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Original Research

Enhancement of Mammogram Images Using Digital Image Processing Techniques for Breast Cancer Detection

Tekleweyni Berhe & Eshetu Diriba*

Department of Physics, Haramaya University, Dire Dawa, Ethiopia

Abstract

The purpose of this study was to improve the visual clarity of mammography images by minimizing noise and improving contrast through various image enhancement techniques. Mammogram samples were collected from the Abel Clinic Centre in Addis Ababa and the Mammographic Image Analysis Society (MIAS), using different tube voltage (kVp) and tube current (mAs) settings. Eight mammogram films were digitised and resized to a standard resolution of 256×256 pixels. The RGB images were converted to grayscale for processing. Two primary enhancement steps were applied: noise reduction using mean and median filters with kernel dimensions of 3×3, 5×5, 7×7, and 9×9 are utilised, alongside three contrast enhancement methods: contrast-limited adaptive histogram equalisation (CLAHE), histogram equalisation (HE), and contrast stretching (CS). In this study, the median filter using a 3×3 kernel size proved to be the most effective. For contrast enhancement, CLAHE was identified as the most suitable method for improving image visibility. The effectiveness of these techniques was evaluated using measures like the mean square error (MSE) and the peak signal-to-noise ratio (PSNR). Hence, the median filter effectively reduces noise, while CLAHE significantly enhances image contrast, making these methods valuable for early and accurate detection of breast cancer in mammographic images.

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*Corresponding Author:

Eshetu Diriba

E-mail: eshetudiriba444@gmail.com

INTRODUCTION

Abnormal and unregulated growth of breast cells causes breast cancer, which eventually results in tumour formation. It is the second leading cause of death from cancer among women across the world, including Ethiopia (Kebede et al., 2024; Mutlag et al., 2020). In digital mammograms, tumours typically show medium gray to white spots and can be classified as benign or malignant (Sohibnazarova, 2024). Malignant refers to cancerous tumours, while benign is classified as non-cancerous (Jung et al., 2023). Some common criteria used by radiologists in identifying breast cancer include masses, calcifications, and architectural distortions (Khamaneh et al., 2023).

Mammography remains the most reliable method for detecting small breast tumours at an early stage (Nicosia et al., 2023). This process permits proper access to the early treatment of cancer by maximising the chances of survival and reducing mortality. Yet, it's a very difficult task to properly interpret mammograms, given that there are several other factors or contributors: the small size of the tumours, low contrast, noise, and blurring. Therefore, image processing techniques are employed to improve the mammograms used for detecting tiny breast lesions and to reduce screening costs (Kebede et al., 2024). Enhanced medical imaging improves the visibility of critical structures, thus leading to more accurate diagnosis and treatment (Norouzi & Goudarzi, 2022; Ruiz et al. 2022).

Nevertheless, despite the advancements in improving the mammogram, most works reviewed focused on noise removal and contrast enhancement methods without addressing the effects of varying median filter kernel sizes and different clip limits in Contrast Limited Adaptive Histogram Equalisation (CLAHE). However, this study has presented an avenue for filling this gap using both median and mean filters for noise removal, and contrast enhancement methods such as Histogram Equalisation (HE), CLAHE, and Contrast Stretching (CS) were used. These methods seek to enhance the quality and interpretability of mammograms for an easier understanding of the features, such as masses and micro-calcifications.

Assessment of these techniques has been performed using metrics like Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). By enhancement of mammographic images, the present study attempts to help radiologists for early detection and diagnosis of breast cancer with the result being improvement in the overall health of the patients.

In this paper, images obtained from a database and clinic have been used to study noise removal and local contrast enhancement techniques. Many literary works use two or three breast cancer enhancement techniques (Avcı & Karakaya, 2023), and a few scholars (Santos et al., 2024) used four techniques to investigate the image's visibilities. However, this study has shown five image techniques and two performance measuring parameters, and a comparison was made with each technique to identify the best noise removal and local contrast enhancement.

MATERIALS AND METHODS

Sampling Techniques

In this study, eight mammography images were collected from two sources: the Abel Radiological Diagnostic Clinic Centre and the Mammographic Image Analysis Society (MIAS) database. These images represent a diverse range of breast tissue and potential abnormalities. The combination of clinical and publicly available datasets ensures a more comprehensive evaluation of the image enhancement techniques applied.

Image analysis

An image processing method was developed using the MATLAB software platform to reduce noise and enhance the visual quality of mammogram images. The key steps involved in this process are outlined in Figure 1, summarising the workflow used for enhancing the mammogram images. This approach aims to improve the clarity of the images, making it easier to detect abnormalities and supporting more accurate diagnosis.

The Acquisition of Images

The captured image data was loaded into a computer for further analysis. The digitalised mammogram images loaded were resized to 256 ×256 and kept in the JPEG format.

Image Pre-Processing

The mammography image enhancement technique is carried out using de-noising techniques such as mean and median filters and contrast enhancements like histogram equalisation, CLAHE, and contrast stretching.

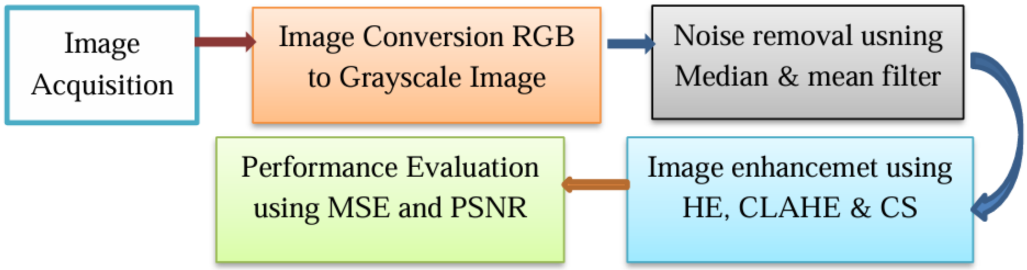


Figure 1. *The proposed method's flow chart.*

Contrast Enhancement

Image enhancement aims to enhance the contrast between the dense structures and the surrounding textures of breast tissues. This process involves adjusting the brightness levels of different elements in the image to make them more distinguishable and easier to see.

Histogram Equalisation

The gray level was redistributed to achieve a consistent histogram to enhance the clarity of mammography images, which might be important for appropriate viewing of details in over or under-exposed images (Dhal et al., 2021). An image's histogram displays how often each gray level appears in the image. The normalised histogram can be expressed as the ratio of the frequency of the k^{th} intensity level, $n(k)$, to the total number of pixels, n, in the grayscale image.

$$p(k) = \frac{n(k)}{n} \qquad (1)$$

The traditional method of histogram equalisation relies on the cumulative distribution function (CDF), which is represented by the following equation:

$$C(k) = \sum_{j=0}^{k} p(k) \qquad (2)$$

Where $C(k)$ is the Cumulative Distribution Function.

Contrast limiting sets CLAHE apart from standard Adaptive Histogram Equalisation (AHE) (Härtinger & Steger, 2024; Stimper et al., 2019). While CLAHE is effective for enhancing image contrast, its impact can be too intense for certain applications. In CLAHE, contrast limiting must be applied to each local region from which a transformation function is calculated.

Contrast stretching

Contrast stretching, or normalisation, enhances an image by expanding its range of intensity values to fully utilise the possible spectrum. This method increases the dynamic range of gray levels while limiting contrast to homogeneous areas to avoid amplifying noise. As a result, contrast stretching is particularly useful for improving local contrast and revealing finer details, rather than adjusting the overall contrast (Maurya et al., 2022). The process involves setting upper and lower pixel value limits, the minimum and maximum intensity values are represented by the lowest and highest intensity levels. The simplest normalisation scans the image for these limits, and then each pixel P is scaled using the formula:

$$P_{out} = \frac{(P_{in} - c)(b - c)}{(d - c)} \qquad (3)$$

where P_{in} is the input pixel value, c and d refer to the minimum and maximum intensity values, respectively, while **b** denotes the new maximum pixel value in the image after stretching.

Performance Measurement

The performance of the enhanced images is measured based on the mean square error. Suppose an original image is $f(i,j)$ and its size is $M \times N$, the enhanced image is $f_{out}\ (i,j)$ and its size $M \times N$ is M, where $i = 1, 2, \dots, M$, $j = 1, 2, \dots.,$ N. The mean squared error is computed as

$$\mathrm{MSE} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (f_{out}(i,j) - f(i,j))^2 \qquad (4)$$

Where M and N represent the total number of pixels in the image's column and row, respectively.

The PSNR is used as a metric to quantitatively assess the effectiveness of different digital filtering methods.

$$PSNR = 10\,log\left(\frac{a_{max}^2}{MSE}\right)(db) \qquad (5)$$

Where $a_{max} = 2^{k-1}$ is the maximum value of pixel present in the image and k denotes the number of a pixel binary bit.

RESULTS AND DISCUSSION

Experimental Results

The digitalized mammogram image is loaded onto a computer, stored in RGB format, resized to a standard dimension, and transformed into a grayscale image format.; Figure 2 depicts its histogram.

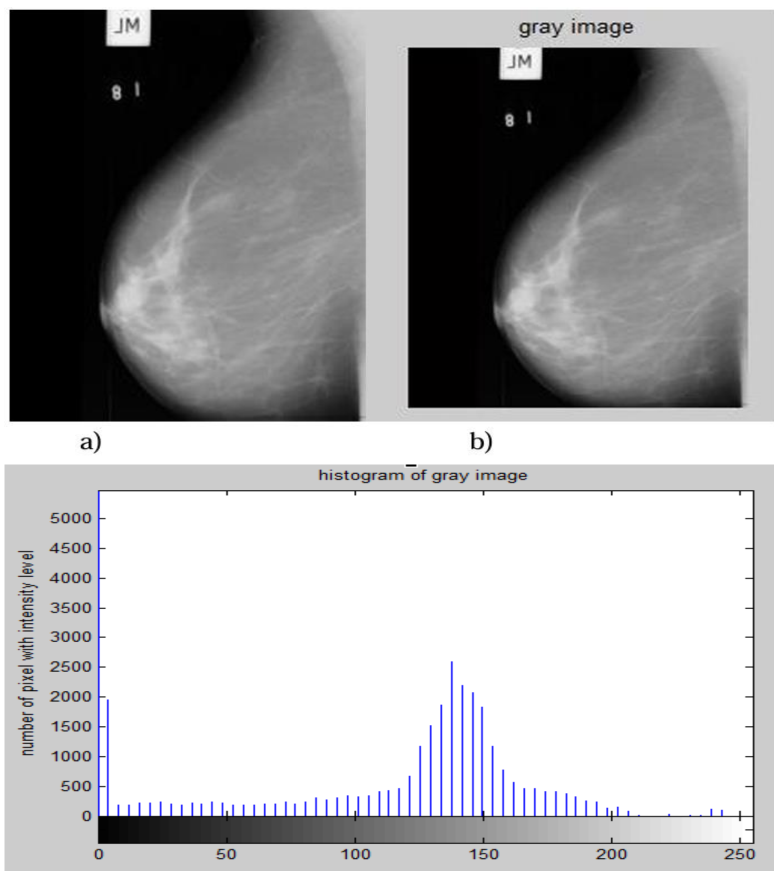


Figure 2. *a) RGB image, b) gray-scale, and c) gray-scale histogram.*

The gray-scale image is filtered by a median filter with a neighbourhood size 3×3 and a mean filter with a kernel size (3×3)/9 for smoothing, noise removal, and highlighting some information without affecting the image. The result of the filtered image using mean and median filters is depicted in Figure 3.

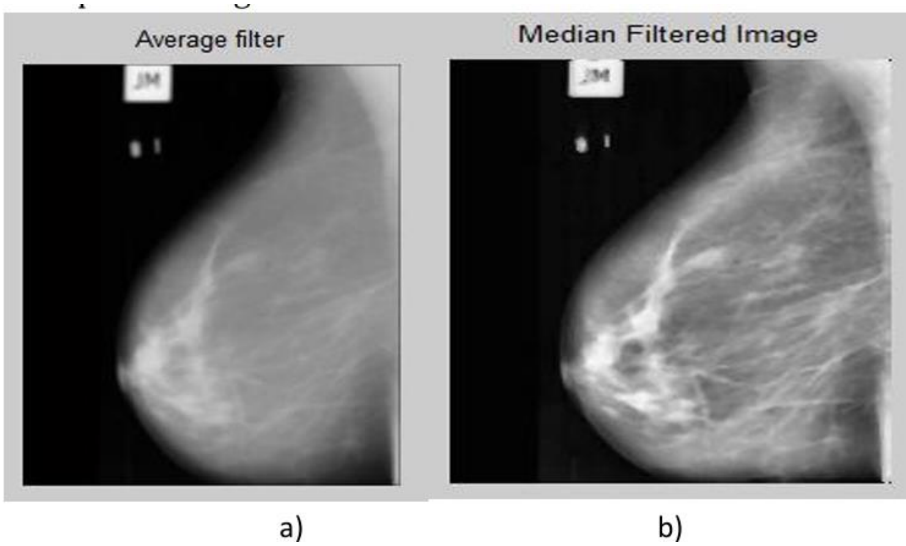


Figure 3. *Filtered mammogram image using a) mean and b) median filters*

Different kernel sizes of median and mean filtering $(3 \times 3, 5 \times 5, 7 \times 7 \text{ and } 9 \times 9)$ were used to remove the noise from mammography images; amongst these kernel sizes, the one that reduced the noise the best for mammography images was a kernel size of 3×3

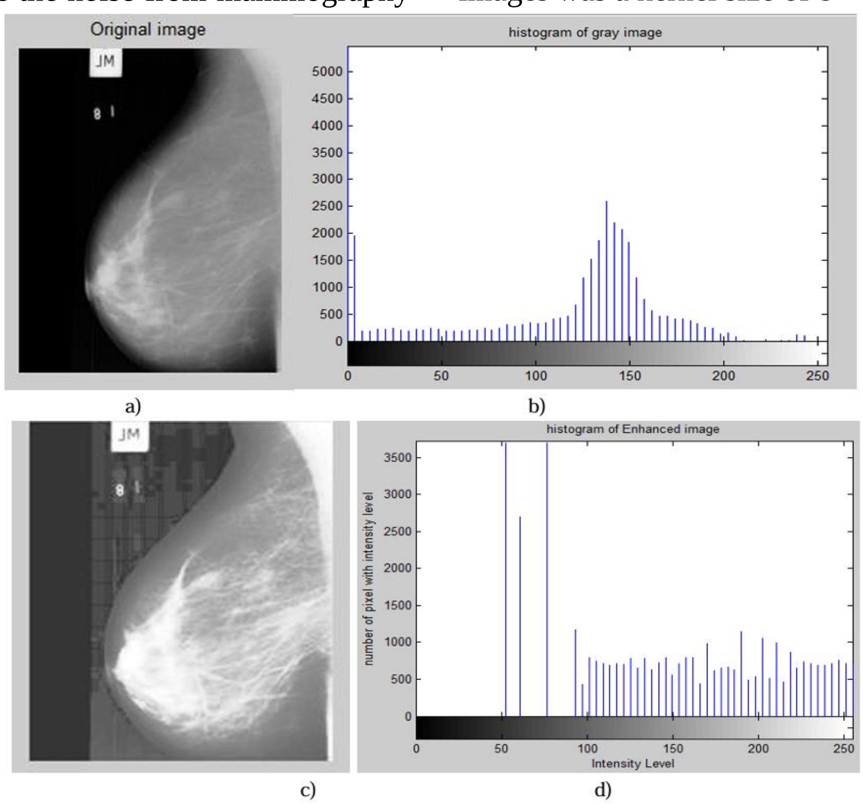
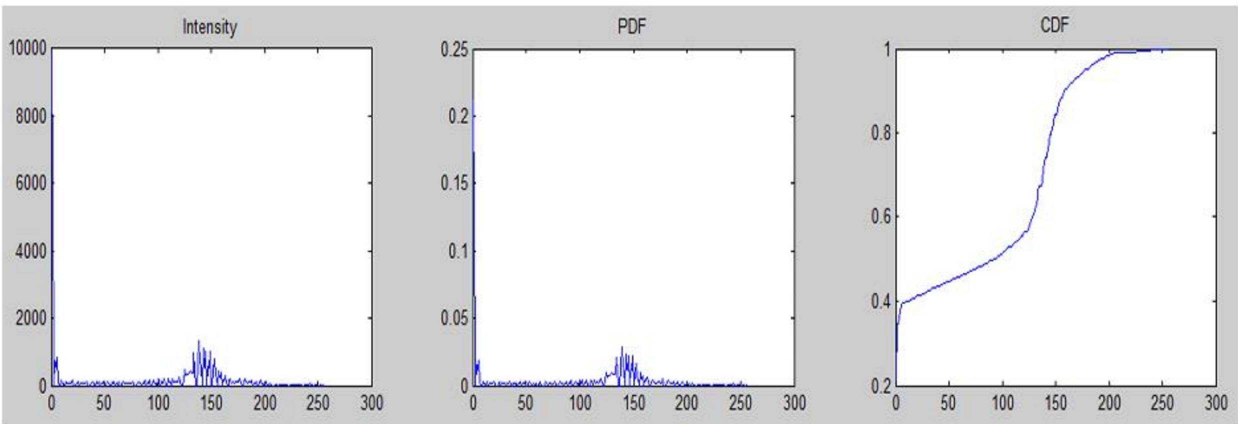


Figure 4. *Enhanced mammogram image and its histogram equalisation.*

Histogram equalisation was applied to adjust image intensities to enhance the contrast of mammogram images. A restriction of the intensity value (0–255) has been applied to the range of the histogram in order to focus on the areas corresponding to the right range of the histogram, and the contrast was adjusted using the histeq built-in MATLAB function. Figure 4 illustrates a) the original image, b) the histogram of the grayscale image, c) the image after enhancement through histogram equalisation, and d) the histogram of the enhanced image. In these histograms, the horizontal axis represents the intensity levels (ranging from 0 to 255), while the vertical axis indicates the frequency of pixels for each intensity value. The enhanced histogram graph shows that as the intensities increased, the visibility of the mammogram images also increased.



a) b) c)

Figure 5. *Intensity, PDF, and CDF values of the enhanced mammogram image.*

Figure 5 illustrates the intensity histogram, the probability density function, and the cumulative distribution function of pixel intensities in a grayscale cancer image. The intensity histogram shows that most pixel values are concentrated between 120 and 160, indicating limited contrast across the image. The probability density function (PDF) reflects a sharp peak in this range, further confirming that the image predominantly contains pixels with similar intensity values. The CDF exhibits a steep increase within this narrow range, suggesting that pixel intensities rapidly accumulate and plateau outside this region, indicating few extremely dark or bright pixels. From an analysis perspective, the narrow intensity distribution and rapid accumulation in the CDF suggest that the image may not provide sufficient contrast for effectively distinguishing between cancerous and healthy tissues. For better visual separation of these regions, contrast enhancement techniques such as histogram equalisation or contrast stretching are necessary to spread the pixel intensities across a broader range, which could aid in more accurate cancer detection. As illustrated in Figure 5, the enhanced image has a maximum intensity level of 150. This implies that the lesion part of the breast cancer image is identified at this point.

Figure 6 depicts the enhanced mammogram image using CLAHE, which improves local contrast by adjusting intensities in small regions of the image. Unlike global methods, CLAHE enhances subtle details without amplifying noise, making cancerous areas more distinguishable from healthy tissues. After CLAHE, the intensity histogram would show a broader distribution, allowing better contrast between tissues, while the PDF and CDF would reflect more evenly distributed pixel intensities. This enhancement technique is particularly valuable for highlighting tumours in dense breast tissue, improving early cancer detection and diagnosis.

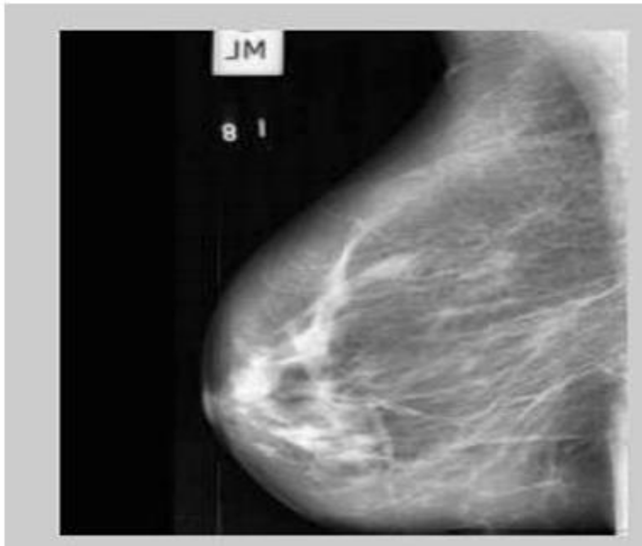


Figure 6. *Enhanced image using CLAHE*.

Figure 7 shows a mammogram image before and after enhancement using the contrast stretching technique. In the original image, the intensity values are clustered within a narrow range, as seen in the corresponding histogram, leading to limited contrast between cancerous and healthy tissues. The enhanced or "stretched" image, on the other hand, has a broader range of pixel intensities, as shown in its histogram.

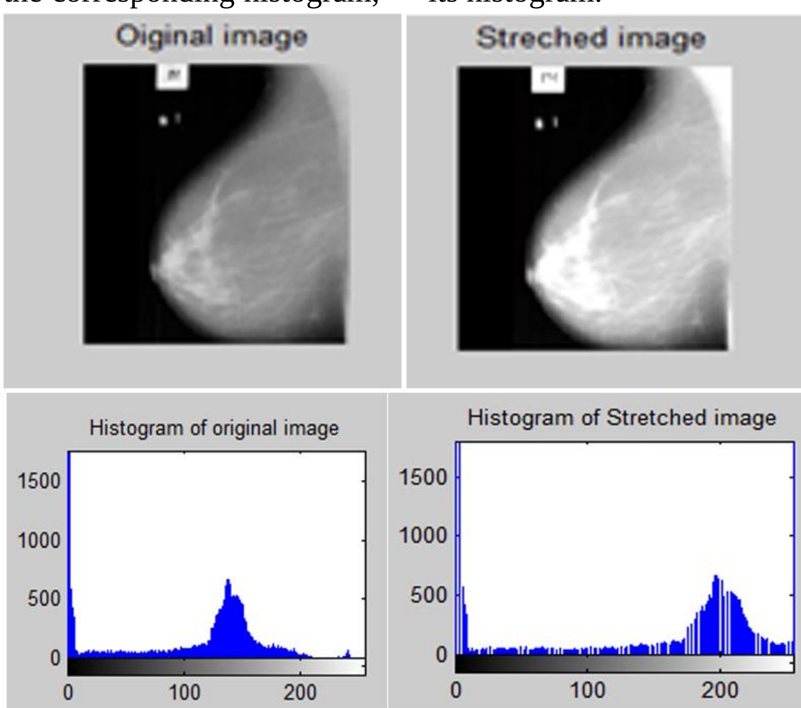


Figure 7. *Histogram of the stretched mammogram images.*

This stretching of the intensity values improves the contrast across the image, making refined differences in tissue density more visible. The enhanced image reveals more detailed structures, potentially aiding in better detection of cancerous areas by distinguishing them from the surrounding healthy tissue more clearly. Contrast stretching thus enhances visual clarity by spreading intensity values across the available range, making critical features like tumours easier to spot.

Performance measurement

The performance metrics, including PSNR and MSE, for all the enhancement techniques implemented with MATLAB codes, are tabulated in Table 1 and Table 2.

Table 1

PSNR values of de-noising and enhancing techniques.

Mammogram Image	PSNR				
	Median	Mean	HE	CLAHE	CS
Img 1	18.6	16.3	18.6	20.4	6.48
Img 2	18.2	15.5	17.4	20.2	6.2
Img 3	18	15.4	17.3	19.5	6.3
Img 4	18.3	15.8	16.8	20.6	6.51
Img 5	18.7	16	17.2	20.8	6.49
Img 6	19.2	16.2	17.3	20.7	6.67
Img 7	18.6	17.23	17.6	20.9	6.83
Img 8	18.4	17.6	18.1	20.6	6.87

Img = Image

The results of peak signal-to-noise ratio values of the filtering and enhancing techniques versus mammogram images are plotted as follows.

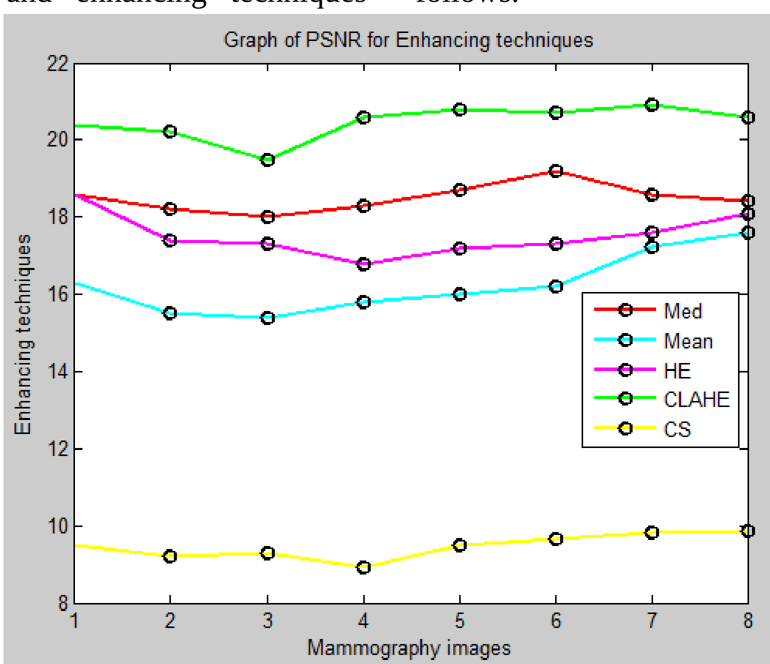


Figure 8. *Performance measurement of PSNR.*

Figure 8 displays the PSNR values for different image enhancement methods applied to mammogram images. Based on the graph, the median filter generally achieves the highest PSNR values, suggesting superior performance in noise reduction and image preservation. The mean filter, while also showing reasonable results, consistently lags behind the median filter. The HE, CLAHE, and CS techniques exhibit varying performance across different mammogram images. HE and CLAHE demonstrate comparable PSNR values, with HE slightly outperforming CLAHE in some cases. CS, however, exhibits the lowest PSNR values, indicating potential issues in preserving image details or introducing artifacts. Overall, the median filter appears to be the most effective technique for enhancing mammogram images in terms of noise reduction and preserving original information.

Table 2

MSE values of de-noising and enhancing techniques.

Mammogram Image	MSE				
	Median	Mean	HE	CLAHE	CS
Img 1	17.21	18.4	12.09	11.05	0.81
Img 2	16.03	17.65	11.82	11.41	0.78
Img 3	15.9	18.13	11.6	12.23	0.78
Img 4	15.8	18.26	12.6	11.60	0.83
Img 5	15.81	17.62	13.61	12.62	0.85
Img 6	16.14	17.08	12.83	12.02	0.87
Img 7	16.07	17.7	12.72	11.34	0.89
Img 8	15.8	17.43	13.84	11.38	0.86

Tables 1 and 2 represent the PSNR and MSE values of the noise filtering and enhancement techniques, respectively. The PNSR and MSE values for median filtering are maximum and minimum, respectively; this implies that median filtering is efficient in reducing noise. CLAHE has a high value of PSNR; this indicates that CLAHE is the best image-enhancing technique.

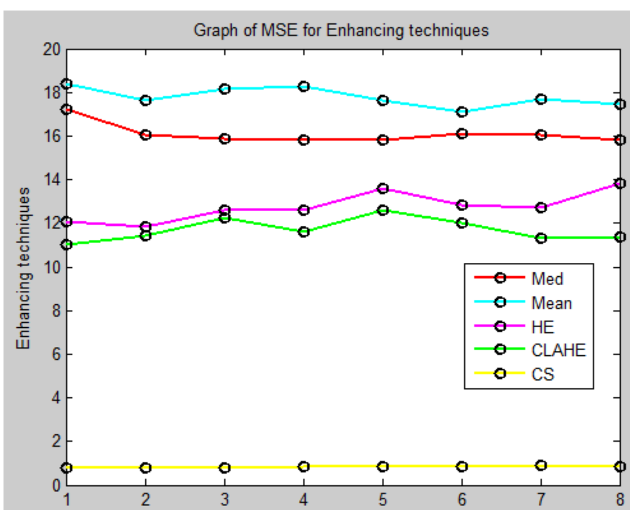


Figure 9. Performance measurement of MSE

Figure 9 shows the mean square error (MSE) values of various techniques for enhancing the quality of mammogram images. Based on the graph, the Median filter generally exhibits the lowest MSE values, suggesting the best preservation of original image information and minimal distortion. The Mean filter has higher MSE values than the median filter. The HE, CLAHE, and CS techniques demonstrate varying performance across different mammogram images. HE and CLAHE exhibit comparable MSE values. CS, however, has the highest MSE values, indicating significant distortion or loss of image details. Therefore, the Median filter appears to be the most effective technique for enhancing mammogram images in terms of minimizing distortion and preserving original image information.

CONCLUSION

In conclusion, the findings of this study can be used to support radiologists in detecting the mammogram image early and to protect cancer cells from spreading to other parts of the body. This in turn increases endurance and decreases the maternal mortality rate. In this study, different mechanisms were applied to eliminate noise from the image, and the effectiveness of the pre-processing techniques was evaluated using MSE and PSNR. These techniques were compared based on their performance with mammogram images. Among all the methods studied, the median filter with a kernel size of 3×3 proved to be the most suitable for reducing noise in mammogram images, as it resulted in a high PSNR and a low MSE.

Credit authorship contribution statement:

Tekleweyni Berhe: Conceptualization, Investigation, Data curation, methodology & Visualization.

Eshetu Diriba: Supervision & Validation, Writing – original draft, Writing –review & editing.

Declaration of competing interest

The authors declare that they have no conflicts of interest.

Ethical approval statement

The authors obtained ethical clearance from Haramaya University and secured a formal support letter for the study. Additionally, permission to conduct the research was granted by Abel Clinic, Addis Ababa, Ethiopia, after the study's objectives and procedures were clearly explained.

Data availability statement

All data are available from the corresponding author upon reasonable request.

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