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Contrast Enhancement of the Mammographic Image Using Retinex with CLAHE methods

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Abstract

Recently digital mammography is most widely used technology for early detection of breast cancer. The main diagnosing elements such as lesion or masses in digital mammograms are with law contrast. The purpose of this paper is to enhance the mammogram images by increasing its contrast. Different enhancement method are used for this purpose such as histogram equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Morphological, and Retinex. The Retinex method also implement by combining it with HE once, and with CLAHE to improve its performance. The experimental results show that using Retinex with CLAHE can produce an image with enhancement in contrast better than using it with HE method and better than other methods mentioned above.

Keywords: mammogram image, contrast enhancement, Retinex method, Histogram Equalization.

تحسين التباين في الصور الشعاعية للثدي بأستخدام طريقة ال Retinex مع ال CLAHE

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الخلاصة

في الاونة الاخيرة اصبح التصوير الشعاعي للثدي من التقنيات المستخدمة للكشف المبكر عن سرطان الثدي. ان العناصر الاساسية المعتمدة في التشخيص بالصور الرقمية الشعاعية مثل الضرر او الكتل تمتلك تباين واطي. ان الغرض من هذا البحث هو تحسين الصور الشعاعية للثدي عن طريق زيادة التباين.طرق مختلفة للتحسين تم استخدامها لهذا الغرض منها طريقة مساواة المخطط الاحصائي(HE)،الطريقة الشكلية(Morphological)،طريقة التباين المحدد للمخطط الاحصائي المطورة(CLAHE)،طريقة الشبكية(Retinex). ان طريقة الشبكية(Retinex) تم تنفيذها عن طريق دمجها مع طريقة ال(CLAHE) لاجل تحسين أداءها. النتائج العملية بينت ان استخدام الRetinex مع الCLAHE انتجت صورة مع تحسين بالتباين افضل من استخدامها مع ال HE ومع الطرق الاخرى المذكورة اعلاه.

Introduction

Breast cancer has become the main causes of mortality in women [1] Early detection of breast cancer contributes in lessening the mortality rate and improve the breast cancer prognosis. According GloboCan (WHO), for the year 2012, India record 70218 deaths due to breast cancer more than any

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other country in the world [2, 3]. In the United State breast cancer considered to be the most common malignancy in women and is second only to lung cancer as a cause of cancer death [4].

In 2015, an estimated 231,840 new cases of invasive breast cancer will be diagnosed among U.S. women, as well as estimated 60-290 additional cases of in situ breast cancer [5]. Mammography is the most efficient, effective and reliable technique currently being used by most of the radiologist to detect breast cancer at various stages [6]. Masses, calcification and architectural distortion are the three signs distinguished as causes for cancer identified by radiologist [1]. Digital mammography uses X-ray to project structures in the 2D female breast on to 2D image [7]. Tumor appears as a medium-gray to white areas in digital mammograms [8].

In mammography, low dose X-ray is used for imaging. In low contrast mammogram, it is difficult to interpret between the normal tissue and malignant tissue. In addition the radiologist miss about 10% of all cancerous lesions when using the poor contrast mammogram.

The aim of this work is to enhance the contrast of the mammographic images to achieve better visibility and easy to interpret by the radiologist. In recent years, there are many research studies have been conducted on contrast enhancement methods to solve the problems produced by poor contrast images, the following introduces some of them:

M.Sundarama et al. [9] described histogram modified local contrast enhancement for mammogram images. He referred that histogram modified local contrast enhancement method the resultant image will be more sharper than the original image by adjusting the level of contrast enhancement so that the local details in the original image can be interpret easily. Histogram modifications as an optimization technique and a local contrast enhancement technique are the two stage processing that used in this method. Sundaram et al. [10] proposed the contrast enhancement method based on histogram to improve the mammography quality, but this method has not suppressed the amplified noise in histogram equalization progress. Mohideen et al. [11] used multiwavelet with hard threshold to denoise and enhance mammographic image contrast. Kumar et al. [12] proposed the algorithm based on morphology and wavelet transform for enhancement of mammographic images. Morrow et al. [13] designed a region based contrast enhancement algorithm for mammograms. This method uses each pixel in the image as a seed to grow a region. Contrast is then enhanced by applying an empirical transformation based on each region's seed pixel value, its contrast and background information. Stoji´c et al. [14] developed an algorithm using mathematical morphology to enhance local contrast of mammography. Stahl et al. [15] applied the method of nonlinear multiscale processing based on Laplace pyramid for digital radiography enhancement. However, the binomial filter was used at each pyramid level with a nonlinear factor for contrast enhancement, which was sensitive to noise. Salem Saleh Al-amri, N.V.Kalyankar, and S.D.Khamitkar [16] attempted to undertake the study two types of the contrast enhancement techniques, linear contrast techniques and non-linear contrast techniques. In linear contrast techniques applying three methods, Max-Min contrast method, Percentage contrast method and Piecewise contrast technique. Non-linear contrast techniques applying four contrast methods, Histogram equalization method, Adaptive histogram equalization method, Homomorphic Filter method and Unsharpe Mask. In the Homomorphic Filter method applying by using two type of filter, Low Pass Filter (LPF) and High Pass Filter(HPF).this applying to choose the base guesses for contrast enhancement image.

M.Sundarama et.al [17] described histogram modified local contrast enhancement for mammogram images. In histogram modified local contrast enhancement method the resultant image will be more sharper than the original image by adjusting the level of contrast enhancement so that the local details in the original image can be interpret easily. Histogram modifications as an optimization technique and a local contrast enhancement technique are the two stage processing that used in this method. A.Papadopoulos [18] described microcalcification cluster detection in mammography using image enhancement techniques in which five image enhancement algorithms were used such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Local Range Modification (LRM) and Redundant Discrete Wavelet (RDW), linear stretching and shrinkage algorithms. In CLAHE algorithm the image will be divided into regions and histogram equalization will be applied in each region. By changing the intensity values of the image the pixel contrast can be maximized and thus the hidden features of the image will be more visible. H.D. Cheng et al. [19] described a novel fuzzy logic approach for mammogram enhancement. To enhance mammographic features an adaptive fuzzy logic contrast enhancement method is used. Using adaptive fuzzy logic contrast enhancement the mammogram can enhance by normalization process in which the intensity values of the mammogram can be changed to reduce the effects of different illuminations. In this approach after normalization fuzzification can be done based on the maximum fuzzy entropy principle. The main advantage of these method is it uses both normalization and fuzzification technique to enhance the mammogram so that the fine details of mammograms can be enhanced and the noise can be suppressed.

Methodology

Contrast enhancement is one of the important research issues of image enhancement. The purpose of image enhancement is to improve contrast between the mass structure and surrounding texture of the breast tissues, and it is considered to be the first step in breast cancer detection. The image enhancement techniques used in this work are:

1- Morphological filter

Image morphology is an important tool in image processing. Mathematical morphology is a very powerful tool for analyzing the shapes of the objects presents in images [20].

In this work the morphological opening and closing operations were applied to process the different multiscale sub band images. The opening and closing operations are produced by combining dilation and erosion operator, respectively. Furthermore, a structuring element SE of rectangle shape is used in dilation and erosion operator, respectively. The erosion of a gray-scale digital image (x, y) by a structural element SE(i, j) is defined as follows: [21-24]

$$(I \otimes \text{SE})\,(m, n) = \min\,\{I\,(m - i, + j) - \text{SE}\,(i, j)\} \quad \ldots \quad (1)$$

The gray-scale dilation can be described as

$$(I \oplus \text{SE})\,(m, n) = \max\,\{I\,(m - i, n - j) + \text{SE}\,(i, j)\} \quad \ldots \quad (2)$$

The Opening of image I(x, y) with a structure element SE is an erosion followed by a dilation operation, while closing is a dilation followed by an erosion operation as follows: [20]

$$I \circ \text{SE} = (I \otimes \text{SE}) \oplus \text{SE} \quad \ldots \quad (3)$$

$$I \cdot \text{SE} = (I \oplus \text{SE}) \otimes \text{SE} \quad \ldots \quad (4)$$

Because opening suppress bright details, and closing suppresses dark details, they are used often in combination as morphological filters for image smoothing, noise removal and prevent the image distortion.

Combining image subtraction with opening and closing results in so-called Top-Hat (TH) and Bottom-Hat (BH) transformation [21] .

The top-hat transformation by opening is defined as the difference between the original image and its gray scale opening using structuring element SE and it is defined as:

$$\text{TH} = I - (I \circ \text{SE}) \quad \ldots \quad (5)$$

Similarly the bottom-hat transformation applyed by closing is the difference between the gray-scale closing image and original image as follows:

$$\text{BH} = (I \cdot \text{SE}) - I \quad \ldots \quad (6)$$

The TH transformation produce only the bright peaks of an image, thus it is an effective technique for enhancing small bright details from the background. While the BH produces the dark valley of an image or the dark features in the image. [20]

In order to enhance the local contrast of the mammograms, the processing procedure is adding original image to the top-hat transformed image, and subtracting the bottom-hat image. Furthermore, its efficiency in image contrast enhancement has been proved by [23]. The calculated formula is given as follows:

$$C = I + \text{TH} - \text{BH} \quad \ldots \quad (7)$$

where I is the original image, C represents the final enhanced image, TH represents the extracted white image regions and BH represents the extracted black image regions at the size of the structuring element used. Equation (7) has been used in this work to enhance the features and contrast of mammographic image. Figure-1 shows the various steps involved in morphological filtering of the image at a single scale for enhancing the contrast of the image. The contrast is enhanced by applying the white and black top hat transformation.

2. CLAHE (Contrast Limited Adaptive Histogram Equalization)

A very popular technique for image enhancement is histogram equalization (HE). This technique is commonly employed for image enhancement because of its simplicity and comparatively better performance on almost all types of images [25].

HE has been applied in various fields such as medical image processing and radar image processing. This technique has certain limitations since the calculation is not computationally intensive. It is powerful in highlighting the borders and edges between different objects, but may reduce the local details within these objects, especially smooth and small ones. Another disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal. This technique may produce images with over enhancement. Some researchers have also focused on improvement of histogram equalization based contrast enhancement such as Contrast-Limited Adaptive Histogram Equalization (CLAHE) which helps to enhance the contrast locally. It is an adaptive contrast enhancement method which is based on adaptive histogram equalization. Adaptive Histogram Equalization is an extension to conventional Histogram Equalization technique. This technique computes several histograms, each corresponding to a distinct section of the image known as tiles, rather than the entire image. Each tile's contrast is enhanced to redistribute the pixel values of the image. The neighboring tiles are then combined using bilinear interpolation in order to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited in order to avoid amplification of the noise which might be present in the image. This method is therefore suitable for improving the local contrast of an image and bringing out more detail. This method emphasizes local contrast, rather than overall contrast. [26]

3. Retinex algorithm

It is a general purpose image enhancement algorithm. Many digital medical images suffer from lack of contrast and sharpness. The Retinex automatically provides both enhanced contrast and sharpness [27].

At first the illumination information is estimated and then the reflectance is obtained from using division. It is based on the image formation model which is given by: [28]

$$I(x, y) = L(x, y)\, r(x, y) \quad \ldots\ldots (8)$$

Where I is the input image, L is illumination and r is reflectance. The image is first converted into the logarithmic domain [28] in which multiplications and divisions are converted to additions and subtractions that makes the calculation simple. The sensitivity of human vision reaches a logarithmic curve. The flowchart of general Retinex algorithm is shown in Figure-2. S represents the input image. The illumination is estimated.

Retinex is based on the center/surround algorithm [29].The given centre pixel value is compared with the surrounding average pixel values to get the new pixel value. The input value of the center surround functions is obtained by its centre input value and its neighborhood.

The Retinex enhancement algorithms can be applied on all pictures. It provides better dynamic range compression and color rendition. It is an automatic process independent of inputs. There are different types of retinex algorithms: Single Scale Retinex algorithm (SSR), Multiscale Retinex algorithm (MSR), and Multiscale retinex with Color Restoration algorithm (MSRCR).

3.1 Single Retinex

Single Scale Retinex is the most basic method for Retinex algorithm. It takes an input digital image I and produces an output image R on a pixel by pixel basis in the following manner: [27]

$$R(x,y) = \log(I(x,y)) - \log(I(x,y) * M(x,y)) \quad \ldots\ldots (9)$$

$$= \log\left(\frac{I(x,y)}{I(x,y) * M(x,y)}\right)$$

Where $M(x,y) = \exp\left(\frac{x^2+y^2}{\sigma^2}\right)$

σ is a constant which controls the extent of M, and * represent spatial convolution.

3.2 Multi Retenix

Single-scale Retinex cannot provide both the dynamic range compression and tonal rendition.Multi Scale Retinex (MSR) [9] is developed to combine the strength of different surround spaces. The

Gaussian filters of different sizes are used to process input image several times. The resulting images are weighted and summed to get output of MSR [31]. It is given by [18]

$R_i(x, y) = W_n \log I_i(x, y) - \log [F_n(x, y) * I_i(x, y)]$ …………………………………………... (10)

where i=1, W_n represents the weight for the net scale, n is number of scales. MSR [32, 33] provide color enhancement. It also provides dynamic range compression and tonal rendition. A fundamental concept behind Retinex computation of lightness at a given image pixel is the comparison of the pixel's value to that of other pixels. The main difference between the Retinex algorithms is the way in which the other comparison pixels are chosen, including the order in which they are chosen. They use the same calculations but have dramatically different computational efficiencies in dealing with large real images.

3.3 Frankle-McCann Retinex

Frankle-McCann Retinex computes long-distance interactions between pixels first and then progressively moves to short-distance interactions. In Frankle-McCann, the spacing between the pixels being compared decreases with each step. The direction between pixels also changes at each step, in clockwise order. At each step, the comparison is implemented using the ratio product-reset-average operation. The process continues until the spacing decreases to 1 pixel. In the case of Frankle-McCann, it is based on the pixel located at a distance of s–row, s–col. The square spiral path structure in this implementation means that when this function is called, one of the two parameters will always be zero.

Frankle-McCann Retinex uses single pixel comparisons with variable separations. An important feature of this method is that there are no paths. A single pixel eventually averages different products from all other pixels. The advantage of this structure, and also for the multiresolution approach, is that long-distance interactions are propagated with fewer comparisons. In this method the contrast of the output is controlled by the number of iterations. This parameter can vary the output from radical to no dynamic range compression. The input data also plays a major role. The total dynamic range of input data determines the magnitude of radiance ratio associated with each digit. [34]

In this work, Frankle-McCann Retinex method was used to enhance the contrast by combined it with CLAHE method.

Experimental part:

Result and Discussion

In this work, different methods for enhancement of the contrast of a mammogram image are used, the Top-Hat and Bottom-Up morphological operations, HE (histogram equalization), CLAHE (contrast Limited Adaptive Histogram Equalization), and the Retinex. A combination of methods (Retinex with CLAHE) and (Retinex with HE) was used to improve the performance of Retinex. In Retinex the number of iteration control the output of image, so we found that the number of iteration equal to 50 will produce a good contrast than other iterations. Figure-3 show the flowchart of the combination between Retinex and CLAHE. The algorithms was implemented in Matlab environments. three mammogrm medical images were selected from the Mammographic Image Analysis Society (MIAS) database evaluate the performance of various enhancement techniques.[35] Figures-4, 5 and 6 shows the result of applying the above mentioned approaches on a three mammogram images. The performances of these methods are evaluated using two of image quality metrics to estimate the enhancement quality such as PSNR (peak signal to noise ratio) which is commonly used as a measure in image enhancement applications with respect to peak signal power, which is given by: [20]

$$PSNR = 20 \ \log_{10} \frac{255^2}{RMSE} \quad \text{……………………………………………………………... (11)}$$

where

$$RMSE = \sqrt{\frac{(f(i,j)-F(i,j))^2}{MN}} \quad \text{…………………………………………………...……… (12)}$$

where, f (i, j) is noisy image, F (i, j) is enhanced image.

The second metric used is a Contrast Index Improvement (CII) which is define as follows: [20]

$$CII = \frac{C_{proceesed}}{C_{original}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where $C_{original}$, and $C_{proceesed}$ represent the contrast values of the original and processed images respectively. The contrast C of a region was defined by:[21]

$$C = \sum_{k=0}^{L-1} \sqrt{(k-m)^2 * p(k)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

where m is the mean value, p(k) is the probability of the gray level in image. Tables- 1, 2, and 3 shows the performance analysis of the approaches with the regard to mammographic medical images for breast cancer detection.

Conclusion

According to the results we found that CLAHE having a good contrast than other method, so when applied it on the output of Retinex an improvement noticed in its contrast based on the value of CII as shown in Tables-1, 2 , and 3.

The results also showed that using a combination of Retinex with CLAHE achieved an improvement in contrast of about 48%, 66%, and 90% in images of Figures- 4, 5, and 6 respectively, depending on the following equation:

$$\frac{C_{processed} - C_{original}}{C_{original}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

where C represents the contrast value. This result prove that the use of Retinex with CLAHE gives the better contrast enhancement than another methods used in this work and therefore it improve the quality of Retinex. The PSNR result from this combination produce a value between the Retinex and the CLAHE.

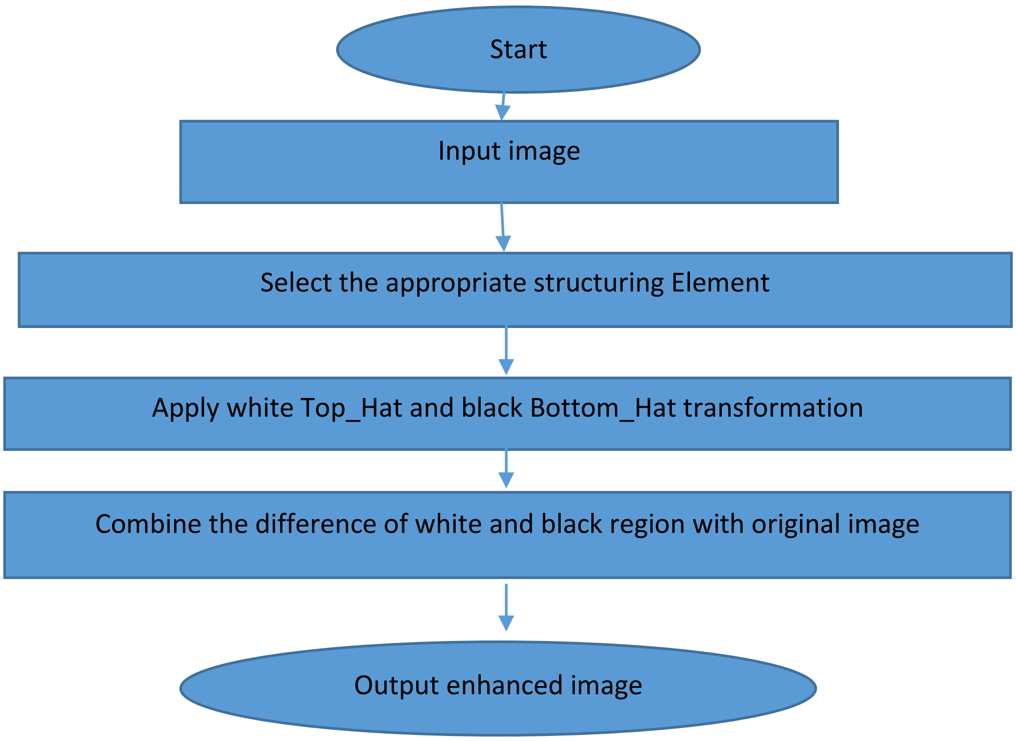

Figure 1- flowchart of Top_Hat and Bottom_Hat Morphological filter.

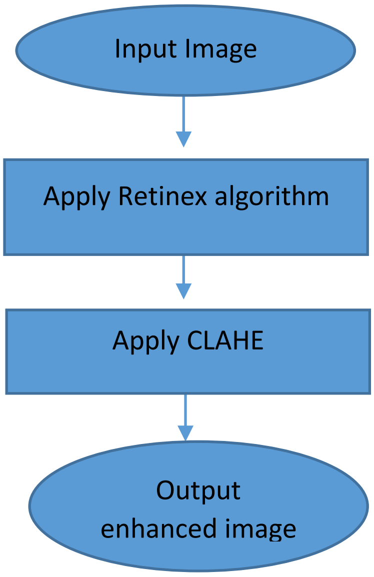

Figure 2- the General flowchart of Retinex technique.

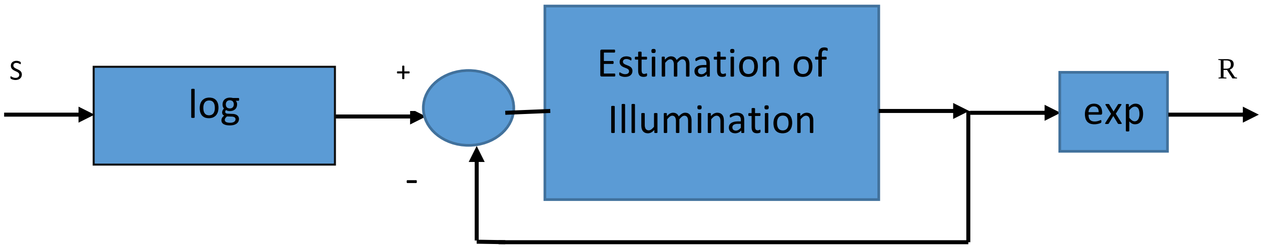

Figure 3- flowchart represent the combination between Retinex and CLAHE techniques

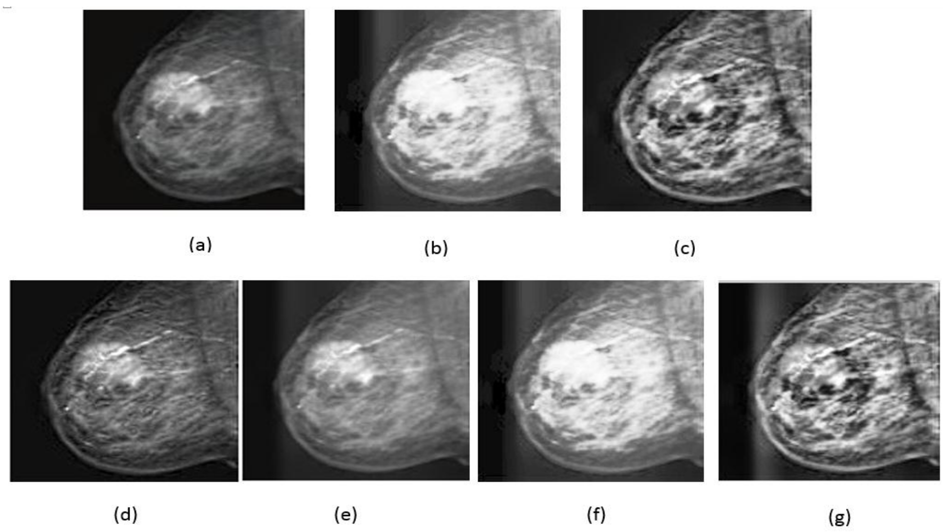

Figure 4- implementation of contrast enhancement techniques on a mammogram image **(a)** original image **(b)** Histogram Equalization **(c)** CLAHE **(d)** Morphological technique **(e)** Retinex **(f)** Retinex with histogram equalization **(g)** Retinex with CLAHE.

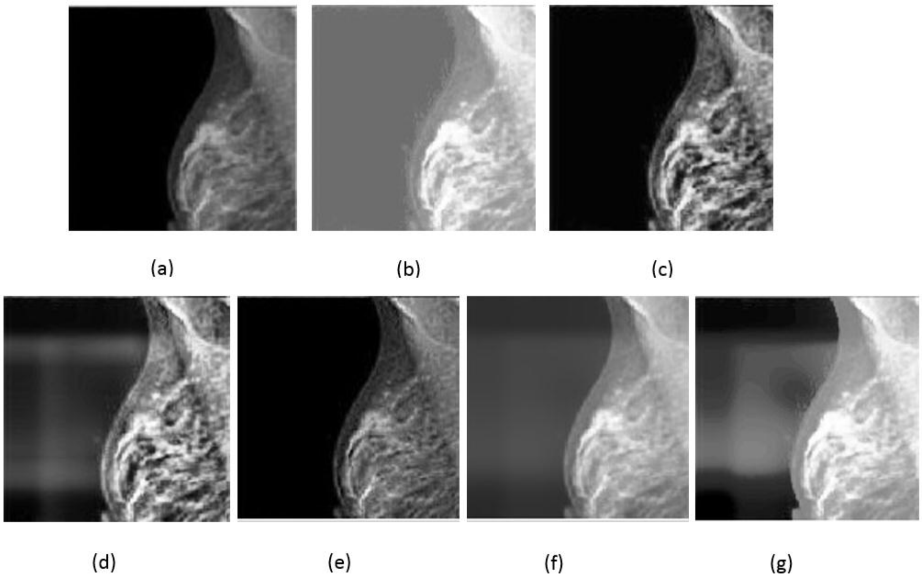

Figure 5- implementation of contrast enhancement techniques on a mammogram image **(a)** original image **(b)** Histogram Equalization **(c)** CLAHE **(d)** Morphological technique **(e)** Retinex **(f)** Retinex with histogram equalization **(g)** Retinex with CLAHE.

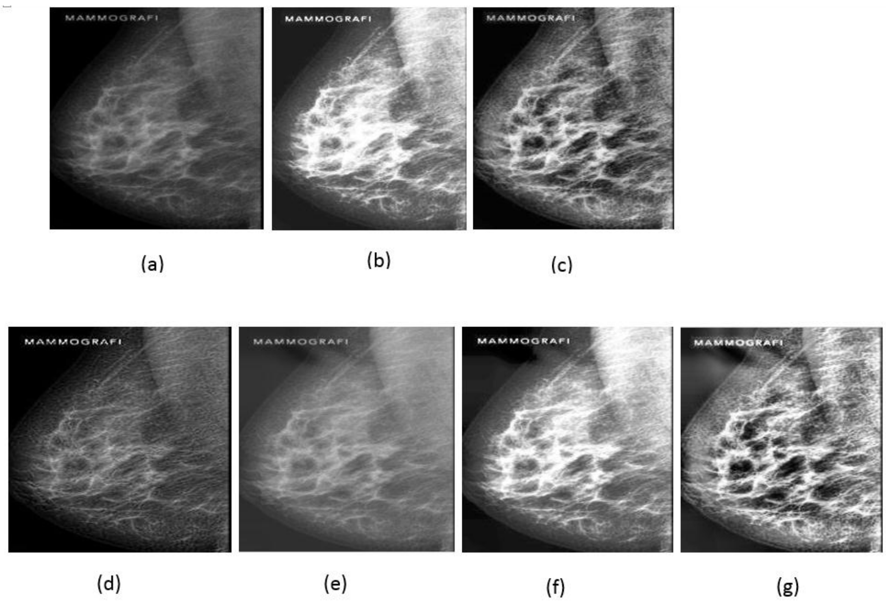

Figure 6- implementation of contrast enhancement techniques on a mammogram image **(a)** original image **(b)** Histogram Equalization **(c)** CLAHE **(d)** Morphological technique **(e)** Retinex **(f)** Retinex with histogram equalization **(g)** Retinex with CLAHE.

Tabel 1- metric for evaluation using contrast index improvement (CII), and Peak Signal to Noise Ratio (PSNR) for image in Figure- 4.

Method	**PSNR**	**Contrast**	**CII**
Original		568.4177	1.0000
HE	120.0718	224.1899	0.7241
CLAHE	130.7981	809.8611	1.3763
Morphological	136.3957	613.0963	1.0786
Retinex I=50	134.9519	678.4253	1.1935
Retinex with HE	119.9293	468.8648	0.8249
Retinex with CLAHE	126.5343	842.9870	1.4830

Tabel 2- the metric for evaluation using contrast index improvement (CII), and Peak Signal to Noise Ratio (PSNR) for image in Figure- 5.

Method	PSNR	Contrast	CII
Original		530.2953	1.0000
HE	111.9495	224.1899	0.4228
CLAHE	135.8612	809.8611	1.5272
Morphological	140.5594	639.1258	1.2052
Retinex I=50	120.0541	682.7647	1.2875
Retinex with HE	115.1838	496.5097	0.9363
Retinex with CLAHE	124.1049	880.4059	1.6602

Tabel 3- The metric for evaluation using contrast index improvement (CII), and Peak Signal to Noise Ratio (PSNR) for image in Figure- 6.

Method	PSNR	Contrast	CII
Original		388.0121	1.0000
HE	117.3302	438.3565	1.1297
CLAHE	127.5779	718.7602	1.8524
Morphological	154.2697	470.4507	1.2125
Retinex I=50	126.2928	408.9215	1.0539
Retinex with HE	117.2884	508.6400	1.3109
Retinex with CLAHE	117.9478	876.9220	2.2600

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