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Evaluating Mammograms Enhancement Techniques Using Quantitative Metrics

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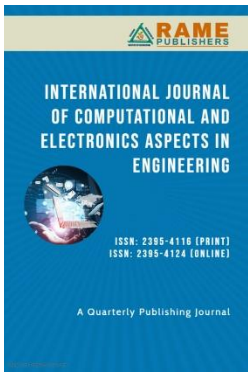

Abstract: In medical field, image enhancement techniques could play a crucial role in terms of providing accurate diagnosing and tumour classification. For instance, mammography is an imaging technique that is widely used to detect and diagnose breast cancer. Hence, improving the quality of the mammograms helps physicians by providing clear and fine images. This research investigates the performance of three enhancement techniques to improve and enhance the mammograms. These techniques are Gamma Correction (GC), Adaptive Histogram Equalization (AHE), and Linear Contrast Enhancement (LCE), and were chosen due to their efficiency in medical image enhancement. Signal to Noise Ratio (SNR), Entropy, Structural Similarity Index (SSIM), and Average Gradient (AG) are the performance metrics that were used to evaluate the three techniques. Results showed that AHE outperformed the GC and LCE in terms of producing high SNR, Entropy and AG. However, GC and LCE showed better values for the SSIM and similar values for the SNR, Entropy, and AG. This study concludes that AHE could be preferable choice for enhancing mammograms.

Keywords: Adaptive Histogram Equalization, Gamma Correction, Linear Contrast Enhancement, and Mammograms

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1. Introduction

Breast cancer was found to be a fatal disease and may be treated effectively if identified in its first stages. The World Health Organization (WHO) estimates that breast cancer causes around 685,000 deaths annually. Specifically there were around 2.3 million diagnoses for women in 2020 [1]. In 2018, a study indicated that incidence rate of breast cancer was 7.5 for every 100,000 among Saudi students, and it was reported that breast cancer is ranked among the nine main causes of mortality [2].

Currently, Mammography is the most effective imaging modality for diagnosing breast cancer. Basically, Mammography is a technique that uses X-ray to diagnose breast cancer by producing images that is widely known as mammograms. However, mammograms are characterized by having low contrast, background noise, and incoherent contrast among areas, which complicates breast cancer detection. Moreover, it is a challenging for the radiologist to establish an accurate diagnosis using regular mammograms. It was found that radiologists may only see 10–30% of lesions in mammograms due to present of noise and artefacts that are required to be removed and enhanced [3][4][5]. These drawbacks of mammography can be resolved by the application of suitable images enhancing techniques [6][7][8]. Next paragraphs list the previous studies in terms of image enhancements.

Morphological enhancement in addition to gamma correction and histogram equalization were used to enhance mammograms, where minimum entropy difference (MED) was used as a performance metric to evaluate these techniques [9]. Results showed that morphological enhancement that combines top-hat and bottom-hat operations are the best enhancement technique among the rest.

However, only one performance metric was used in this study which may lead to false results. Furthermore, contrast limited adaptive histogram equalization (CLAHE) and gamma correction alongside log transform were also used to enhance dental-x-ray images. Entropy and histogram distribution were considered as performance metrics in this study [10]. According to authors, highest entropy and flattened histogram were achieved using CLAHE indicating that this technique is most suitable. Although that this study considered two performance metrics to evaluate the techniques' effectiveness, histogram distribution could be altered by most techniques given misleading results.

Ref. [11] proposed a Dual-energy imaging technique that could improve breast lesion visualization by increasing contrast between normal and abnormal tissues. Low-energy and high-energy images are taken and merged to show malignancy-related vascularity. Furthermore, various studies revealed that contrast-enhanced digital mammography (CEDM) can be effectively used to identify and characterize breast cancer, especially in complicated circumstances when standard mammography may be insufficient. According to the findings, CEDM may improve breast cancer diagnosis and treatment decisions, this emphasizes the necessity of improved imaging in breast cancer identification and treatment.

Ref. [5] also proposed a technique to solve challenges such as noise present, low contrast, and pectoral muscle interference. The proposed pre-processing techniques, including morphological operations, significantly improved image quality, while K-means clustering effectively segmented abnormal regions. The method achieves 92% accuracy on a dataset of 2,892 images from the Qassim Health Cluster and 97% accuracy on the Mammogram Image Analysis Society (MIAS) database, outperforming existing approaches [12]. This study highlights the potential of combining image enhancement and machine learning for early and accurate breast cancer detection, offering a scalable tool for clinical applications [13][14][15].

Ref. [16] invented a method that automatically analyses mammograms for breast form and calcium deposits. The authors recommend a step-by-step approach to unequal signal dispersion, pectoral muscle interference, and image concerns. This method finds that skin-air border with a gradient weight map could recognize the boundary between the chest and breast using pixel labelling. Tests on the Mammogram Image Analysis Society (MIAS) database showed very high accuracy. The system also showed high accuracy when applied on Full-Field Digital Mammography (FFDM) datasets. This study shows that the proposed method could help analyse mammograms and improve the early detection of breast cancer.

Although that many techniques were used to enhance the medical images, quantitative comparison between those techniques have not been properly discussed. Moreover, performance metrics that can been used to evaluate the enhancement techniques were inadequately explained. Therefore, this research investigates the performance of popular techniques to enhance mammograms by examining quantitative metrics. Next section explains the materials and methods that were used in this study, section three discusses the results, and section four concludes the study.

2. Material and Methods

This study evaluates and compares the performance of three image enhancement techniques that can be applied on mammograms to obtain proposedly better images. The three techniques were evaluated using four popular metrics in addition to eye investigation. Following subsections explain the techniques and the metrics subsequently:

2.1. Image Enhancement Techniques

Gamma Correction (GC), Adaptive histogram Equalization (AHE) and Linear Contrast Enhancement (LCE) were used to enhance 10 mammograms taken from Mammographic Image Analysis Society. Each image is characterised by having 1024x1024 pixels, which provides a good resolution for the purpose of the image enhancement [9]. The employed techniques focused on improving key points to enhance contrast, brightness and detailed information for each image, which is important for diagnosis and identifying pathological features in mammograms [17]. Fig. 1 illustrates the steps in this study. Next paragraphs explain the three techniques in details and their functions upon the images.

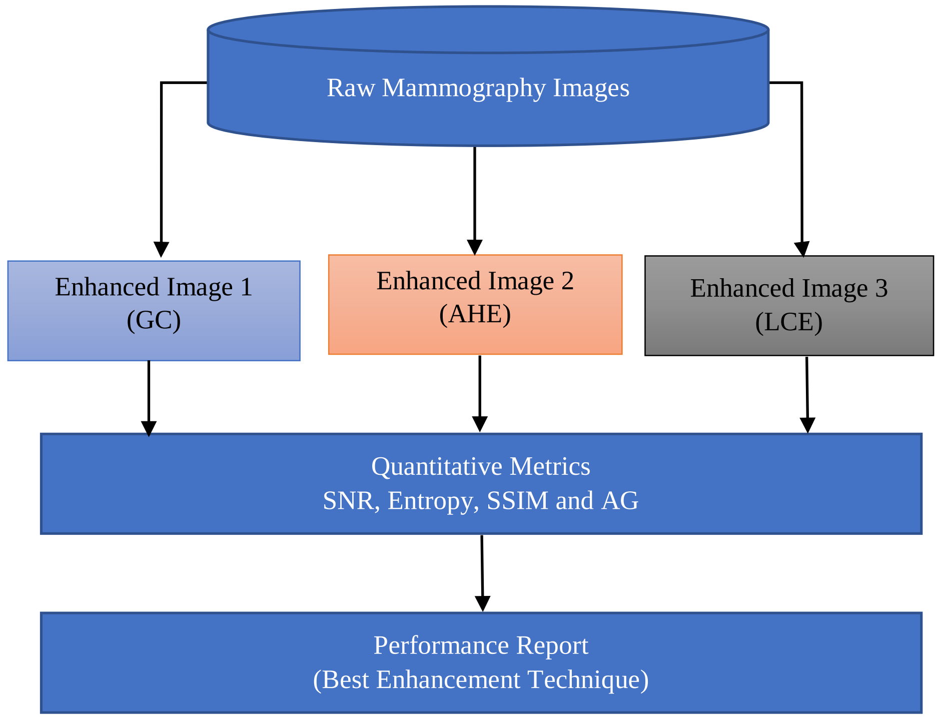

Figure 1. Diagram of the Proposed Study

I. *Gamma Correction (GC):* It is a non-linear technique that is used to adjust brightness values to fit a logarithmic curve. Gamma correction compensates for the relationship between a pixel's digital value and its actual brightness. Moreover, GC has shown good performance in terms of enhance the intensity distribution of an image by adjusting the brightness. Such technique provides a useful tool to clarify bright or dark images and can be mathematically represented as follows:

$$I_{enhanced} = C * I_{original}^{\gamma} \quad (1)$$

Where, $I_{enhanced}$ represents the enhanced pixel's intensity of an image, while $I_{original}^{\gamma}$ refers to the original intensity of the input pixel raised to the power of Gamma (γ). Gamma (γ) value was set to (0.8) which was previously used and shown excellent results [9]. Finally, C represents a scaling constant and was set to a value of (1) in our study. Hence, GC is considered a non-linear operation that works perfectly to enhance mammograms by preserving visual contexts and preventing noise amplification [18].

II. *Adaptive Histogram Equalization (AHE):* Histogram equalization (HE) refers to the mechanism of redistributing the global intensity histogram. On the other hand, AHE divides the images into tiles or blocks then applies the histogram equalization function to those tiles. 8x8 tiles was chosen to divide the mammograms to 8 row and 8 columns and produce a total of 64 tiles. Such technique insures that each tile is enhanced independently to the rest of image allowing high visibility to small masses. Moreover, mammograms varied in their contrast due to variation in tissue density of the breast, makes AHE a preferable choice to enhance local contrast of region with varying illumination [19].

III. *Linear Contrast Enhancement (LCE):* It is an image enhancement technique that stretches the contrast of the input image by re-mapping the range intensity of input pixels to a desired values. This method is used when the image has a narrow dynamic range, which may lose important details in both dark and bright areas of a mammogram. The mathematical representation of the LCE is shown in equation (2)

$$I_{enhanced}(x,y) = \frac{I_{original}(x,y) - I_{min}}{I_{max} - I_{min}} * (R_{max} - R_{min}) + R_{min} \quad (2)$$

Where $I_{enhanced}(x, y)$ Represents the intensity of the output pixel at (x,y) coordination, $I_{original}(x, y)$ Represents the intensity of the input pixel at (x,y) coordination, I_{max} and I_{min} Represent the maximum and minimum intensities values in the input image, R_{max} and R_{min}Represent desired maximum and minimum intensity values in the output image, which were set to (255 and 0) respectively as we are dealing with grayscale images. Equation (2) shows that LCE works effectively in low contrast image by stretching the intensities to desired range. Moreover, LCE performs relatively simple arithmetic operation makes it preferable in real-time applications [20].

2.2. Performance Metrics

Although that the aforementioned enhancement techniques are well-known and have shown excellent results in terms of image enhancement, it was required to evaluate their performance based on robust metrics. Hence, four metrics were used to evaluate the performance of the applied enhancements techniques. Those metrics were the Signal to Noise Ratio (SNR), Entropy, Structural Similarity Index (SSIM) and Average Gradient (AG). Each metric provides specific results in terms of noise reduction, detail preservation, contrast and overall clarity. Following paragraphs explain the four metrics in details:

I. *Signal to Noise Ratio (SNR):* identifies the quality of the images by calculating the ratio of the desired information to the noise that present in the image. Basically, high SNR indicates high quality images that has relatively clearer information. Where, SNR plays a crucial role in mammograms as it suppresses noise in low contrast image. SNR is mathematically represented as follows:

$$SNR = \frac{\mu}{\sigma} \tag{3}$$

Where, μ is the mean pixel intensity across the image and represents the desired signal (information), while the σ refers to standard deviation of those intensities and represents the noise. Such metric was suggested as it provides an accurate scale for the mammograms visualization [21].

II. *Entropy:* the entropy of an image describes the amount of information contained in a signal or image (in other words, the amount of information that image provides). Entropy reflects the complexity and the richness of the information present in an image. This metric is based on information theory and high entropy refers to high variability in intensity range over the images pixels. The mathematical representation of the entropy is shown in equation (4)

$$E = -\sum_{i=1}^{n} p_i * log_2(p_i) \tag{4}$$

$$P_i = \frac{number\ of\ pixels\ with\ intensity\ i}{L} \tag{5}$$

Where, E refers to the entropy, n is the number of intensities levels, p_i represents the probability of intensity level compared to other levels, and L is the total number of pixels in the image. Hence, efficient enhancement technique is supposed to increase the image Entropy and reveal the fine details in the image [22].

III. *Structural Similarity Index (SSIM):* measures the structural characteristics of the output image in terms of retaining the edges, textures and pattern that are present in the image. Considering that every enhancement technique modifies image's contrast and brightness, SSIM provides a good indication on how the enhancement technique preserves the structural information of the original image. In general, a higher SSIM score indicates that the enhancement method preserves the structural features of the breast, which is critical for maintaining diagnostic accuracy. Consequently, SSIM compares between two images (the original and the enhanced) and mathematically represented as follows:

$$\boldsymbol{SSIM(x, y)} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{6}$$

Where, $\boldsymbol{x\ and\ y}$ represent original and enhanced images, $\boldsymbol{\mu_x\ and\ \mu_y}$ represent mean intensities for original and enhanced images respectively, $\boldsymbol{\sigma_{xy}}$ represents the similarity between the two images by calculating the covariance, $\boldsymbol{\sigma_x^2\ and\ \sigma_y^2}$ represent the contrast of original and enhanced images by calculating the variance of two images. Finally, $\boldsymbol{C_1 and\ C_2}$ are constants with small values that are added to avoid denominator close to zero. SSIM ranges from (0) to (1), where 1 refers that the two images (original and enhanced) are structurally identical, while (0) indicates that enhanced image was completely altered by applying the enhancement technique [23].

IV. *Average Gradient (AG):* this metric evaluates the ability of a specific enhancement technique to improve the fine details especially the edges in the image. Basically, effective enhancement technique raises the AG value to provide better sharpness for the edges in the enhanced images, and ultimately can aid in detection of small tumours that are hard to differentiate from surrounding tissue. Equation (7) shows the mathematical representation of the AG

$$\boldsymbol{AG = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{(G_x(i,j))^2+(G_y(i,j))^2}} \quad (7)$$

Where, $\boldsymbol{M\ and\ N}$ refer to image dimensions, $\boldsymbol{G_x}$ gradient over the horizontal axis, and $\boldsymbol{G_y}$ gradient over vertical axis. AG was suggested to measure how the three techniques enhanced the mammograms in terms clarifying the images edges [24].

To summarize, the four metrics have their own characteristics. For instance, SNR and AG focus on signal clarity, noise suppression, and edge sharpness, while entropy assesses the complexity of the detail that present in the image [25]. SSIM, however, compares the structural details between the original and enhanced image. Consequently, the four metrics were chosen to evaluate the three enhancement techniques in terms of improving the contrast, brightness, edge clarification, and structural preservation. Next section discusses the results and decides the best enhancement technique based on the four metrics.

3. Results and Discussion

As mentioned in previous section, three popular image enhancement techniques were applied on 10 mammograms to further improve their quality and ultimately diagnosis aspects. Fig. 2 shows an example of how the original mammogram was modified by applying the three techniques. Although that the three techniques have adjusted the original image in different means based on their functions, it is hard to decide the efficient technique from fig. 2. Therefore, fig. 3 was suggested to show the performance metrics of each enhancement technique over the 10 mammograms. It is clearly shown that AHE has outperformed the GC and LCE in terms of three metrics that are SNR, Entropy and AG. However, AHE showed the smallest SSIM value among the three enhancement techniques indicating that this technique has dramatically modified the original image's structure.

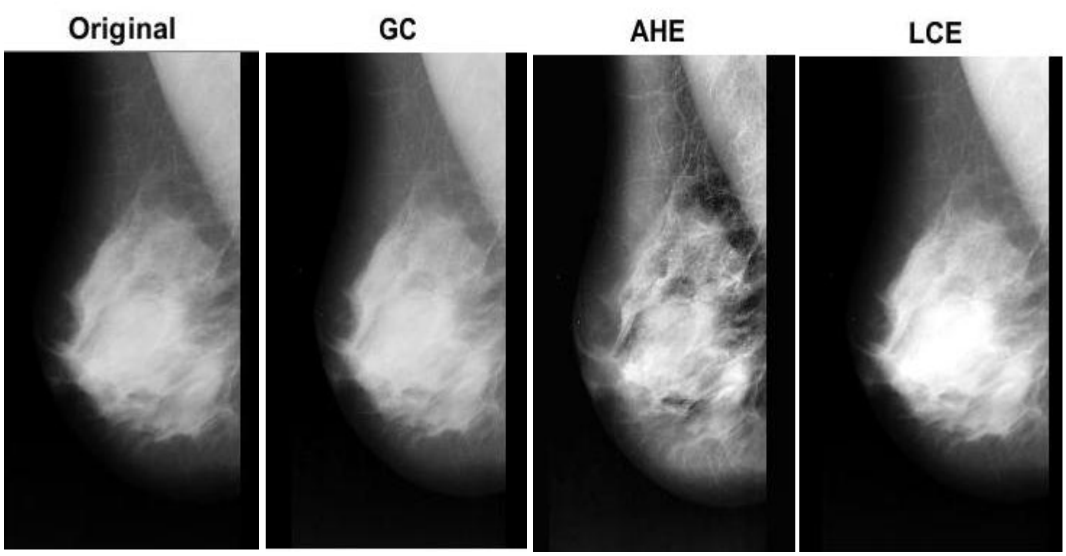

Figure 2. Comparison of Original and Enhanced images

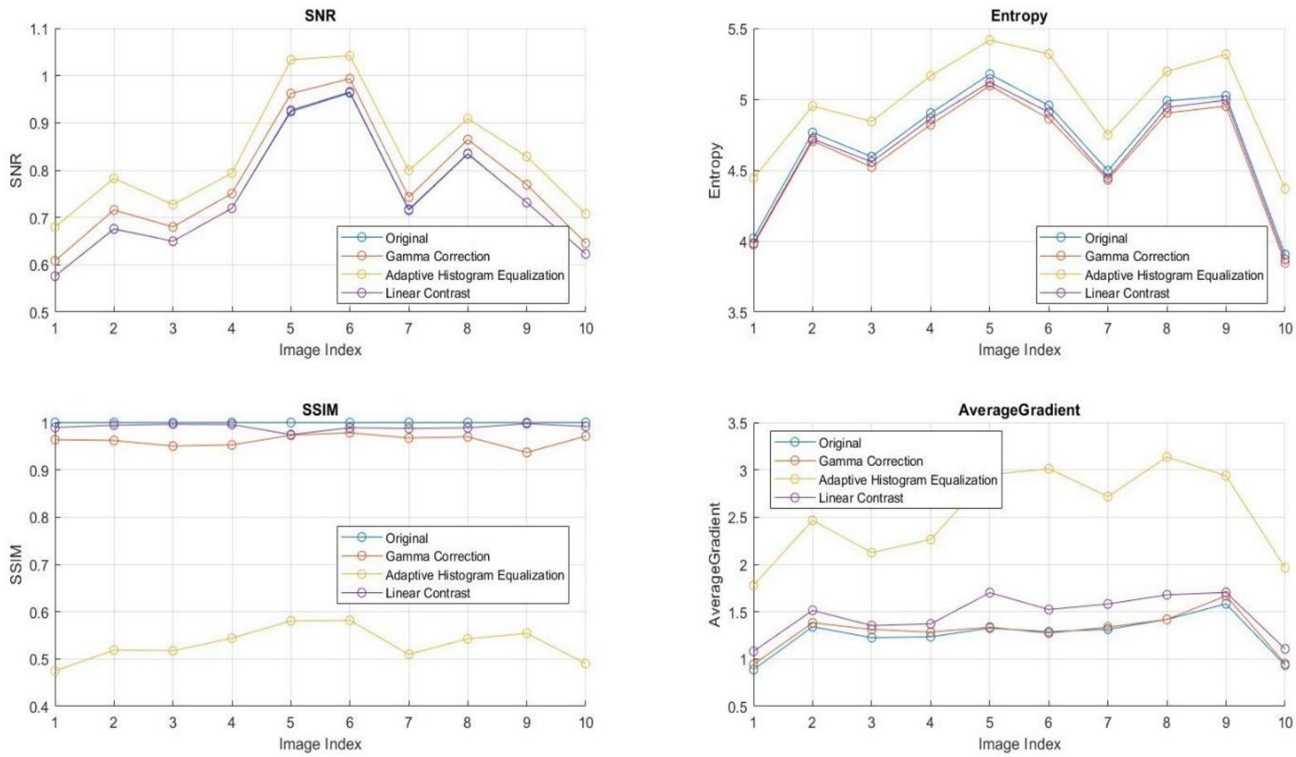

Figure 3. Enhancement Techniques Performance based on Metrics' Values

Moreover, fig. 3 shows that GC and LCE techniques have exhibited approximately similar values for the four metrics (SNR, Entropy, SSIM and AG). Specifically, GC has slightly showed better values for SNR, while LCE prevailed over GC in Entropy, SSIM and AG. In terms of numbers, table (1) was placed to clarify the mathematical calculation for the four metrics of each enhancement technique when applied to mammograms. Table (1) repeats each image four times to clarify the produced number by each technique for the four metrics. It is clearly shown that AHE showed best performance as indicated by SNR, Entropy and AG values. However, table (1) also shows that AHE showed the least value for the SSIM which agrees with fig. 3. Furthermore, SSIM showed value of (1) for the original images as these images are compared with themselves and hence no structural modification is detected.

T-test was also suggested to show the effectiveness of the applied enhancement techniques by clarifying the significant difference as shown table (2). Basically, t-test statistically measures the difference for specific metric between the original and enhanced ones considering the three enhancement techniques. As shown in table (2), there is a significant difference for the four metrics' values produced by the three enhancement techniques, indicating that these techniques have likely had significant effect on the original image.

Table 1. Performance Metrics Values for Enhancement Techniques over each Image

Image	Method	SNR	Entropy	SSIM	Average Gradient
1	Original	0.5760784	4.019582	1	0.888451044
1	Gamma Correction	0.60856527	3.975904	0.963654	0.942772319
1	Adaptive Histogram Equalization	0.67987009	4.444239	0.474879	1.77972784
1	Linear Contrast	0.576211	3.984861	0.989449	1.081772774
2	Original	0.67556493	4.765811	1	1.340701917
2	Gamma Correction	0.71573415	4.705056	0.962101	1.38289562
2	Adaptive Histogram Equalization	0.7825259	4.951988	0.518767	2.466419527

2	Linear Contrast	0.67605369	4.720033	0.9945	1.514285577
3	Original	0.6499195	4.595056	1	1.22604474
3	Gamma Correction	0.68008293	4.522924	0.950237	1.312651969
3	Adaptive Histogram Equalization	0.72721602	4.843352	0.517505	2.124371964
3	Linear Contrast	0.64986621	4.558161	0.996475	1.353483229
4	Original	0.71947653	4.902165	1	1.235057821
4	Gamma Correction	0.75078816	4.820894	0.952692	1.284282345
4	Adaptive Histogram Equalization	0.79369147	5.165009	0.544082	2.264593734
4	Linear Contrast	0.71964372	4.863559	0.995817	1.371427308
5	Original	0.92382733	5.176128	1	1.326785403
5	Gamma Correction	0.96201949	5.095852	0.973171	1.336912974
5	Adaptive Histogram Equalization	1.03333531	5.416498	0.580558	2.948391896
5	Linear Contrast	0.92660331	5.120085	0.974524	1.701122101
6	Original	0.96349586	4.955936	1	1.288872417
6	Gamma Correction	0.99351214	4.863682	0.978494	1.27293925
6	Adaptive Histogram Equalization	1.04206329	5.319348	0.581933	3.011589833
6	Linear Contrast	0.96548738	4.908746	0.988947	1.522842566
7	Original	0.71546231	4.495824	1	1.314127491
7	Gamma Correction	0.74300091	4.431184	0.967369	1.3370086
7	Adaptive Histogram Equalization	0.79946785	4.749378	0.509972	2.718014898
7	Linear Contrast	0.7172248	4.445961	0.987574	1.581878294
8	Original	0.8340927	4.987779	1	1.418390625
8	Gamma Correction	0.86463138	4.903881	0.969918	1.418057307
8	Adaptive Histogram Equalization	0.9089413	5.195952	0.542819	3.135714999
8	Linear Contrast	0.83522175	4.942731	0.988802	1.679023858
9	Original	0.73171578	5.023165	1	1.583179321
9	Gamma Correction	0.76931743	4.951548	0.936766	1.66786118
9	Adaptive Histogram Equalization	0.82902617	5.317203	0.554299	2.9376364
9	Linear Contrast	0.73146405	4.99345	0.997848	1.70396924
10	Original	0.6228825	3.904888	1	0.934801746
10	Gamma Correction	0.64578324	3.846178	0.971317	0.951390901
10	Adaptive Histogram Equalization	0.70761415	4.36982	0.490274	1.963962544
10	Linear Contrast	0.62314019	3.87198	0.991762	1.107199613

Table 2. T-test for each Performance Metric considering the 10 Images

Method	**P-Value (SNR)**	**P-Value (Entropy)**	**P-Value (SSIM)**	**P-Value (AG)**
Gamma Correction	$1.25*10^{-8}$	$7.91*10^{-8}$	$6.14*10^{-6}$	0.010619116
Adaptive Histogram Equalization	$8.04*10^{-9}$	$3.49*10^{-6}$	$1.37*10^{-11}$	$6.16*10^{-7}$
Linear Contrast	0.02886405	$7.50*10^{-8}$	0.00161982	$1.78*10^{-5}$

Despite the fact that AHE technique outperformed the other two techniques in terms of SNR, Entropy and AG, AHE may dramatically affect the image quality by enhancing noise. Moreover, number of tiles could also affect the enhancing efficiency. Specifically, fine details of the image are enhanced using small tiles, while large tiles helps supressing noise and artefacts. On the other hand, GC is sensitive to the noise in region with low intensities, and hence (γ) value should be carefully identified to avoid brighter and darker regions. Finally, LCE could also negatively affect the enhancement procedure by globally applies its function on the entire image. Moreover LCE depends on the differences on the intensities range for the input and output images, and LCE would not have a positive effect if those intensities are matched. To conclude, AHE showed the best performance compared to GC and LCE, however special attention should be considered when dealing with images structurally complicated [26][9][27].

4. Conclusion and Future Works

Three enhancement techniques, that are Gamma Correction (GC), Adaptive Histogram Equalization (AHE), and Linear Contrast Enhancement (LCE), were used to enhance and improve the quality of 10 mammograms. Four performances metrics were calculated to evaluate the performance of the aforementioned techniques. Those metrics were the Signal to Noise Ratio (SNR), Entropy, Structural Similarity Index (SSIM), and Average Gradient (AG). Results showed that AHE exhibited high SNR, entropy, and AG, while lowest value was achieved for the SSIM. Moreover, GC and LCE showed approximately similar values for the four metrics. These results make AHE preferable choice to enhance mammograms.

Future works could involve applying combined enhancement techniques to mammograms and evaluated their performance accordingly.

Competing interests
The authors declare that they have no competing interests.

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Authors' contributions
Authors have contributed equally.

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