + (Y\_median - Y\_ML2{+}1)\, C_{S4}(Y) \tag{22}$$

$$X_{R1}(Y) = Y\_median{+}1 + (Y\_MU1 - Y\_median{+}1)\, C_{R1}(Y) \tag{23}$$

$$X_{R2}(Y) = Y\_MU1{+}1 + (Y\_MU - Y\_MU1{+}1)\, C_{R2}(Y) \tag{24}$$

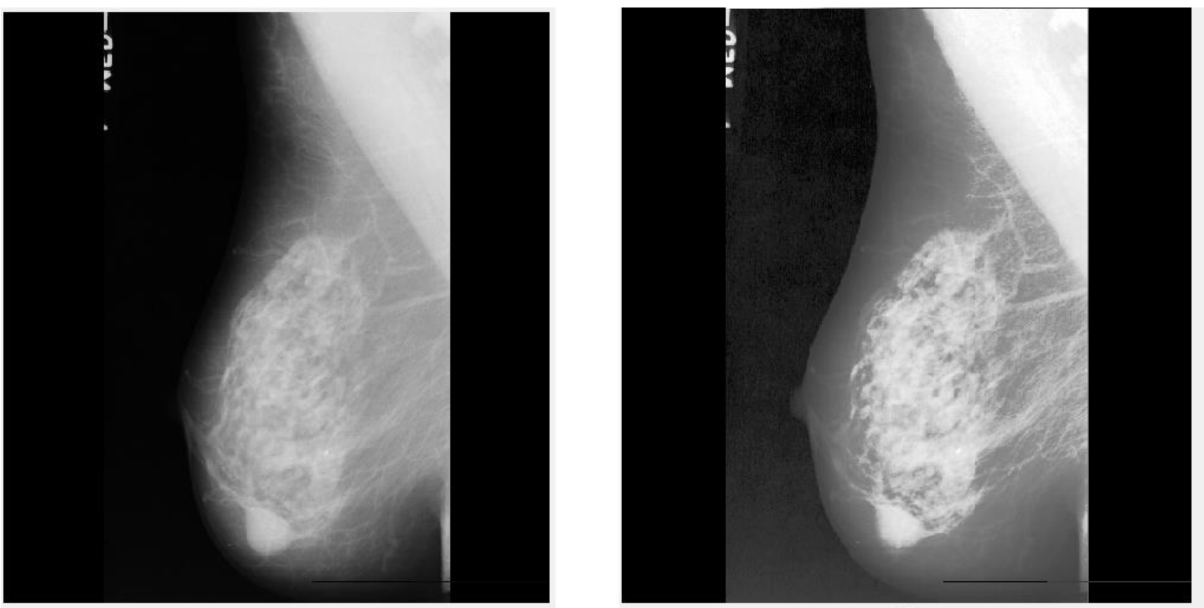
$$X_{R3}(Y) = Y\_MU{+}1 + (Y\_MU2 - Y\_MU{+}1)\, C_{R3}(Y) \tag{25}$$

$$X_{R4}(Y) = Y\_MU2{+}1 + (Y\_L{-}1 - Y\_MU2{+}1)\, C_{R4}(Y) \tag{26}$$

Here $X_{S1}(Y)$, $X_{S2}(Y)$, $X_{S3}(Y)$, $X_{S4}(Y)$, $X_{R1}(Y)$, $X_{R2}(Y)$, $X_{R3}(Y)$, $X_{R4}(Y)$, are transformation function for sub-images Y_S1, Y_S2, Y_S3, Y_S4, Y_R1, Y_R2, Y_R3, and Y_R4 respectively. $C_{S1}(Y)$, $C_{S2}(Y)$, $C_{S3}(Y)$, $C_{S4}(Y)$, $C_{R1}(Y)$, $C_{R2}(Y)$, $C_{R3}(Y)$, $C_{R4}(Y)$ are cumulative density functions for sub-images Y_S1, Y_S2, Y_S3, Y_S4, Y_R1, Y_R2, Y_R3, and Y_R4 respectively. After histogram equalization, all sub-images are merged using union operation resultant image is obtained. The transformation function for merging os all the images is defined as:

$$R_{img} = X_{S1}(Y) \cup X_{S2}(Y) \cup X_{S3}(Y) \cup X_{S4}(Y) \cup X_{R1}(Y) \cup X_{R2}(Y) \cup X_{R3}(Y) \cup X_{R4}(Y) \tag{27}$$

R_{img} is the resultant image of the RMBHE technique. This Proposed technique is now implemented on image mdbo21 which is represented in Figure 3.7(a). The result of the proposed technique is shown in Figure 3.7(b). This shows that the proposed technique gives a good contrast image.



(a) (b)

Figure 3.7 (a) Original image (b) Contrast-Enhanced image using RMBHE

Contrast enhancement gives a processed image that has better contrast than the unprocessed image. We can identify this type of enhancement by visual inspection of the image. However, by visual inspection, we cannot get complete and specific characterization. Although there is no parameter or method that can give both subjective and objective specialization. We have used quality parameters: MSE, PSNR, SNR for the performance evaluation of different enhancement techniques. We have applied this technique on different images and analyzed the result using MSER, PSNR, SNR values. Table 3.10 represents the MSE, PSNR, and SNR values of different images after applying the RMBHE technique.

Table 3.10: Performance of RMBHE technique based on MSE, PSNR AND SNR values

Image	MSE	PSNR	SNR
Mdb021	469.5958	21.4316	14.1391
Mdb013	224.2834	24.6228	16.1580
Mdb005	586.3005	20.4496	13.2876
Mdb007	502.5349	21.1191	13.2494
Mdb014	236.0485	24.4008	16.5021

Comparison of MSE values from Table 3.10 for the RMBHE technique to the MSE value values from Table 3.7 for different contrast enhancement techniques shows that the RMBHE technique gives the lowest MSE value for all mammogram images among different contrast enhancement technique. The same comparison of PSNR value from Table 3.10 for the RMBHE technique and Table 3.8 for different contrast enhancement techniques for mammogram images shows that the RMBHE technique gives the highest PSNR value among all the techniques. Comparison of SNR value of Table 3.10 for the RMBHE technique and Table 3.9 for different contrast enhancement techniques for different mammogram images shows that the RMBHE technique gives the highest SNR value among all contrast enhancement techniques. Therefore, it can be concluded that the RMBHE technique does best contrast enhancement of mammogram images.

CHAPTER-4

IMPLEMENTATION AND RESULTS

4.1 Datasets Used

4.1.1 Mammographic Image Analysis Society (MIAS) Dataset: MIAS is a widely used dataset. This dataset is easily available. MIAS is generally an institution of different research bodies of the United Kingdom. All these research bodies are interested in cognizance of mammogram images. They want to understand mammogram images and improve them. For this, they have formed a dataset of digital mammograms.

United Kingdom national breast screening program take films of mammogram images. After that, these films are converted to a 50 micro pixel edge digital image. It is done using a Joyce-loebl scanning microdensitometer, which is a machine with density from zero to 3.2. Here eight-bit represents a pixel in the image.

This system mark area of abnormalities in the breast with the help of radiology instrument "truth". The pixel edge of the mammogram images is decreased to 200micron to make mammogram pictures of size 1024*1024. He pilot European Image processing Archive is responsible for providing breast images. It is present at the University of Essex. This dataset has 323 mammogram pictures. In this dataset, images are classified into three types.

The first one is glandular dense, second if fatty and third is fatty glandular. These are again categorized into three categories based on the tissue. In breast, normal, benign, malignant tissue are present. Then images that are not normal for example benign and malignant are further divided according to abnormalities present in them for example symmetry, calcification, and mass. In the dataset, normal images are 207, benign abnormal images are 64 and malignant abnormal images are 52. Images at odd numbers show the left breast. The image at even number shows the right breast.

The details of the dataset are as follows: It has seven columns. The first contains the MIAS database reference number. The second contains the category of tissue. The third shows Categories of abnormality. The fourth column represents the types of abnormality. Fifth, sixth columns denote a, b pictures point of the center of abnormality respectively. The seventh column shows an approximate radius (in pixels) of a circle enclosing the abnormality.

4.2 Technologies Used

4.2.1 MATLAB: MATLAB is a high-level programming language. It is a fourth-generation language. This language gives a suitable environment for numeric calculation, visualization, and functions that permit matrix operations, graph formation of functions, execution of algorithms, interactive user platform creation, interaction with algorithms of another language such as C, FORTRAN, C++, and JAVA.

This language performance analysis of data, generate algorithms and make applications. This language has incorporated math programs and commands, which are used for mathematical computation, draw graphs.MATLAB has some advanced functions, which increase code performance, ability to maintain, and increase efficiency. It gives a connecting environment to expand documents, design, and solve problems.

It has some tools to form applications that have user-defined graphics. MATLAB has some mathematics programs for filters, to solve differentiation and optimization, and to solve an integral equation. In MATLAB we need not declare a variable. We can give any type of value to different variables. This language does not perform compilation, it direct does the interpretation. This language performs well for several datasets. IT can perform compilation and design together.

4.2.2 Some Standard Built-In Functions That Are Used:

Imread(img): It is used to read the image img, instead of just image name we can specify its complete path.

Immse(p, q): This function determines the MSE between images p and q.

Imfilter(p, q): This function is used to filter image p using filter q.

Imshow(I): This function is used to display or plot the image I.

Title(“a”): This function is used to add the title to the displayed image.

Imhist(I): This function is used to draw a histogram of the image I.

Subplot(a,b,c): Subplot function divide display window into rows, b columns, and display image c.

Imnoise(a, b): This function is used to introduce noise b in the image a.

fprintf(“ “): This function is used to display the value or string or numeric number written in-between “ “.

Size(img): This function display the size of the image. This function will display size in terms of rows and columns.

4.3 Implementation

Implementation is done in the MATLAB language using its built-in functions. Code implementation of the MBHE technique, all filters, all contrast enhancement technique, RMBHE technique is given below.

4.3.1 Code

4.3.1.1 Code for MBHE Technique:

```
o_img=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm");
figure;
imshow(o_img);
sz = size(o_img);
o_mean = round(median(o_img(:)));
%  HISTOGRAM
h_l = zeros(256,1);
h_u = zeros(256,1);
for i = 1:sz(1)
    for j = 1:sz(2)
        g_val = o_img(i,j);
        if(g_val<=o_mean)
           h_l(g_val+1) = h_l(g_val+1) + 1;
        else
            h_u(g_val+1) = h_u(g_val+1)+ 1;
        end
    end
end
nh_l = h_l/sum(h_l);
nh_u = h_u/sum(h_u);
% CDF
hist_l_cdf = double(zeros(256,1));
hist_u_cdf = double(zeros(256,1));
hist_l_cdf(1) = nh_l(1);
hist_u_cdf(1) = nh_u(1);
for k = 2:256
    hist_l_cdf(k) =  hist_l_cdf(k-1) + nh_l(k);
```

```
    hist_u_cdf(k) =  hist_u_cdf(k-1) + nh_u(k);
end
equalized_img = zeros(sz);
 range_l = [0 o_mean];
range_u = [(o_mean+1) 255];
for i =1:sz(1)
    for j =1:sz(2)
      g_val = o_img(i,j);
      if(g_val<=o_mean)
                equalized_img(i,j)=range_l(1)+round(((range_l(2)range_l(1))*
                                                   hist_l_cdf(g_val+1)));
      else
                 equalized_img(i,j)=range_u(1)+round(((range_u(2)-range_u(1))*
                                                  hist_u_cdf(g_val+1)));
        end
    end
end
 b=uint8(equalized_img);
% figure,imshow(uint8(equalized_img));
figure;
imshow(b);title("MBHE");
err=immse(o_img,b);
[peaksnr, snr] = psnr(o_img,b);
fprintf(' %0.4f ', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f', snr);
```

4.3.1.2 Code for Different Filters:

```
a=imread('C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb014.pgm');
b=imnoise(a,'speckle');
c=fspecial('average',3);
d=imfilter(b,c);
err=immse(a,d);
```

```
[peaksnr, snr] = psnr(a,d);
fprintf('\n Mean filter');
fprintf(' %0.4f ', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
e=medfilt2(b,[3,3]);
err=immse(a,e);
[peaksnr, snr] = psnr(a,e);
fprintf('\n Median filter');
fprintf(' %0.4f ', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f', snr);
f=wiener2(b,[3,3]);
err=immse(a,f);
[peaksnr, snr] = psnr(a,f);
fprintf('\n weiner filter');
fprintf(' %0.4f ', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
p=fspecial('gaussian');
r=imfilter(b,p);
err=immse(a,r);
[peaksnr, snr] = psnr(a,r);
fprintf('\n Gaussian filter');
fprintf('%0.4f ', err);
fprintf('%0.4f', peaksnr);
fprintf(' %0.4f ', snr);

x=amedfilt2_calc(b);
err=immse(a,x);
[peaksnr,snr]=psnr(a,x);
fprintf('\n Adaptive median filter');
fprintf(' %0.4f ',err);
fprintf(' %0.4f ',peaksnr);
```

```
fprintf('%0.4f ',snr);
figure;imshow(a);title('original image');
figure;imshow(b);title('Noisy image');
figure;imshow(d);title('Mean filter');
figure;imshow(e);title('Median filter');
figure; imshow(f);title('Wiener filter');
figure;imshow(r);title('Gaussian filter');
figure;imshow(x);title('Adaptive filter');
function J=amedfilt2_calc(b)
sm=9;
J=b;
[nr nc]=size(b);
la=ceil(s/2);
lb=floor(s/2);
for r=la:nr-lb
    for c=l1:nc-lb
        w_in=-lb:lb;
        reg=b(r+w_in,c+w_in);
        cp=region(la,la);
        for s=3:2:sm
            [rmn,rmx,rmd]=roi_stats(region,sm,s);
            if rmd>rmn && rmd<rmx
                if cp<=rmn || cp>=rmx
                    J(r,c)=rmd;
                end
                break;
            end
        end
    end
end
end
function [rmn,rmx,rmd]=roi_stats(region,smx,s)
la=ceil(smx/2)-floor(s/2);
lb=ceil(smx/2)+floor(s/2);
```

```
v=ones(sm*sm,1);
cnt=1;
for i=la:lb
    for j=la:lb
        v(cnt)=region(i,j);
        cnt=cnt+1;
    end
end
v=visort(v,s*s);
rmd=v(ceil(s*s/2));
rmn=v(1);
rmx=v(s*s);
end
function v=visort(v,N)
tmp=v;
for i=1:N-1
    ma=v(i);
    ka=1;
    for j=i+1:N
        if v(j)<ma
            ma=v(j);
            ka=j-i+1;
        end
    end
    for j=1:ka-1
        v(i+j)=tmp(i+j-1);
    end
    v(i)=ma;
    for j=1:N
        temp(j)=v(j);
    end
end
end
```

4.3.1.3 Code for Different Contrast Enhancement Technique:

```
I=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm");
J=histeq(I);
C=adapthisteq(I,'cliplimit',0.02);
str = imadjust(I, stretchlim(I, [0.05, 0.95]),[]);
o_img=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm");
sz = size(o_img);
o_mean = round(mean(o_img(:)));
%  HISTOGRAM
h_l = zeros(256,1);
h_u = zeros(256,1);
for i = 1:sz(1)
   for j = 1:sz(2)
       g_val = o_img(i,j);
       if(g_val<=o_mean)
          h_l(g_val+1) = h_l(g_val+1) + 1;
       else
           h_u(g_val+1) = h_u(g_val+1)+ 1;
       end
   end
end
% NORMALIZED HISTOGRAM OR PDF
nh_l = h_l/sum(h_l);
nh_u = h_u/sum(h_u);
% CDF
hist_l_cdf = double(zeros(256,1));
hist_u_cdf = double(zeros(256,1));
hist_l_cdf(1) = nh_l(1);
hist_u_cdf(1) = nh_u(1);
for k = 2:256
   hist_l_cdf(k) =  hist_l_cdf(k-1) + nh_l(k);
   hist_u_cdf(k) =  hist_u_cdf(k-1) + nh_u(k);
end
```

```
% IMAGE MODIFICATION
equalized_img = zeros(sz);
range_l = [0 o_mean];
range_u = [(o_mean+1) 255];
for i =1:sz(1)
   for j =1:sz(2)
      g_val = o_img(i,j);
      if(g_val<=o_mean)
        equalized_img(i,j)=range_l(1) + round(((range_l(2)-range_l(1))*hist_l_cdf(g_val+1)));
      else
        equalized_img(i,j)=range_u(1)+round(((range_u(2)-range_u(1))*hist_u_cdf
                                (g_val+1)));
      end
   end
end
 be=uint8(equalized_img);
% figure;imshow(uint8(equalized_img));
PicGray = imread('C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm');
figure(1),imshow(PicGray);
h=imhist(PicGray);figure(2),plot(h);
[m,n]=size(PicGray);
PicHEt=zeros(m,n);
o_max = double(max(PicGray(:)));
o_min = double(min(PicGray(:)));
r=1; length=2^r; Xm=zeros(1,length); Xm(1)=o_max+1; Xm(2)=o_min+1;
for i=1:r
   for j=1:2^(i-1)
      Xm(2^(i-1)+j+1)= averpixcal(h,Xm(2^(i-1)-j+2),Xm(2^(i-1)-j+1));
   end
   Xm=sort(Xm,'descend');
end
Xm=sort(Xm);
for i=2:2^r
   [row,col]=find((PicGray>=Xm(i-1)-1)&(PicGray<=Xm(i)-2));
```

```
    PicHEt=FuncHE(PicGray,PicHEt,row,col,h,Xm(i-1)-1,Xm(i)-2,m,n);
end
[row,col]=find((PicGray>=Xm(2^r)-1)&(PicGray<=Xm(2^r+1)-1));
PicHEt=FuncHE(PicGray,PicHEt,row,col,h,Xm(2^r)-1,Xm(2^r+1)-1,m,n);
PicHE=uint8(PicHEt); h1=imhist(PicHE);
img=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm");
mx=max(img,[],'all');
mn=min(img,[],'all');
[m,n]=size(img);
c=zeros(m,n);
for i=1:m
    for j=1:n
        if(img(i,j)<=mn)
            c(i,j)=0;
        elseif(img(i,j)>mn && img(i,j)<mx)
            c(i,j)=(img(i,j)-mn)/(mx-mn);
        else
            c(i,j)=1;
        end
    end
end
o_img=zeros(m,n);
for i=1:m
    for j=1:n
        if(0<=c(i,j) && c(i,j)<=0.5)
            o_img(i,j)=2*(c(i,j)^2);
        else
            o_img(i,j)=1-2*((1-c(i,j))^2);
        end
    end
end
 sz = size(o_img);

o_mean = round(median(o_img(:)));
```

```
%  HISTOGRAM
h_l = zeros(256,1);
h_u = zeros(256,1);
for i = 1:sz(1)
    for j = 1:sz(2)
        g_val = o_img(i,j);
        if(g_val<=o_mean)
           h_l(g_val+1) = h_l(g_val+1) + 1;
        else
            h_u(g_val+1) = h_u(g_val+1)+ 1;
        end
    end
end
% NORMALIZED HISTOGRAM OR PDF
nh_l = h_l/sum(h_l);
nh_u = h_u/sum(h_u);
% CDF
hist_l_cdf = double(zeros(256,1));
hist_u_cdf = double(zeros(256,1));
hist_l_cdf(1) = nh_l(1);
hist_u_cdf(1) = nh_u(1);
for k = 2:256
    hist_l_cdf(k) =  hist_l_cdf(k-1) + nh_l(k);
    hist_u_cdf(k) =  hist_u_cdf(k-1) + nh_u(k);
end
% IMAGE MODIFICATION
eq_img = zeros(sz);
range_l = [0 o_mean];
range_u = [(o_mean+1) 255];
for i =1:sz(1)
    for j =1:sz(2)
        g_val = o_img(i,j);

        if(g_val<=o_mean)
```

```
            eq_img(i,j) = range_l(1) + round(((range_l(2)-range_l(1))*hist_l_cdf(g_val+1)));
         else
            eq_img(i,j) = range_u(1) + round(((range_u(2)-range_u(1))*hist_u_cdf(g_val+1)));
         end
      end
   end
    P_img=zeros(m,n);
    mfn=min(eq_img,[],'all');
    mfx=min(eq_img,[],'all');
    for i=1:m
       for j=1:n
          if(eq_img(i,j)<=mfn)
             P_img(i,j)=0;
          elseif(eq_img(i,j)>mfn && eq_img(i,j)<mfx)
             P_img(i,j)=(mfx-mfn)*(eq_img(i,j)+mfn);
          else
             P_img(i,j)=255;
          end
       end
    end
   img=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm");
   str = imadjust(img, stretchlim(img, [0.05, 0.95]),[]);
   mx=max(img,[],'all');
   mn=min(img,[],'all');
   [m,n]=size(img);
   c=zeros(m,n);
   for i=1:m
      for j=1:n
         if(img(i,j)<=mn)
            c(i,j)=0;
         elseif(img(i,j)>mn && img(i,j)<mx)
            c(i,j)=(img(i,j)-mn)/(mx-mn);
         else
            c(i,j)=1;
```

```
        end
    end
end
o_img=zeros(m,n);
for i=1:m
    for j=1:n
        if(0<=c(i,j) && c(i,j)<=0.5)
            o_img(i,j)=2*(c(i,j)^2);
        else
            o_img(i,j)=1-2*((1-c(i,j))^2);
        end
    end
end
 sz = size(o_img);
o_mean = round(median(o_img(:)));
%  HISTOGRAM
h_l = zeros(256,1);
h_u = zeros(256,1);
for i = 1:sz(1)
    for j = 1:sz(2)
        g_val = o_img(i,j);
        if(g_val<=o_mean)
           h_l(g_val+1) = h_l(g_val+1) + 1;
        else
            h_u(g_val+1) = h_u(g_val+1)+ 1;
        end
    end
end
% NORMALIZED HISTOGRAM OR PDF
nh_l = h_l/sum(h_l);
nh_u = h_u/sum(h_u);

% CDF
hist_l_cdf = double(zeros(256,1));
```

```
hist_u_cdf = double(zeros(256,1));

hist_l_cdf(1) = nh_l(1);
hist_u_cdf(1) = nh_u(1);

for k = 2:256
    hist_l_cdf(k) =  hist_l_cdf(k-1) + nh_l(k);
    hist_u_cdf(k) =  hist_u_cdf(k-1) + nh_u(k);
end
% IMAGE MODIFICATION
eq_img = zeros(sz);
range_l = [0 o_mean];
range_u = [(o_mean+1) 255];
for i =1:sz(1)
    for j =1:sz(2)
        g_val = o_img(i,j);
        if(g_val<=o_mean)
           eq_img(i,j) = range_l(1) + round(((range_l(2)-range_l(1))*hist_l_cdf(g_val+1)));
        else
           eq_img(i,j) = range_u(1) + round(((range_u(2)-range_u(1))*hist_u_cdf(g_val+1)));
        end
    end
end
 P_img=zeros(m,n);
 mfn=min(eq_img,[],'all');
 mfx=min(eq_img,[],'all');
 for i=1:m
     for j=1:n
         if(eq_img(i,j)<=mfn)
             P_img(i,j)=0;
         elseif(eq_img(i,j)>mfn && eq_img(i,j)<mfx)
             P_img(i,j)=(mfx-mfn)*(eq_img(i,j)+mfn);
         else
             P_img(i,j)=255;
```

```
        end
    end
 end
figure;
subplot(1,2,1);imshow(I);title("original image");
subplot(1,2,2);imshow(J);title('histogram equalization');
figure;
subplot(1,2,1);imshow(C);title('clahe technique');
subplot(1,2,2);
imshow(be);title('Brightness preserving');
figure;
imshow(PicHE);title('recursive mean');
figure;
imshow(str);title("contrast stretching image");
figure;
imshow(uint8(P_img)); title("adaptive fuzzy logic enhnaced image");
err=immse(J,I);
[peaksnr, snr] = psnr(J,I);
fprintf(' %0.4f ', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
err=immse(C,I);
[peaksnr, snr] = psnr(C,I);
 fprintf(' %0.4f ', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
err=immse(I,be);
 [peaksnr, snr] = psnr(I,be);
 fprintf(' %0.4f',err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
err=immse(PicGray,PicHE);
[peaksnr, snr] = psnr(PicGray,PicHE);
 fprintf(' %0.4f ',err);
```

```
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
err=immse(img,uint8(P_img));
[peaksnr, snr] = psnr(img,uint8(P_img));
 fprintf('%0.4f',err);
fprintf('%0.4f', peaksnr);
fprintf('%0.4f ', snr);
err=immse(img,str);
[peaksnr, snr] = psnr(img,str);
fprintf(' %0.4f', err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
err=immse(img,uint8(P_img));
[peaksnr, snr] = psnr(img,uint8(P_img));
 fprintf(' %0.4f ',err);
fprintf(' %0.4f', peaksnr);
fprintf(' %0.4f ', snr);
function Xm=averpixcal(h,begin,ending)
PixSum=0; Sum=0;
for i=begin:ending
    PixSum=(i-1)*h(i)+PixSum; Sum=h(i)+Sum;
end
Xm= double(round(PixSum/Sum));
end
function PicHEt=FuncHE(PicGray,PicHEt,row,col,h,min,max,m,n)
pix=size(col,1);
%PZ=zeros(1,Xm(2)-1); PZ=zeros(1,max-min+1);
for i=min+1:max+1
    PZ(i-min)=h(i)/pix;
end
%S=zeros(1,Xm(2)-1); S=zeros(1,max+1);
S(min+1)=PZ(1);
for i=min+2:max+1
    S(i)=PZ(i-min)+S(i-1);
```

```
end
FunHE=min+(max-min)*S;
for k=1:pix
   PicHEt(row(k),col(k))=floor(FunHE(PicGray(row(k),col(k))+1));
end
end
```

4.3.1.4 Code for Model for Pre-processing of Mammogram Images:

```
format long g;
format compact;
fontSize = 15;
I=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb021.pgm");
u=medfilt2(I,[3,3]);
C=adapthisteq(u,'cliplimit',0.02);
figure;imshow(I);title('Original image');
figure;imshow(u);title('filtered image');
figure;imshow(C);title('Enhnaced image');
```

4.3.1.5 Code for RMBHE Technique:

```
I=imread("C:\Users\MONIKA ROJARIA\Downloads\Desktop\mdb013.pgm");
o_img=medfilt2(I,[3,3]);
figure;
imshow(o_img);
sz = size(o_img);
o_mean = round(median(o_img(:)));
%  HISTOGRAM
h_l = zeros(256,1);
h_u = zeros(256,1);
for i = 1:sz(1)
   for j = 1:sz(2)
      g_val = o_img(i,j);

      if(g_val<=o_mean)
         h_l(g_val+1) = h_l(g_val+1) + 1;
```

```
        else
            h_u(g_val+1) = h_u(g_val+1)+ 1;
        end
    end
end
l_median=round(median(h_l(:)));
h_l1=zeros(256,1);
h_l2=zeros(256,1);
for i=1:sz(1)
    for j=1:sz(2)
        l_val=o_img(i,j);
        if(l_val<=l_median)
            h_l1(l_val+1)=h_l1(l_val+1)+1;
        end
        if(l_val>l_median && l_val<=o_mean)
            h_l2(l_val+1)=h_l2(l_val+1)+1;
        end
    end
end
lo_median=round(median(h_l1(:)));
uo_median=round(median(h_l2(:)));
h_l11=zeros(256,1);
h_l21=zeros(256,1);
for i=1:sz(1)
    for j=1:sz(2)
        lo_val=o_img(i,j);
        if(lo_val<=lo_median)
            h_l11(lo_val+1)=h_l11(lo_val+1)+1;
        end
        if(lo_val>lo_median && lo_val<=l_median)
            h_l21(lo_val+1)=h_l21(lo_val+1)+1;
        end
    end
end
```

```
nh_l11=h_l11/sum(h_l11);
nh_l21=h_l21/sum(h_l21);
hist_l11_cdf=double(zeros(256,1));
hist_l21_cdf=double(zeros(256,1));
hist_l11_cdf(1)=nh_l11(1);
hist_l21_cdf(1)=nh_l21(1);
for k=2:256
   hist_l11_cdf(k)=hist_l11_cdf(k-1)+nh_l11(k);
   hist_l21_cdf(k)=hist_l21_cdf(k-1)+nh_l21(k);
end
equi_img11=zeros(sz);
range_l11=[0 lo_median];
range_l21=[(lo_median+1) l_median];
for i=1:sz(1)
   for j=1:sz(2)
      lo_val=o_img(i,j);
      if(lo_val<=lo_median)
         equi_img11(i,j)=range_l11(1)+round(((range_l11(2)-range_l11(1))*hist_l11_cdf
                                 (lo_val+1)));
      end
      if(lo_val>lo_median && lo_val<=l_median)
         equi_img11(i,j)=range_l21(1)+round(((range_l21(2)-
range_l21(1))*hist_l21_cdf(lo_val+1)));
      end
   end
end
h_l12=zeros(256,1);
h_l22=zeros(256,1);
for i=1:sz(1)
   for j=1:sz(2)
      lo_val=o_img(i,j);
      if(lo_val>l_median && lo_val<=uo_median)
         h_l12(lo_val+1)=h_l12(lo_val+1)+1;
      end
```

```
        if(lo_val>uo_median && lo_val<=o_mean)
            h_l22(lo_val+1)=h_l22(lo_val+1)+1;
        end
    end
end
nh_l12=h_l12/sum(h_l12);
nh_l22=h_l22/sum(h_l22);
hist_l12_cdf=double(zeros(256,1));
hist_l22_cdf=double(zeros(256,1));
hist_l12_cdf(1)=nh_l12(1);
hist_l22_cdf(1)=nh_l22(1);
for k=2:256
    hist_l12_cdf(k)=hist_l12_cdf(k-1)+nh_l12(k);
    hist_l22_cdf(k)=hist_l22_cdf(k-1)+nh_l22(k);
end
equi_img12=zeros(sz);
range_l12=[l_median uo_median];
range_l22=[(uo_median+1) o_mean];
for i=1:sz(1)
    for j=1:sz(2)
        lo_val=o_img(i,j);
        if(lo_val>l_median && lo_val<=uo_median)
            equi_img12(i,j)=range_l12(1)+round(((range_l12(2)-
range_l12(1))*hist_l12_cdf(lo_val+1)));
        end
        if(lo_val>uo_median && lo_val<=o_mean)
            equi_img12(i,j)=range_l22(1)+round(((range_l22(2)-range_l22(1))*hist_l22_cdf
                              (lo_val+1)));
        end
    end
end
u_median=round(median(h_u(:)));
u_l1=zeros(256,1);
u_l2=zeros(256,1);
```

```
for i=1:sz(1)
   for j=1:sz(2)
      u_val=o_img(i,j);
      if(u_val<=u_median && u_val>o_mean)
         u_l1(u_val+1)=u_l1(u_val+1)+1;
      end
      if(u_val>u_median)
         u_l2(u_val+1)=u_l2(u-val+1)+1;
      end
   end
end
lu_median=round(median(u_l1(:)));
uu_median=round(median(u_l2(:)));
u_l11=zeros(256,1);
u_l21=zeros(256,1);
for i=1:sz(1)
 for j=1:sz(2)
      lo_val=o_img(i,j);
      if(lo_val<=lu_median && lo_val>o_mean)
         u_l11(lo_val+1)=u_l11(lo_val+1)+1;
      end
      if(lo_val>lu_median && lo_val<=u_median)
         u_l21(lo_val+1)=u_l21(lo_val+1)+1;
      end
   end
end
nh_u11=u_l11/sum(u_l11);
nh_u21=u_l21/sum(u_l21);
hist_u11_cdf=double(zeros(256,1));
hist_u21_cdf=double(zeros(256,1));
hist_u11_cdf(1)=nh_u11(1);
hist_u21_cdf(1)=nh_u21(1);
for k=2:256
   hist_u11_cdf(k)=hist_u11_cdf(k-1)+nh_u11(k);
```

```
    hist_u21_cdf(k)=hist_u21_cdf(k-1)+nh_u21(k);
end
equi_img21=zeros(sz);
range_u11=[(o_mean+1) lu_median];
range_u21=[(lu_median+1) u_median];
for i=1:sz(1)
    for j=1:sz(2)
        u_val=o_img(i,j);
        if(u_val <=lu_median && u_val>o_mean)
            equi_img21(i,j)=range_u11(1)+round(((range_u11(2)-
range_u11(1))*hist_u11_cdf(u_val+1)));
        end
        if(u_val>lu_median && u_val<=u_median)
            equi_img21(i,j)=range_u21(1)+round(((range_u21(2)-
range_u21(1))*hist_u21_cdf(u_val+1)));
        end
    end
end
u_l12=zeros(256,1);
u_l22=zeros(256,1);
for i=1:sz(1)
    for j=1:sz(2)
        lo_val=o_img(i,j);
        if(lo_val<=uu_median && lo_val>u_median)
            u_l12(lo_val+1)=u_l12(lo_val+1)+1;
        end
        if(lo_val>uu_median)
            u_l22(lo_val+1)=u_l22(lo_val+1)+1;
        end
    end
end
nh_u12=u_l12/sum(u_l12);
nh_u22=u_l22/sum(u_l22);
hist_u12_cdf=double(zeros(256,1));
```

```
hist_u22_cdf=double(zeros(256,1));
hist_u12_cdf(1)=nh_u12(1);
hist_u22_cdf(1)=nh_u22(1);
for k=2:256
   hist_u12_cdf(k)=hist_u12_cdf(k-1)+nh_u12(k);
   hist_u22_cdf(k)=hist_u22_cdf(k-1)+nh_u22(k);
end
equi_img22=zeros(sz);
range_u12=[(u_median+1) uu_median];
range_u22=[(uu_median+1) 255];
for i=1:sz(1)
   for j=1:sz(2)
      u_val=o_img(i,j);
      if(u_val >u_median && u_val<=uu_median)
         equi_img22(i,j)=range_u12(1)+round(((range_u12(2)-
range_u12(1))*hist_u12_cdf(u_val+1)));
      end
      if(u_val>uu_median)
         equi_img22(i,j)=range_u22(1)+round(((range_u22(2)-
range_u22(1))*hist_u22_cdf(u_val+1)));
      end
   end
end
figure;
imshow(equi_img11);
figure;
imshow(equi_img12);
figure;
imshow(equi_img21);
figure;
imshow(equi_img22);
b1=imfuse(equi_img11, equi_img21,'blend','scaling','joint');
b2=imfuse(equi_img12, equi_img22,'blend','scaling','joint');
b=imfuse(b1,b2,'blend','scaling','joint');
```

```
figure;
imshow(b);title("RMBHE");
err=immse(o_img,b);
[peaksnr, snr] = psnr(o_img,b);
fprintf(' %0.4f ', err);
fprintf('%0.4f', peaksnr);
fprintf('%0.4f ', snr);
```

4.4 Results and Analysis

In this section, all the results of all techniques are shown pictorially as well as analyzed on suitable metrics. The experiment is performed on standard images from the MIAS dataset. All the techniques are applied to several mammogram images from the MIAS dataset to prove the effectiveness of the techniques.

4.4.1 Result Analysis of the MBHE Technique:

4.4.1.1 Experiment Results: Results of implementation of the MBHE technique are projected using Figure 4.1, Figure 4.2, Figure 4.3, Figure 4.4, Table 4.1, Table 4.2, and Table 4.3. Figure 4.1(b), Figure 4.1(c), Figure 4.1(d) shows results of HE, CLAHE, BBHE techniques respectively on the original image, mdb021, which is shown in Figure 4.1(a). Figure 4.2(a), Figure 4.2(b), Figure 4.2(c), Figure 4.2(d) shows results of RMSHE, Adaptive fuzzy logic contrast enhancement, contrast stretching and MBHE techniques respectively on the original image, mdb021, which is shown in Figure 4.1(a).

It is observed from Figure 4.1, Figure 4.2 that HE enhances all the pixels to a uniform level, and thus it just shows a brighter image. CLAHE technique gives better results for mammogram images compare to other techniques except contrast stretching and proposed technique. It shows details in the image relative to the background.

BBHE technique gives better results for the image. RMSHE technique gives better results compared to the BBHE technique but worse than the CLAHE technique. The contrast stretching technique gives the best results for mammogram images after the proposed technique. The proposed technique gives the best result among all the techniques. The adaptive fuzzy logic contrast enhancement technique gives the worst result compared to all other techniques except HE.

Figure 4.3(b), Figure 4.3(c), Figure 4.3(d) shows results of HE, CLAHE, BBHE technique respectively on the original image, mdb004, which is shown in figure 4.3(a). Figure 4.4(a), Figure 4.4(b), Figure 4.4(c), Figure 4.4(d) shows results of RMSHE, contrast stretching, and Adaptive fuzzy logic contrast enhancement, and MBHE technique respectively on the original image, mdb004, which is shown in Figure 4.3(a).

Similarly, it is observed from Figure 4.3 and Figure 4.4 that the HE technique extremely increases the contrast and give the image that looks unnatural. CLAHE technique increases the contrast respective to the background and gives a much better result. BBHE technique gives the average result. RMSHE technique gives a better result than BBHE, adaptive fuzzy logic contrast enhancement, HE techniques. Contrast stretching increases the intensity of the image up to a limit. Adaptive fuzzy logic just makes darker park more dark and brighter part brighter. The proposed technique gives the best results for the image, mdb003 also among all the techniques.

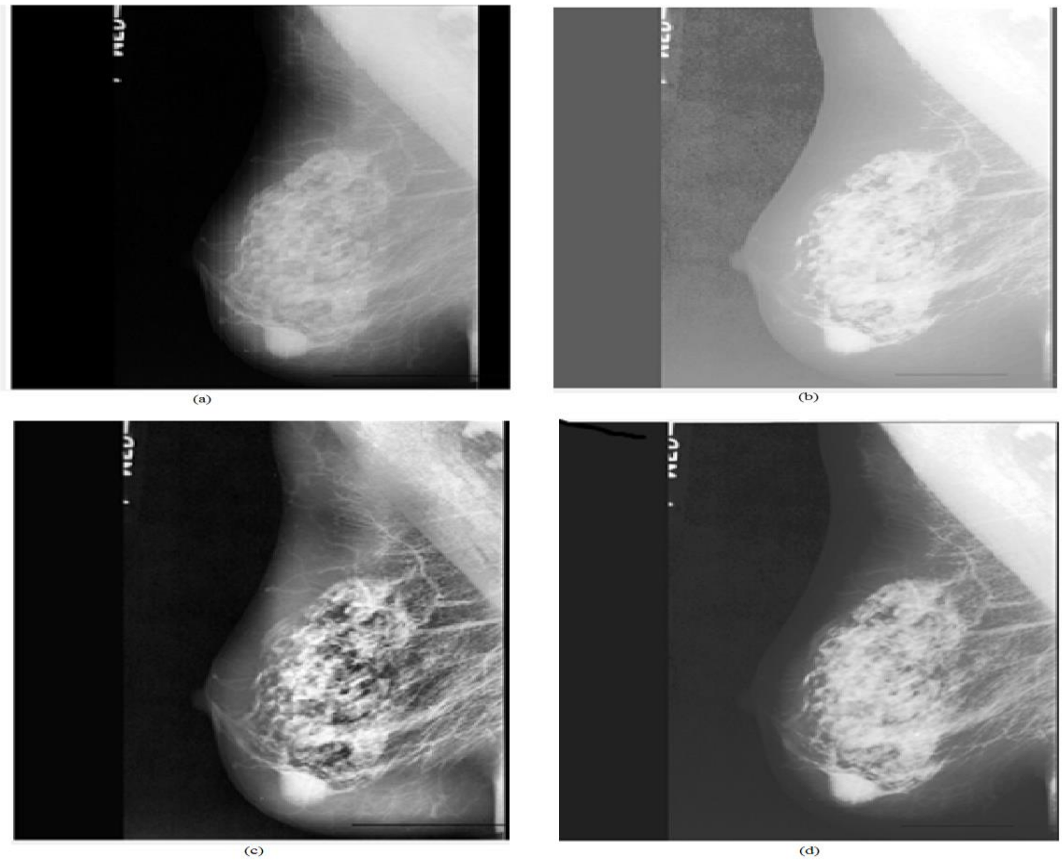


Figure 4.1 (a) Original image (b) Contrast-enhanced image using HE (c) contrast-enhanced image using CLAHE (d) contrast-enhanced image using BBHE

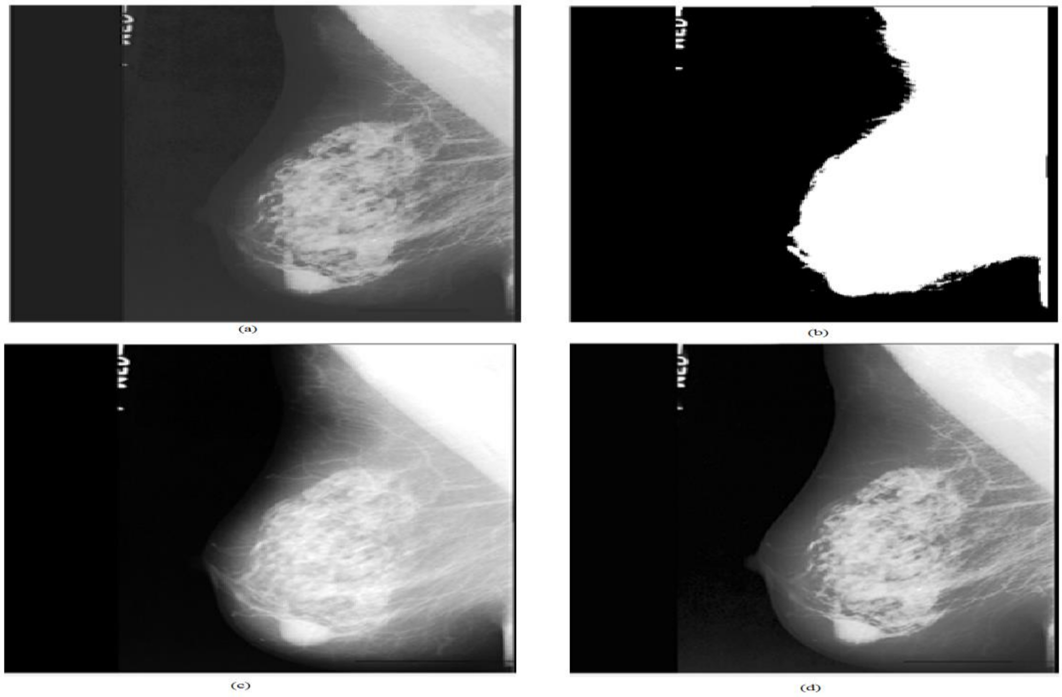


Figure 4.2 (a) Contrast-enhanced image using RMSHE (b) Contrast-enhanced image using adaptive fuzzy logic contrast enhancement technique (c) Contrast-enhanced image-using contrast stretching enhancement technique (d) Contrast-enhanced image-using MBHE

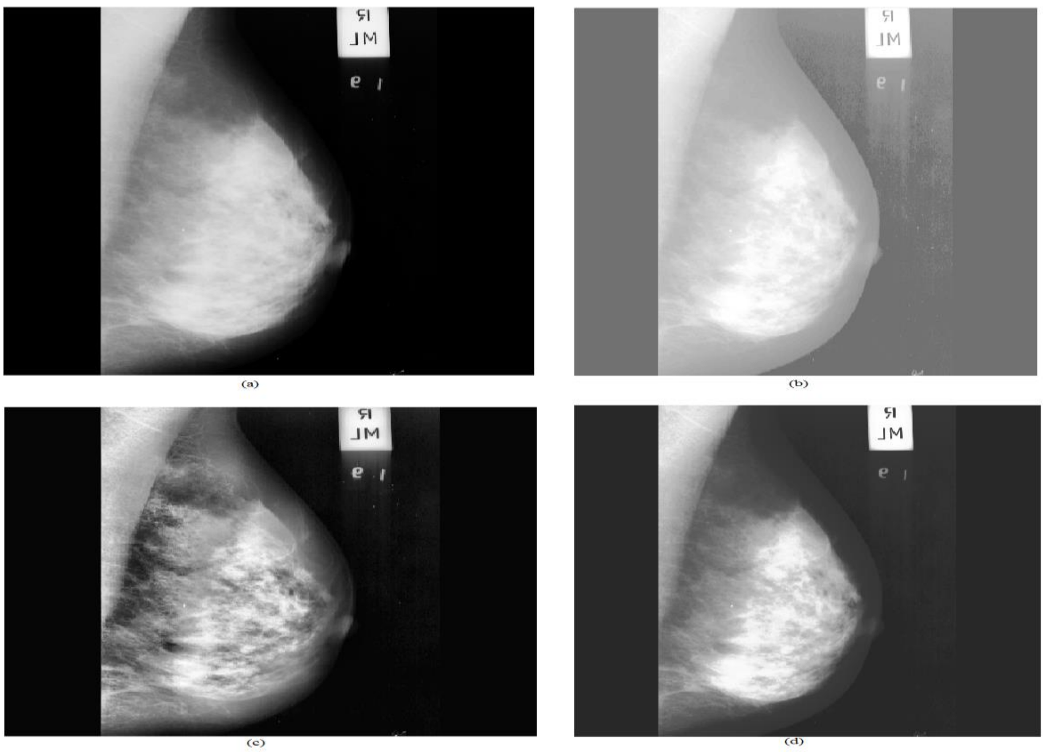


Figure 4.3 (a) Original image (b) Contrast-enhanced image using HE (c) Contrast-enhanced image using CLAHE (d) Contrast-enhanced image using BBHE

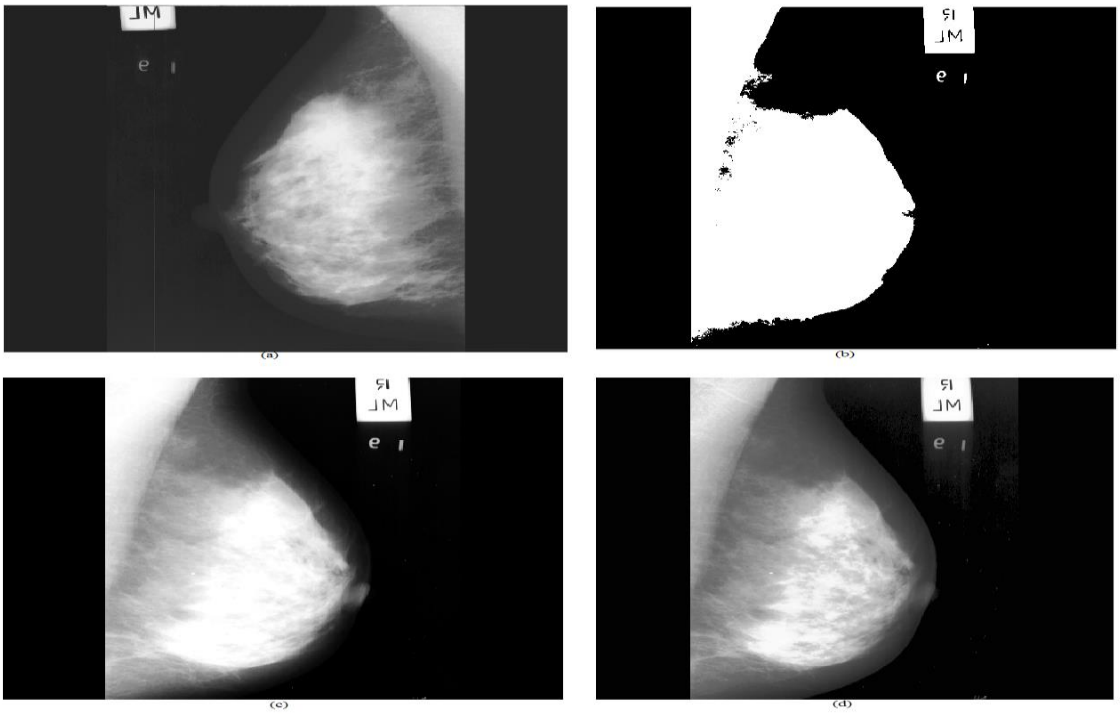


Figure 4.4 (a) Contrast-enhanced image using RMSHE (b) Contrast-enhanced image using adaptive fuzzy logic contrast enhancement technique (c) Contrast-enhanced image-using contrast stretching enhancement technique (d) contrast-enhanced image-using MBHE

4.4.1.2. Performance Evaluation

Contrast enhancement techniques are used for enhancement of the quality of the image. Contrast enhancement gives a processed image that has better contrast than the unprocessed image. We can identify this type of enhancement by visual inspection of the image. However, by visual inspection, we cannot get complete and specific characterization. Although there is no parameter or method that can give both subjective and objective specialization. We have used quality parameters: mean square error (MSE), peak signal to noise ratio (PSNR), Signal to noise ratio (SNR) to evaluate the performance of different enhancement techniques. All enhancement techniques are applied to the number of images and their performance is evaluated using MSE, PSNR, and SNR.

Table 4.1, Table 4.2, Table 4.3 shows the results of HE technique, CLAHE technique, BBHE technique, RMSHE technique, adaptive fuzzy logic contrast enhancement technique, contrast stretching technique, and proposed technique-MBHE. In analyzing table 4.1, it is noted that the proposed new technique gives the least MSE value for all images among all the contrast enhancement techniques. After the proposed technique, the contrast stretching technique and CLAHE technique gives good results.

Table 4.1 Performance of different Enhancement technique based on MSE

Image	HE	CLAHE	BBHE	RMSHE	Adaptive Fuzzy	Contrast Stretching	MBHE
mdb021	8126.14	541.4066	958.0308	892.3173	2715.6478	496.1570	181.4657
mdb002	12964.87	630.9662	867.048	742.0717	2351.5869	371.3197	363.7279
Mdb013	15796.721	389.1220	1427.8652	1229.8841	2412.0760	848.5835	227.504
Mdb004	10167.23	503.5756	1211.105	1146.632	2280.1826	367.5808	158.692
Mdb005	7780.204	690.2713	1712.767	1402.126	5196.7918	1257.6404	727.285
Mdb007	13857.83	528.7091	1265.621	1080.996	3308.2357	1438.5546	506.492
Mdb014	12243.84	507.6258	1659.996	1541.372	2586.0998	789.0313	238.797

Table 4.2 Performance of different enhancement technique based on PSNR

Image	HE	CLAHE	BBHE	RMSHE	Adaptive Fuzzy	Contrast Stretching	MBHE
Mdb021	9.0320	20.7956	18.3170	18.6256	13.7921	21.1746	25.5429
Mdb002	7.0031	20.1307	18.7504	19.4263	14.4172	22.4333	22.5230
Mdb013	6.1451	22.2299	16.589	16.9918	14.3069	18.8439	24.5609
Mdb004	8.0588	21.1102	17.2990	17.5366	14.5511	22.4773	26.1252
Mdb005	9.2209	19.7406	15.7938	16.6629	10.9735	17.1352	19.5138
Mdb007	6.7139	20.8986	17.1078	17.7926	12.9348	16.5515	21.0851
Mdb014	7.2516	21.0754	15.9297	16.2517	14.0044	19.1599	24.3505

Table 4.3 Performance of different enhancement technique based on SNR

Image	HE	CLAHE	BBHE	RMSHE	Adaptive Fuzzy	Contrast Stretching	MBHE
mdb021	0.7476	12.5112	10.6243	10.2510	8.4787	14.6568	17.7382
mdb002	-2.2257	10.9019	10.9945	10.6921	7.4415	14.8987	14.6171
mdb013	-2.77449	13.3099	8.4372	8.4593	8.4823	12.3133	16.1103
mdb004	0.0894	13.1408	9.5358	9.3641	9.0973	15.9910	18.1894
mdb005	0.6467	11.1665	9.1843	9.5946	6.5929	11.2996	12.2507
mdb007	-2.7584	11.4263	9.0754	9.3392	7.1546	10.2158	13.2296
mdb014	-0.7874	13.0363	8.5398	8.3618	8.8495	1.2280	16.4657

Similarly, in analyzing Table 4.2, it is observed that the proposed new technique gives the highest PSNR value for all images among all the contrast enhancement techniques. For PSNR, contrast stretching and CLAHE technique, give good results after the proposed method. In the same way on analyzing on Table 4.3, it is observed that proposed new technique give the maximum SNR value for all images among all the contrast enhancement technique followed by, contrast stretching and CLAHE technique.

Thus, based on performance analysis on MSE, PSNR, and SNR it can be concluded that the proposed technique (MBHE) gives the best-enhanced image in comparison to HE technique, CLAHE technique, BBHE technique, RMSHE technique, adaptive fuzzy logic contrast-enhanced image and contrast stretching technique.

4.4.2 Preformation Analysis of Model Proposed for Pre-processing of Mammogram Images and RMBHE Technique

Results are analyzed for the proposed model for mammogram images. The proposed model says that for pre-processing of mammogram images consist of two steps first one is Noise removal and the second is contrast enhancement. For the first step different types of filters are applied to the different images to remove different noises from the mammogram images. After that, we concluded that the median filter is the best filter technique among all the filters. for the second step, different contrast enhancement techniques are applied to different images to enhance their quality. After that best contrast enhancement technique is purposed. CLAHE technique gives the best contrast enactment for mammogram images among existed contrast enhancement techniques. In this work, one new contrast enhancement technique named as RMBHE that give best contrast enhancement among all the technique is also proposed. So here, first, noise is removed using the median filter. After that contrast is enhanced using the CLAHE technique and also using the proposed technique.

The experiment of the Proposed model is performed on different mammogram images for the MIMA dataset and results are analyzed. Figure 4.5(a) represents the original image mdb013. Figure 4.5(b) represents the median filtered image. Figure 4.5(c) represents a Contrast-enhanced image using the CLAHE technique. Figure 4.5(d) represents a contrast-enhanced image using the RMBHE technique.

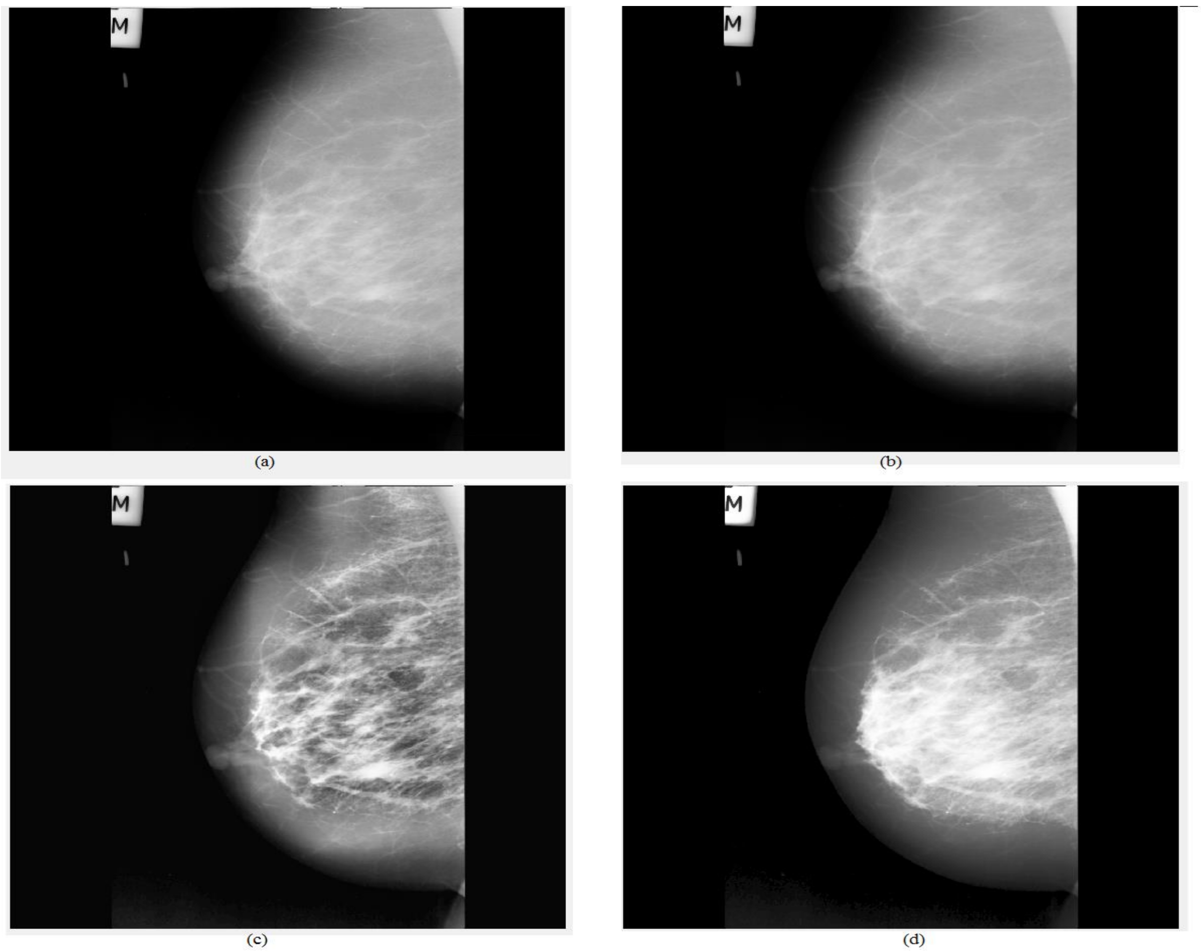


Figure 4.5: (a) Original image (b) Filtered image using a median filter (c) Contrast-enhanced image using CLAHE technique (d) Contrast-enhanced image using RMBHE technique

Figure 4.5 shows that after applying the proposed model on mammogram images, the quality of images is enhanced. After pre-processing, a noise-free image is obtained. The contrast of this image is also enhanced and due to this, many features and parts of the mammogram image are clearly visible. This preprocessed image will work as input for further stages and increase the probability of good results for further stages

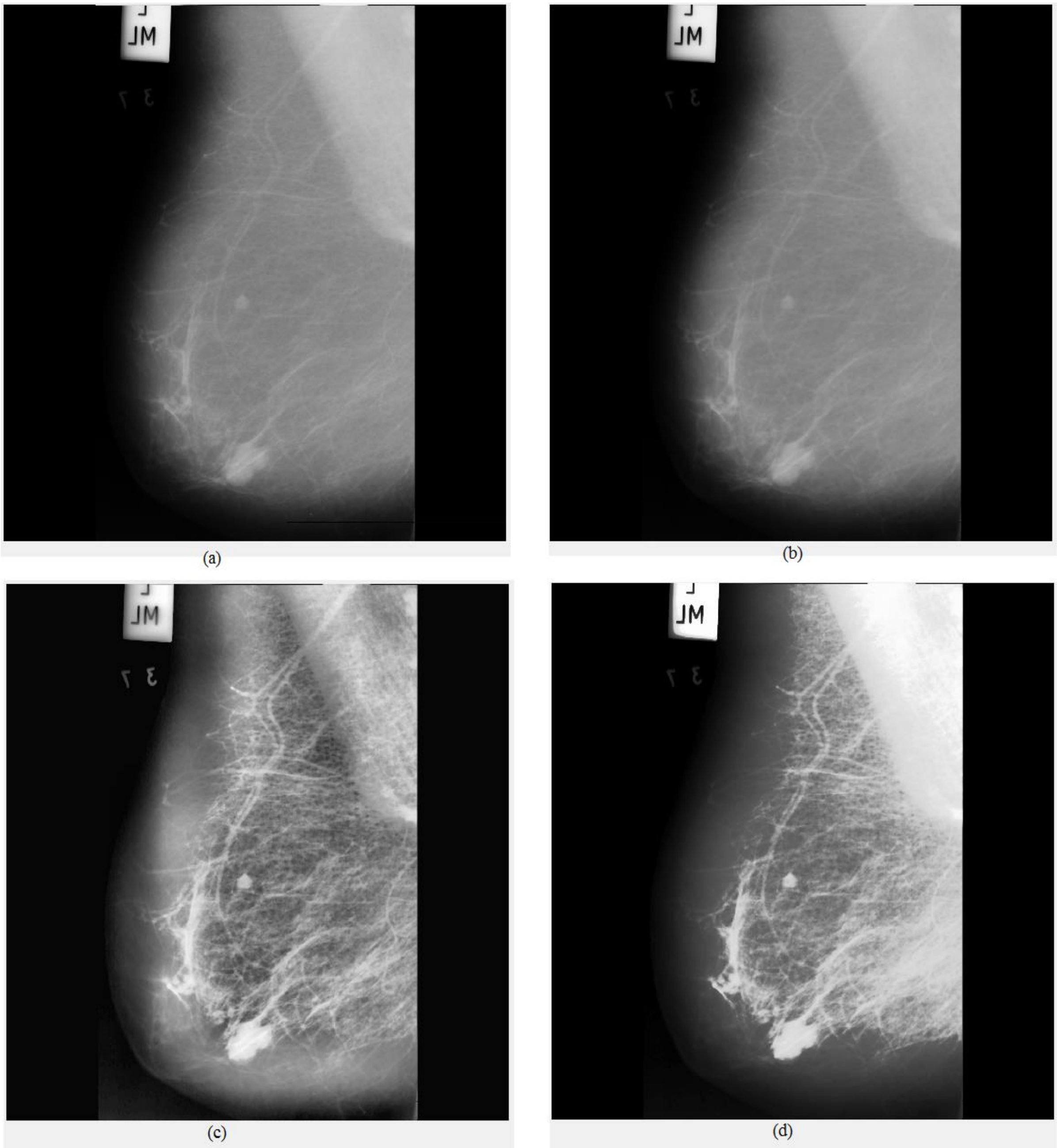


Figure 4.6: (a) Original image (b) Filtered image using a median filter (c) Contrast-enhanced image using CLAHE technique (d) Contrast-enhanced image using RMBHE technique

Figure 4.6(a) represents the original image mdb005. Figure 4.6(b) represents the median filtered image. Figure 4.6(c) represents a contrast-enhanced image using CLAHE Technique. Figure 4.6(d) represents a contrast-enhanced image using the RMBHE technique. Figure 4.7(a) represents the original image mdb007. Figure 4.7(b) represents the median filtered image. Figure 4.7 (c) represents a contrast-enhanced image using the CLAHE technique. Figure 4.7 (d) represents a contrast-enhanced image using the RMBHE technique.

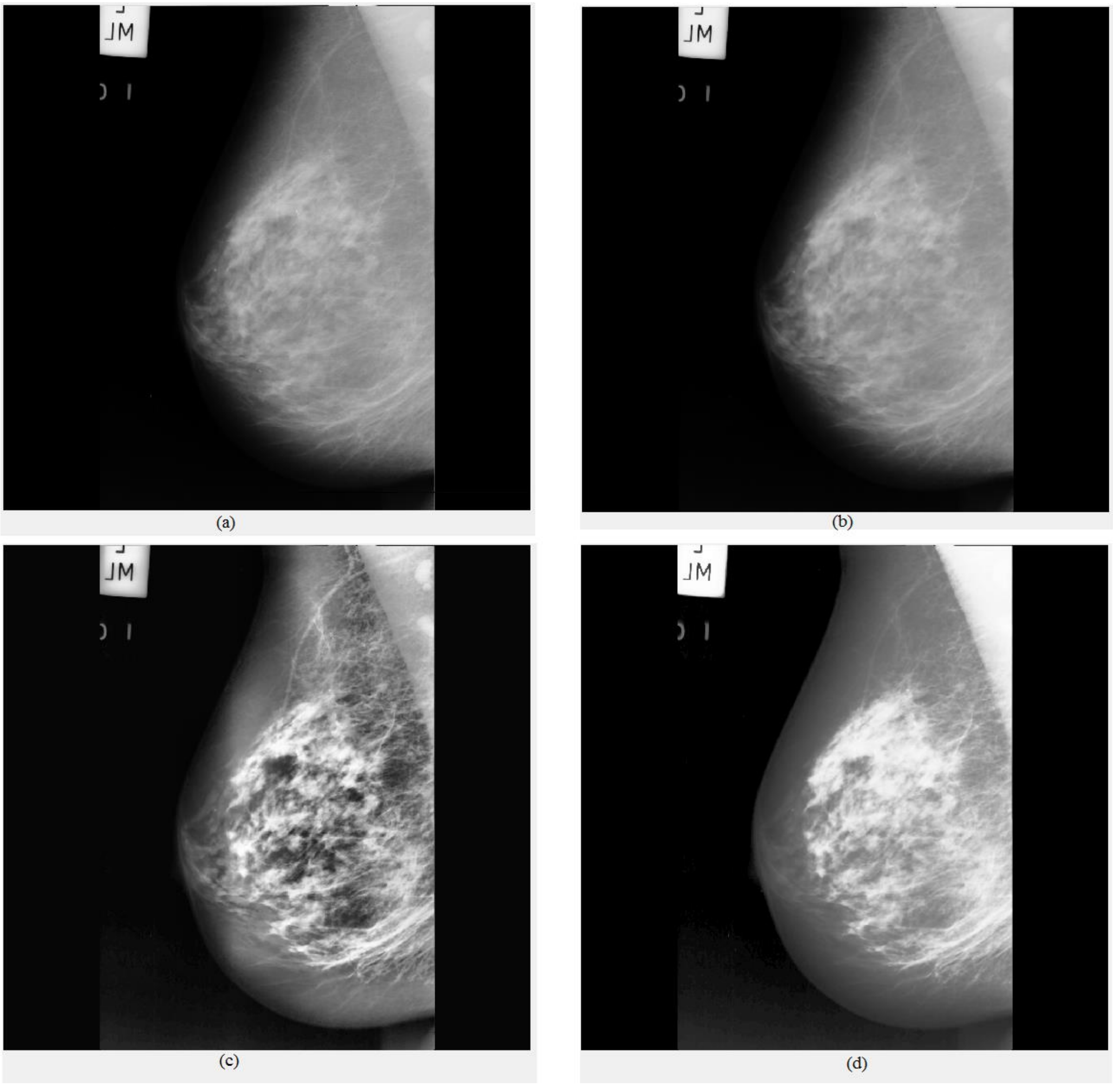


Figure 4.7: (a) Original image (b) Filtered image using a median filter (c) Contrast-enhanced image using CLAHE technique (d) Contrast-enhanced image using RMBHE technique

We can see that the proposed method gives us a pre-processed image, which can be used for further processing of mammogram images. By pre-processing a mammogram image, we can improve the quality of the image and make it more useful for cancer detection in the early stage.

CHAPTER-5

CONCLUSION AND FUTURE WORK

In this report, a new technique is proposed for better enhancement of mammogram images named as median-based brightness conserving histogram equalization (MBHE). The proposed technique, MBHE is compared with HE, BBHE, CLAHE, RMSHE, BBHE, adaptive fuzzy contrast enhancement techniques, and contrast stretching are compared with this proposed method by applying on a number of different mammogram images, which are taken from standard dataset MIAS. With the help of performance analysis using evaluation metrics such as MSE, PSNR, and SNR in this paper, it is evidenced that the proposed technique, MBHE achieves best contrast enhancement for low contrast medical images such as mammogram images and proposed technique also gives better brightness preservation for the mammographic image.

Along with this, a model for pre-processing of mammogram images is also proposed. With this, one new contrast enhancement technique is also proposed for better enhancement of mammogram images named as a recursive median-based histogram equalization technique. In the model, all filters are compared with each other for different noises. After comparison, it is proposed that the median filter outperforms all filters for noise removal. Different contrast enhancement techniques are also compared for mammogram images.

After comparison, it is proposed that the CLAHE technique give the best contrast enhancement for mammogram images. The proposed contrast enhancement technique RMBHE is compared with other contrast enhancement techniques HE, CLAHE, BBHE, RMSHE, and contrast stretching. All these techniques are compared by applying them on a number of different mammogram images, which are taken from standard dataset MIAS. With the help of performance analysis using evaluation metrics such as MSE, PSNR, and SNR in this paper, it is evidenced that the proposed model gives the best-pre-processed mammogram image, which can be used for further processing, and give the better result for early detection for breast cancer. Proposed contrast enhancement technique, RMBHE achieves best contrast enhancement for low contrast medical mammogram images. This proposed technique also gives better brightness preservation for the mammographic image.

References

[1] Abdullah-Al-Wadud, M., Kabir, M. H., Dewan, M. A. A., & Chae, O. (2007). A dynamic histogram equalization for image contrast enhancement. IEEE Transactions on Consumer Electronics, 53(2), 593-600.

[2] Chan, N. H., Hasikin, K., & Kadri, N. A. (2019, March). An Improved Enhancement Technique for Mammogram Image Analysis: A Fuzzy Rule-Based Approach of Contrast Enhancement. In 2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA) (pp. 202-206). IEEE.

[3] Chen, S. D., & Ramli, A. R. (2003). Minimum mean brightness error bi-histogram equalization in contrast enhancement. IEEE transactions on Consumer Electronics, 49(4), 1310-1319.

[4] Dabass, J., Arora, S., Vig, R., & Hanmandlu, M. (2019, March). Mammogram image enhancement using entropy and CLAHE based intuitionistic fuzzy method. In *2019 6th International Conference on Signal Processing and Integrated Networks (SPIN)* (pp. 24-29). IEEE.

[5] George, M. J., & Sankar, S. P. (2017, December). Efficient preprocessing filters and mass segmentation techniques for mammogram images. In *2017 IEEE International Conference on Circuits and Systems (ICCS)* (pp. 408-413). IEEE.

[6] Gosain, A., & Dahiya, S. (2016). Performance analysis of various fuzzy clustering algorithms: a review. *Procedia Computer Science*, *79*, 100-111.

[7] Hendrick, R. E., & Berns, E. A. (2000). Optimizing techniques in screen-film mammography. *Radiologic Clinics of North America*, *38*(4), 701-718.

[8] Jen, C. C., & Yu, S. S. (2015). Automatic detection of abnormal mammograms in mammographic images. *Expert Systems with Applications*, *42*(6), 3048-3055.

[9] Joda, B., & Dereboylu, Z. (2017, September). Digital mammogram enhancement based on automatic histogram clipping. In *2017 9th International Conference on Computational Intelligence and Communication Networks (CICN)* (pp. 34-38). IEEE.

[10] Joseph, A. M., John, M. G., & Dhas, A. S. (2017, March). Mammogram image denoising filters: A comparative study. In *2017 Conference on Emerging Devices and Smart Systems (ICEDSS)* (pp. 184-189). IEEE.

[11] Khera, S., & Malhotra, S. (2014). Survey on medical image de noising using various filters and wavelet transform. *International Journal of Advanced Research in Computer Science and Software Engineering*, *4*(4), 230-234

[12] Kim, Y. T. (1997). Contrast enhancement using brightness preserving bi-histogram equalization. IEEE transactions on Consumer Electronics, 43(1), 1-8.

[13] Kong, T. L., & Isa, N. A. M. (2015, June). Histogram based image enhancement for non-uniformly illuminated and low contrast images. In *2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)* (pp. 586-591). IEEE.

[14] Lee, E., Kim, S., Kang, W., Seo, D., & Paik, J. (2012). Contrast enhancement using dominant brightness level analysis and adaptive intensity transformation for remote sensing images. IEEE Geoscience and remote sensing letters, 10(1), 62-66.

[15] Liu, L., Zeng, L., & Luan, X. (2013). 3D robust Chan–Vese model for industrial computed tomography volume data segmentation. *Optics and Lasers in Engineering*, *51*(11), 1235-1244.

[16] Lu, H. C., Loh, E. W., & Huang, S. C. (2019, May). The Classification of Mammogram Using Convolutional Neural Network with Specific Image Preprocessing for Breast Cancer Detection. In *2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD)* (pp. 9-12). IEEE.

[17] Mahesh, M. (2004). AAPM/RSNA physics tutorial for residents: digital mammography: an overview. *Radiographics*, *24*(6), 1747-1760.

[18] Mane, S. A., & Kulhalli, K. V. (2015). Mammogram Image Features Extraction and Classification for Breast Cancer Detection. *International Research Journal of Engineering and Technology (IRJET)*, *2*(7), 810-814.

[19] Morrow, W. M., Paranjape, R. B., Rangayyan, R. M., & Desautels, J. L. (1992). Region-based contrast enhancement of mammograms. IEEE transactions on Medical Imaging, 11(3), 392-406

[20] Nithya, K., Aruna, A., Anandakumar, H., & Anuradha, B. (2014). A survey on image denoising methodology on mammogram images. *International journal of scientific & technology research*, *3*(11).(Gussian filter).

[21] Pisano, E. D., Cole, E. B., Hemminger, B. M., Yaffe, M. J., Aylward, S. R., Maidment, A. D., ... & Fajardo, L. L. (2000). Image processing algorithms for digital mammography: a pictorial essay. Radiographics, 20(5), 1479-1491.

[22] Pisano, E. D., Zong, S., Hemminger, B. M., DeLuca, M., Johnston, R. E., Muller, K., ... & Pizer, S. M. (1998). Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms. Journal of Digital imaging, 11(4), 193.

[23] Priya, D. S., & Sarojini, B. (2013). Breast Cancer Detection In Mammogram Images Using Region-Growing And Contour Based Segmentation Techniques. *International Journal of Computer & Organization Trends*, *3*(8).(Adaptive median)

[24] Ramani, R., Vanitha, N. S., & Valarmathy, S. (2013). The pre-processing techniques for breast cancer detection in mammography images. *International Journal of Image, Graphics and Signal Processing*, *5*(5), 47.(gauu)

[25] Rangayyan, R. M., Shen, L., Shen, Y., Desautels, J. L., Bryant, H., Terry, T. J., ... & Rose, M. S. (1997). Improvement of sensitivity of breast cancer diagnosis with adaptive neighborhood contrast

enhancement of mammograms. *IEEE transactions on information technology in biomedicine*, *1*(3), 161-170.

[26] Rouhi, R., Jafari, M., Kasaei, S., & Keshavarzian, P. (2015). Benign and malignant breast tumors classification based on region growing and CNN segmentation. *Expert Systems with Applications*, *42*(3), 990-1002.

[27] Roy, V., & Shukla, S. (2013). Spatial and transform domain filtering method for image de-noising: a review. *International Journal of Modern Education and Computer Science*, *5*(7), 41.

[28] Sahakyan, A., & Sarukhanyan, H. (2012). Segmentation of the breast region in digital mammograms and detection of masses. *International journal of advanced computer science and applications*, *3*(2).

[29] Shanmugavadivu, P., & Narayanan, S. L. (2017, February). Psychoanalysis of characteristic contrast enhancement of digital mammogram image. In *2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT)* (pp. 1-4). IEEE.

[30] Sheba, K. U., & Raj, S. G. (2017, July). Adaptive fuzzy logic based Bi—Histogram equalization for contrast enhancement of mammograms. In *2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT)* (pp. 156-161). IEEE.

[31] Sivaramakrishna, R., Obuchowski, N. A., Chilcote, W. A., Cardenosa, G., & Powell, K. A. (2000). Comparing the performance of mammographic enhancement algorithms: a preference study. *American Journal of Roentgenology*, *175*(1), 45-51.

[32] Sundaram, M., Ramar, K., Arumugam, N., & Prabin, G. (2011, July). Histogram based contrast enhancement for mammogram images. In *2011 International conference on signal processing, communication, computing and networking technologies* (pp. 842-846). IEEE.

[33] Suresh, R., Rao, A. N., & Reddy, B. E. (2018, January). Improving the mammogram images by intelligibility mammogram enhancement method. In *2018 2nd International Conference on Inventive Systems and Control (ICISC)* (pp. 1011-1015). IEEE.

[34] Tang, J., Rangayyan, R. M., Xu, J., El Naqa, I., & Yang, Y. (2009). Computer-aided detection and diagnosis of breast cancer with mammography: recent advances. *IEEE transactions on information technology in biomedicine*, *13*(2), 236-251.

[35] Umapathi, V. J., & Narayanan, V. S. (2014). Medical image denoising based on gaussian filter and Dwt Swt based enhancement technique. *International Journal of Soft Computing and Artificial Intelligence*, *2*(2).