
A comparative study of enhancement techniques applied to noisy mammogram images

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Zhian Y. Rajab¹Sardar P. Yaba¹

ABSTRACT

Background and objective: Mammography is a common imaging method, utilizing low-dose X-rays to detect calcifications and other tissue abnormalities. The aim of this study was to determine the most effective techniques for enhancing mammogram images to ensure accurate and reliable breast cancer detection.

Methods: Mammogram images from the MIAS database were enhanced using various techniques to improve image quality for more accurate diagnostic identification. The methodology proceeded in two steps. First, artificial noise — Gaussian, quantum, salt-and-pepper, Poisson, and speckle — was purposefully added to create a controlled testing environment and replicate noisy settings; although mammogram images naturally contain some noise, this artificial addition allowed systematic evaluation of enhancement and denoising techniques. Second, contrast enhancement (histogram equalization and contrast-limited adaptive histogram equalization, CLAHE) and denoising (Gaussian, median, and Wiener filters) were applied to restore image clarity while preserving diagnostically significant information. Peak signal-to-noise ratio (PSNR) was used to evaluate effectiveness, and one-way ANOVA was used to determine the significance of each technique's effect on PSNR values.

Results: The Gaussian filter achieved the best performance, with PSNR values of 66.79 dB and 46.6 dB for salt-and-pepper and Poisson noise, respectively, while CLAHE performed best for Gaussian noise (PSNR=50 dB). PSNR values were significantly affected by the enhancement technique used, according to ANOVA ($F=1.08 \times 10^4$, $p < 0.001$).

Conclusion: The Gaussian filter successfully lowers noise and greatly improves image contrast, making these techniques useful for the precise and early identification of breast cancer in mammograms.

Keywords: Breast cancer, Enhancement technique, Filters, Mammography, Noise

¹ Department of Physics, College of Education, Salahaddin University-Erbil, Kurdistan Region, Iraq.Correspondence: Zhian Y. Rajab, zhyan.rajab@su.edu.krdCopyright © The Author(s) 2026. Open Access. This work is licensed under a [Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License](https://creativecommons.org/licenses/by-nc-sa/4.0/).

Introduction

Breast cancer is the most frequently diagnosed cancer globally, and its prevalence has increased over the past few decades (1). Lowering the mortality rate associated with breast cancer depends on early detection and treatment (2). X-ray mammography remains the most common method for screening breast cancer, but its sensitivity and specificity are noticeably limited (3). Recent developments in image processing have increased the possibility of personalizing mammogram analysis for each patient, providing more accurate information for risk assessment, early prognosis, and treatment decisions (4, 5). Mammogram images frequently contain various kinds of noise, which can deteriorate image quality and make it more difficult to diagnose breast lesions precisely (6). Noise is added to mammogram images during the capture, transmission, and storage phases (7). Currently, one of the healthcare industry's fastest-growing subfields is medical image processing (8). Enhanced mammogram imaging improves the visibility of critical anatomical details, leading to more accurate diagnosis and improved patient care (9). Despite the fact that many denoising and enhancement methods have been used on mammograms, it is still unclear which techniques work best for various kinds of noise while maintaining qualities that are important for diagnosis. Most existing work either concentrates on a single filtering technique or assesses performance in situations with little noise, which limits how generally the findings can be applied. The current work aims to fill this gap by examining and carefully assessing several enhancement techniques under various noise conditions, in order to identify the best techniques for enhancing mammography image quality and provide accurate and reliable breast cancer detection.

Literature Review

Several studies have examined image processing for enhancing breast cancer detection. One approach implemented morphological operations, PCA-based grayscale conversion, region-growing for pectoral muscle removal, and Gaussian Laplacian and anisotropic diffusion filters for contrast refining; this multi-step procedure increased PSNR in the BI-RADS-1 category from 28.13 dB to 32.48 dB, producing noticeable improvements in contrast and EME (10, 11). Another study improved mammography images for breast cancer detection using a denoising technique based on a modified statistical filter. After detecting impulsive noise with the Modified Robust Outlyingness Ratio (mROR), an extended non-local means (NL-means) filter was used to maintain image details; this two-stage enhancement improved image clarity more than filters such as median and adaptive filters, with PSNR values as high as 41.91 dB (12). Another study used two databases — a private database and the MIAS database. In the pre-processing stage, images were first classified, then the pectoral muscle was removed, and finally the image was enhanced with a novel segmentation technique applied to identify abnormal areas for breast cancer detection. The best PSNR for the private database was 30.18 dB, while the proposed method gave a peak signal-to-noise improvement of 3 dB for the MIAS database (13). Another pre-processing approach used filtering to improve image quality, testing various combinations of median filter, CLAHE, and unsharp masking. The CLAHE algorithm was tested separately, followed by combinations including CLAHE & unsharp masking, median filter & unsharp masking, median filter & CLAHE, and median filter & CLAHE & unsharp masking, with every combination applied to each image (14). Another study proposed MIFS, an enhancement technique based on intuitionistic fuzzy sets that enhances contrast

and draws attention to abnormalities through fuzzification, hyperbolization, and image fusion; MIFS performed better at enhancing fine details than conventional techniques, although it demanded faster processing (15). Another investigation used two main stages: a preprocessing step involving noise removal with Gaussian, median, and Wiener filters followed by contrast enhancement, and a second stage using deep learning; results showed that the median filter provided the best results (16).

METHODS

Database

The mammogram images used in this investigation were taken from the Mammographic Image

Analysis Society (MIAS) database, created by British research teams to support the study of mammography images such as those from the UK National Breast Screening Programme. The MIAS database contains 322 digital images from 161 pairs, of which 209 were normal and 113 abnormal. Every image in the database was 1024×1024 after being resized to a 200-micron pixel edge and padded (17). Processing was implemented in MATLAB R2024a. (Figure 1)

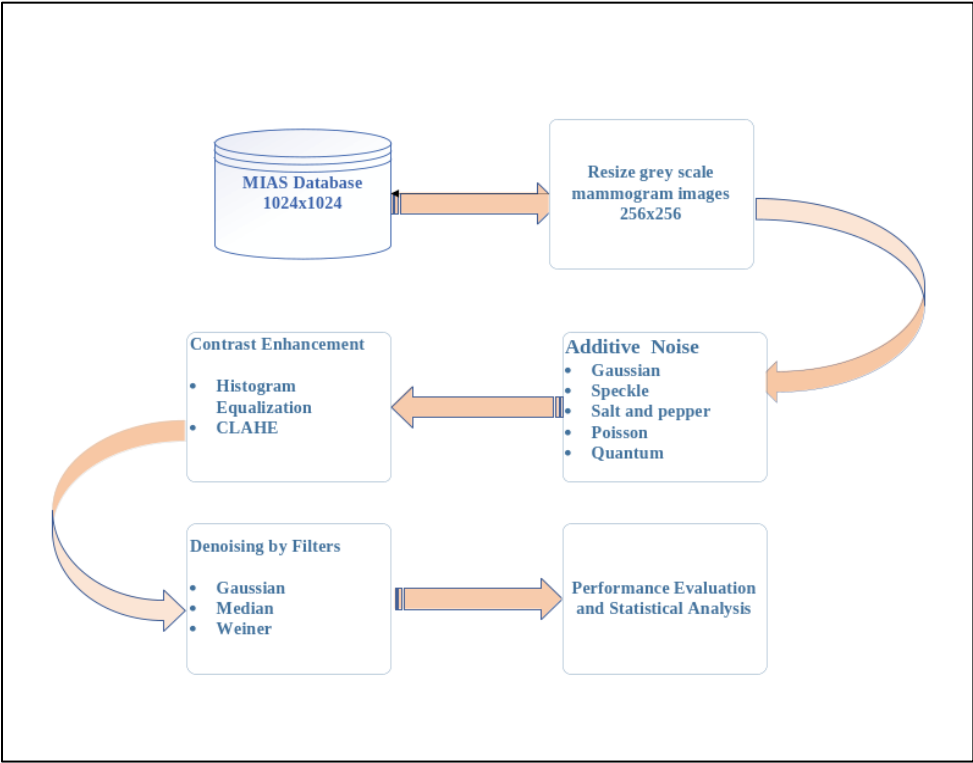


Figure 1. Comprehensive framework illustrating image enhancement methods

Resizing Image

The initial step of the preprocessing procedure involved reducing the image's size to a uniform 256×256 using logical filtering. Resizing is particularly vital in medical imaging, where it is essential to maintain image detail and clarity while adjusting for analysis or presentation needs.

Additive Noise

Noise refers to random changes in an image's color information or brightness that can occur during image capture. Multiple projection image acquisition results in higher detector noise, which can considerably decrease image quality and make it more challenging to see minute abnormalities, especially microcalcifications, which are crucial for early breast cancer diagnosis (18). Since no dataset

including the noise types produced by radiation dose or physical device setup during mammogram procedures was available, artificial noise was added to the original mammogram images instead, using various techniques: Gaussian noise with zero mean (μ) and variance (σ^2) of 0.01; Poisson noise using $\lambda=11$ with an intensity scaling factor of 0.2; salt-and-pepper noise simulated at a density of 0.25; speckle noise with a variance of 0.01; and quantum noise with an intensity of 0.05. These noise types together offer a thorough experimental setting for precisely assessing how well image purification algorithms work and for contrasting how well various models handle each kind of noise, while improving the model's generalization to real-world images that might combine one or more of these noise categories. (Figure 2)

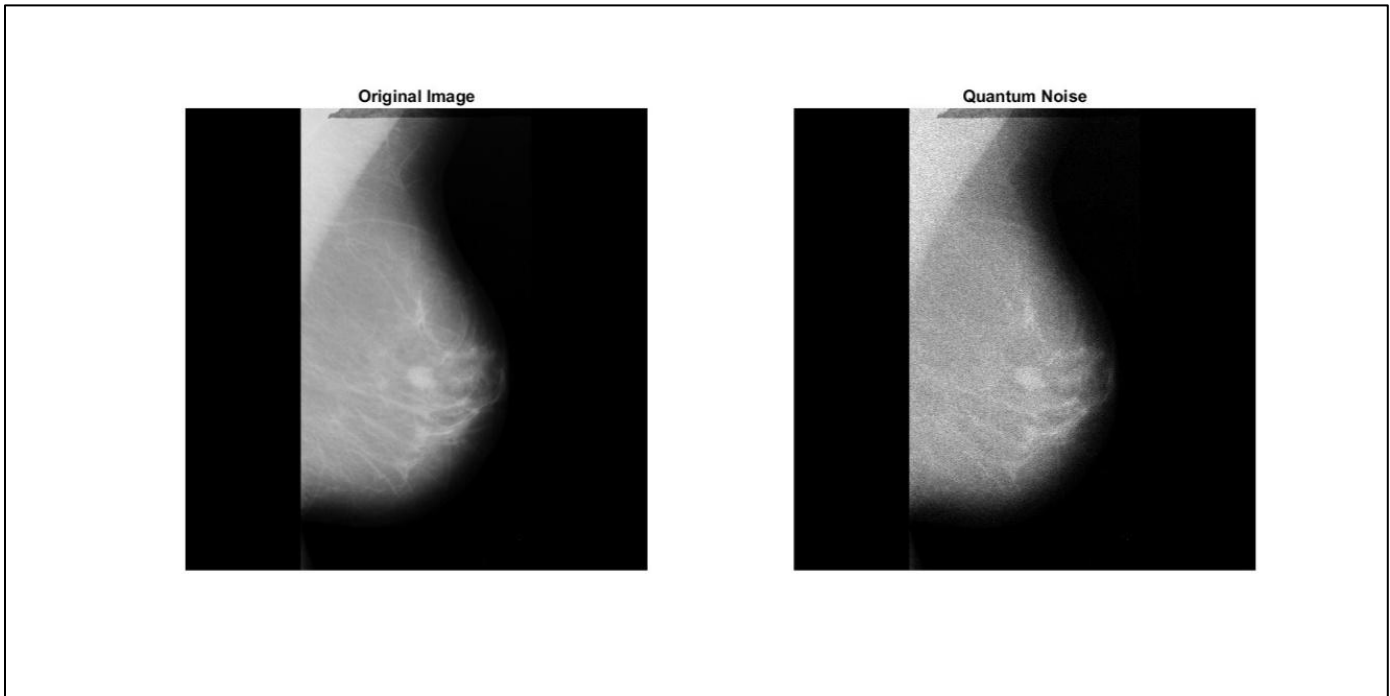


Figure 2. The original image artificially degraded by the addition of quantum noise

Enhancement Techniques

Enhancement techniques were implemented on the mammogram images in two steps. The first step applied contrast enhancement to emphasize small tissue changes and improve the visibility of structural details, using two well-established methods: histogram equalization, which increases overall image contrast by redistributing pixel intensity levels, and CLAHE, which prevents noise from becoming over-amplified while enhancing local contrast. Starting with contrast enhancement ensured that further processing stages worked on images where important diagnostic characteristics could be more easily identified. In the second step, noise reduction techniques were used to further enhance image quality and eliminate undesired artifacts, using three filters: the Gaussian filter, which averages nearby pixels to smooth the effects of intensity changes; the median filter, which works exceptionally well at eliminating impulsive noise while maintaining edges; and the Wiener filter, which minimizes the mean square error between the original and restored image by adjusting to local image statistics. This set of filters was selected to guarantee that mammography images were denoised without sacrificing information crucial for diagnosis.

Performance Evaluation

The peak signal-to-noise ratio (PSNR) (19) was used as a quality index between restored (filtered) and deformed (noisy) images, measuring peak error based on mean squared error (MSE) values, using the formula $PSNR = 10 \log_{10}(R^2/MSE)$, where R represents the input image's ideal variation (255 for 8 bits) and MSE is the mean squared error.

Statistical Analysis

To evaluate the quality of image reconstruction, PSNR values were calculated for each approach.

A one-way analysis of variance (ANOVA) was used to determine whether mean PSNR values from the various approaches differed significantly. ANOVA was selected because it reduces the possibility of Type I error while enabling simultaneous comparison of multiple groups. Results with $p < 0.05$ were considered statistically significant, using a significance threshold of $\alpha = 0.05$. When ANOVA revealed a significant difference, post-hoc pairwise comparisons were used to determine which approaches varied in terms of PSNR (20).

RESULTS

As described in the methodology, a variety of noise types were added to the MIAS database to study their impact on image quality and analyze the model's ability to handle noisy data. An abnormal image was chosen from the database, and a set of filters commonly used in medical image processing was then applied to reduce noise and improve image quality.

In Figures 3, 4, and 5, the image mdb010.pgm — an abnormal image in the MIAS dataset — is taken as the input image, to which Gaussian, quantum, and speckle noise were applied and then removed using different enhancement techniques. Performance indicators for each enhancement technique, as implemented in MATLAB, are presented in Tables 1–4, including PSNR.

Table 1 and Figure 6 show the performance of enhancement techniques. ANOVA confirmed that the enhancement technique had a significant effect on PSNR values ($F = 1.08 \times 10^4$, $p < 0.001$), showing that the primary factor affecting image quality is the image processing technique used. The median filter performed best, giving the highest PSNR (36.79 ± 2 dB) with the most substantial noise reduction; the Gaussian filter was second (35.05 ± 1.55 dB), demonstrating moderate improvement.

The Wiener filter (28.04 ± 0.58 dB) and CLAHE (22.47 ± 1.5 dB) were weaker, while histogram equalization performed worst (9 ± 2.18 dB). The median filter consistently outperformed histogram equalization by more than 25 dB, indicating a significant improvement in noise reduction.

A higher PSNR suggests less noise and more identifiable detail in the image; in mammography, this directly enhances the visibility of microcalcifications or small lesions, which are essential for early cancer identification.

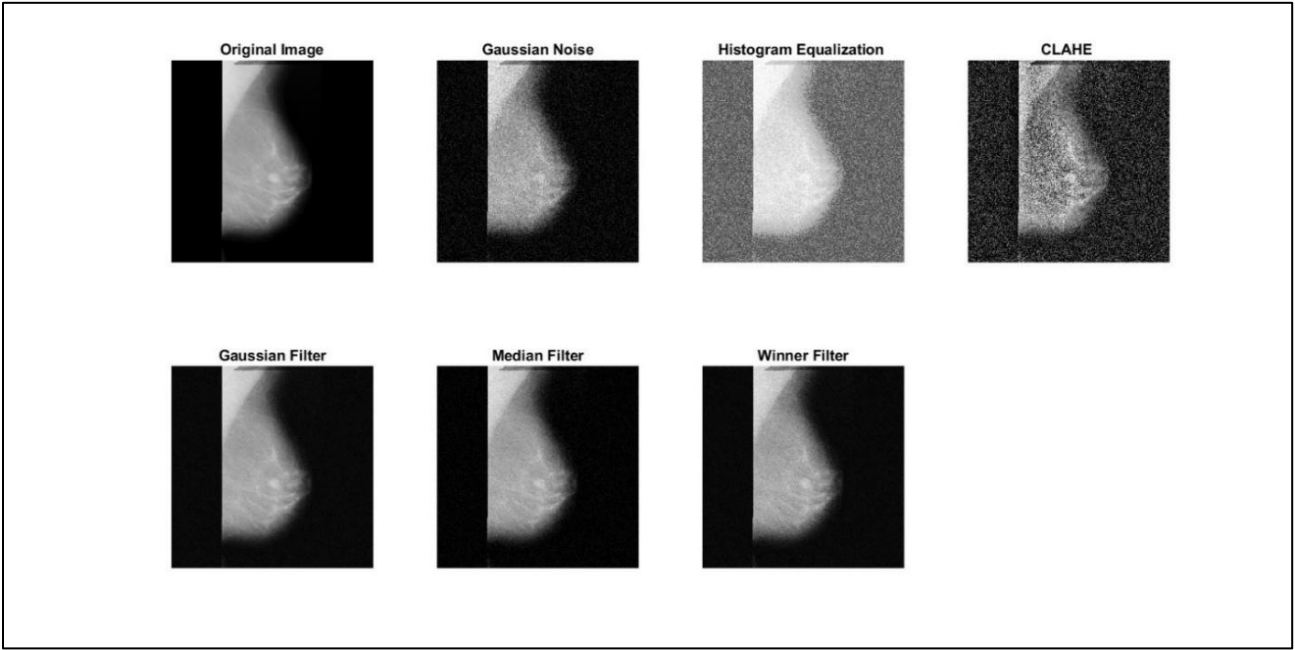


Figure 3. Illustration of Gaussian noise removal in mammogram images using histogram equalization, CLAHE, Gaussian, median, and Wiener filters

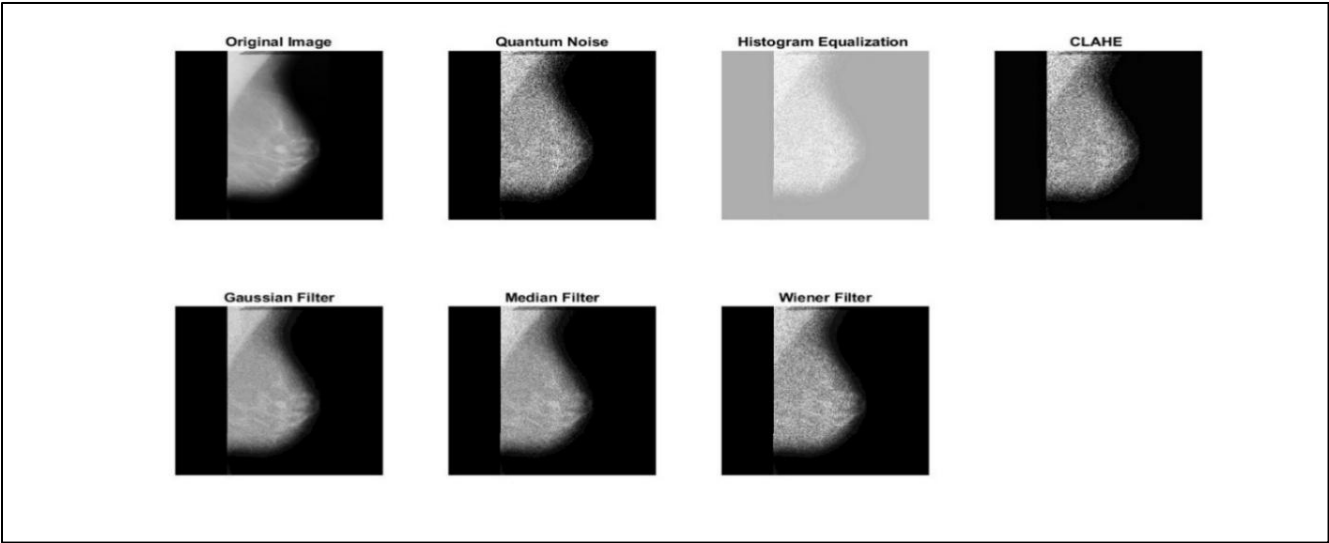


Figure 4. Illustration of quantum noise removal in mammogram images using histogram equalization, CLAHE, Gaussian, median, and Wiener filters

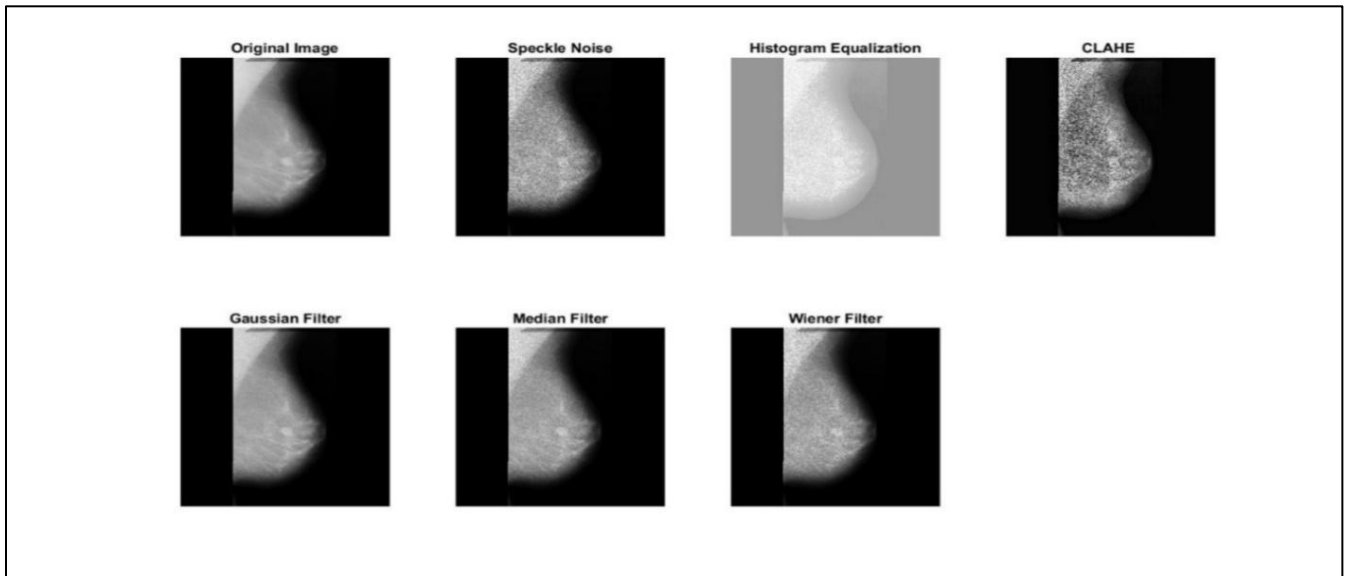


Figure 5. Illustration of speckle noise removal in mammogram images using histogram equalization, CLAHE, Gaussian, median, and Wiener filters

Table 1. Average PSNR (dB) between normal and enhanced images

Technique	Gaussian	Poisson	Quantum	S&P	Speckle
Histogram Eq.	9	4.1	6.75	6.15	7.31
CLAHE [8×8]	21.5	21.5	22.47	9.57	21.29
Gaussian filter	29	19.71	35.05	9.81	22.52
Median filter	33	19.82	34.39	36.79	22.54
Wiener filter	28	19.8	28.04	16.72	22.16

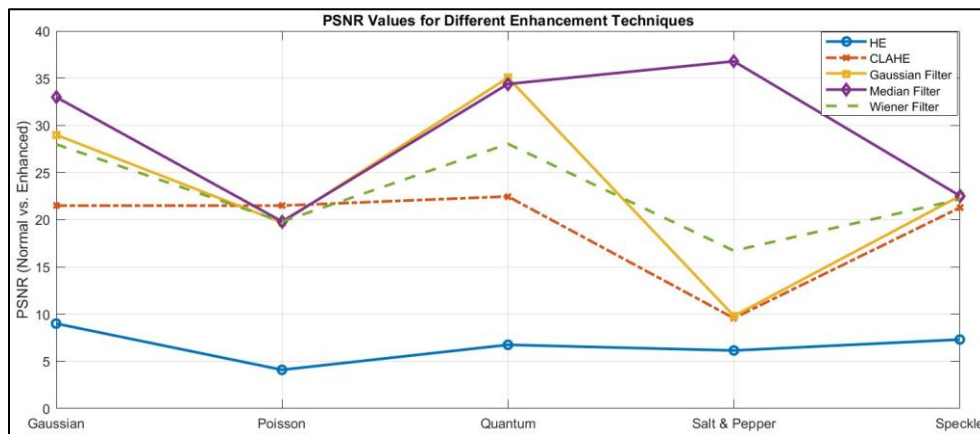


Figure 6. Performance measurement of PSNR, normal vs. enhanced images

Table 2 and Figure 7 present the comparison of PSNR values between noisy and enhanced images. ANOVA confirmed that enhancement techniques differed significantly in performance across all conditions ($p < 0.001$). For salt-and-pepper noise, the Gaussian filter consistently yielded the best results, achieving the highest PSNR (66.75 ± 0.24 dB) with the lowest standard deviation; under Poisson noise, the Gaussian filter also produced favorable results (46.6 ± 1.46 dB). CLAHE (50 ± 0.58 dB) also produced strong results, often ranking just below

Gaussian filtering. The Wiener filter (35.89 ± 3.47 dB) provided stable and competitive performance, while histogram equalization (10 ± 2.67 dB) regularly performed worst. Performance improvements ranged between 24.5 and 58.7 dB, well above the threshold usually regarded as clinically meaningful in mammography, demonstrating the effectiveness of the enhancement techniques used; these improvements should result in more accurate identification of small lesions, better visibility of microcalcifications, and crisper structural detail.

Table 2. Average PSNR (dB) between noisy and enhanced images

Technique	Gaussian	Poisson	Quantum	S&P	Speckle
Histogram Eq.	10	4.66	6.85	8.05	6.65
CLAHE [8×8]	50	27	31.38	21.15	26.13
Gaussian filter	23	46.6	24.37	66.75	30.32
Median filter	22	31.3	24.04	9.8	28.36
Wiener filter	24	38	31.11	12.16	35.98

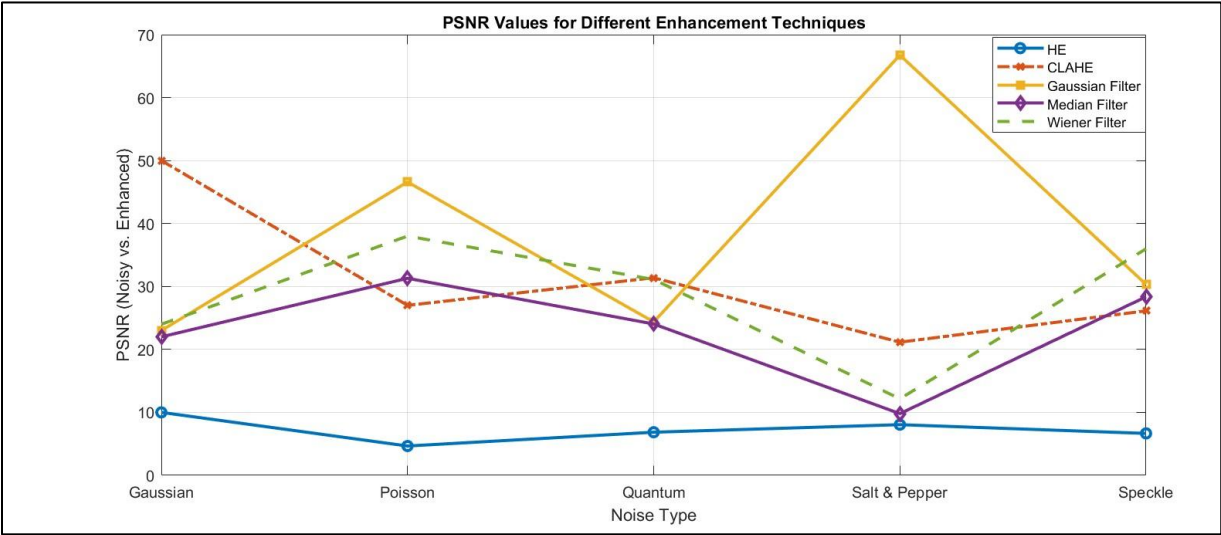


Figure 7. Performance measurement of PSNR, noisy vs. enhanced images

Table 3 and Figure 8 display PSNR values for the comparison between abnormal and enhanced images. ANOVA showed that the enhancement technique significantly influenced PSNR values ($F=9521.9$, $p < 0.001$). The median filter was the most successful enhancement method, consistently producing the highest PSNR (36.67 ± 3.12 dB) with the lowest standard deviation; its performance under quantum and Gaussian-type noise was more

middling (34.07 ± 1.5 dB, 32.5 ± 0.37 dB), while histogram equalization had the worst overall performance (9.2 ± 1.03 dB). The differences of 23–27.47 dB translate into less background noise and more distinct lesion edges, making low-contrast structures easier to spot and subtle architectural distortion and microcalcification visibility easier to identify; as reader confidence rises, noise-related recalls could drop.

Table 3. Average PSNR (dB) between abnormal and enhanced images

Technique	Gaussian	Poisson	Quantum	S&P	Speckle
Histogram Eq.	—	9.2	5.87	7.22	6.63
CLAHE [8×8]	—	21.5	20.34	22.13	9.6
Gaussian filter	—	29	18.95	34.79	9.86
Median filter	—	32.5	19	34.07	36.67
Wiener filter	—	28	19	27.92	16.79

Table reproduced as supplied; the Gaussian-noise column for this table was not populated in the original manuscript.

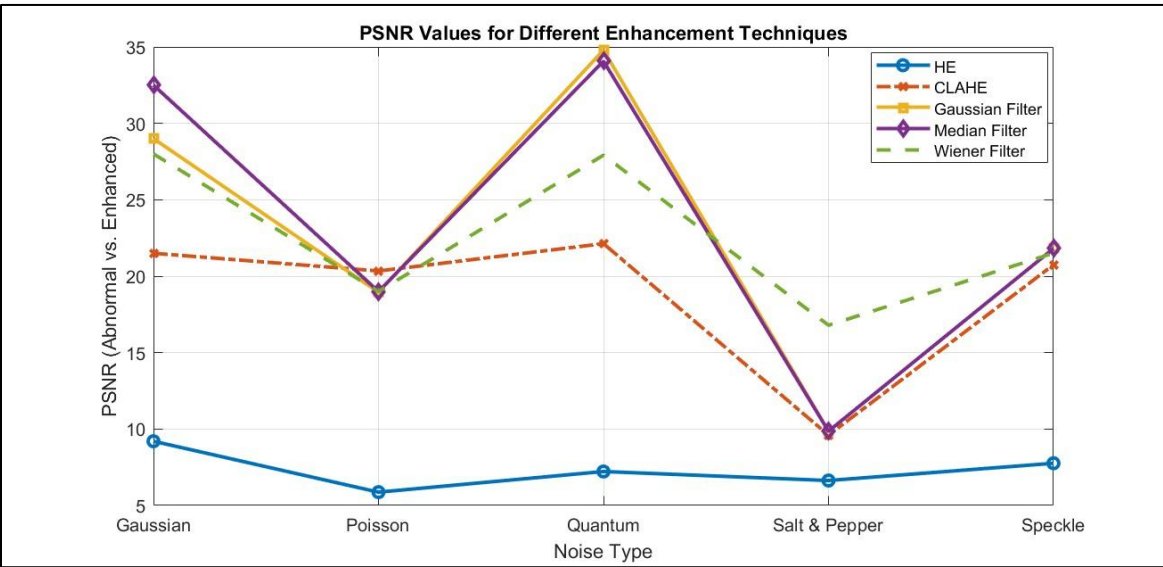


Figure 8. Performance measurement of PSNR, abnormal vs. enhanced images

Table 4 and Figure 9 display PSNR values between noisy and enhanced images for various noise types. ANOVA results confirmed that PSNR was significantly affected by the enhancement technique for all noise levels ($p < 0.001$), suggesting that image quality is determined by the image processing technique rather than by chance variance between cases. The Gaussian filter yielded the highest PSNR (66.79 ± 1.11 dB); CLAHE and the Gaussian filter under Poisson noise performed

moderately (50 ± 0.91 dB, 46.26 ± 1.32 dB), but still substantially lower than the best result, while histogram equalization performed weakest (10 ± 1.67 dB). Significant increases in PSNR lead to smoother, lower-noise mammograms that make delicate diagnostic characteristics like tiny lesions and microcalcifications easier to see; diagnostic variability is reduced, since even small but meaningful improvements guarantee consistent improvement across patients.

Table 4. Average PSNR (dB) between noisy and enhanced images (repeat analysis)

Technique	Gaussian	Poisson	Quantum	S&P	Speckle
Histogram Eq.	10	5	7.35	8.45	7
CLAHE [8×8]	50	26.89	31.02	20.9	25.84
Gaussian filter	23	46.27	24.03	66.79	30.02
Median filter	22	30.87	23.68	9.85	28.06
Wiener filter	24.2	37.25	30.42	12.19	35.28

Note: this table and Table 2 share the same title and describe the same comparison (noisy vs. enhanced images) with closely similar but not identical values (e.g., Gaussian filter/salt-and-pepper: 66.75 dB in Table 2 vs. 66.79 dB here). The Abstract's reported values (66.79 dB, 46.6 dB, 50 dB) match this table exactly. This may indicate Table 2 is an earlier or duplicate run of the same analysis; we recommend confirming with the authors which table reflects the final dataset before publication, and removing the other if it is indeed a duplicate.

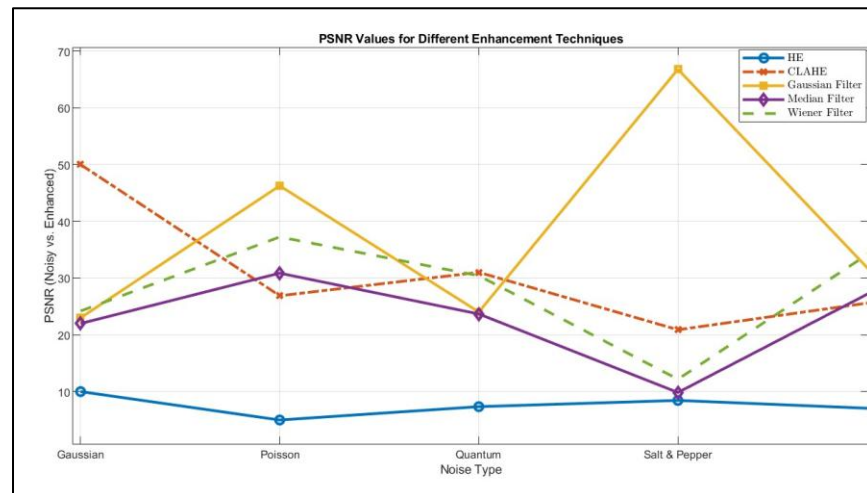


Figure 9. Performance measurement of PSNR, abnormal vs. enhanced images

DISCUSSION

According to the study's findings, the Gaussian filter produced the highest PSNR values under salt-and-pepper noise, because the Gaussian kernel's smoothing effect lessens intensity fluctuations. While salt-and-pepper noise tends to be impulsive, the Gaussian filter's weighted averaging preserves the mammogram's overall structural continuity while suppressing severe pixel changes. These qualities are especially critical in mammography imaging, where the ability to clearly see minute structures like microcalcifications and faint mass borders is essential for accurate diagnosis.

A number of limitations should be recognized despite these encouraging results. Because the dataset was small, the reliability of the findings may have been affected. The evaluation was based on mammograms artificially degraded with simulated noise; although this approach offers a controlled testing environment and enables consistent filter comparison, it does not fully capture the intricate details of actual acquisition noise that arises in clinical settings, where factors such as differences in patient posture, electronic interference, and detector sensitivity produce more diverse noise patterns than the artificial models used here. Caution should therefore be taken when extrapolating these findings to clinical settings, and future research should test these findings on real-world mammograms and larger, more diverse datasets to ensure greater relevance and generalizability across imaging conditions.

The knowledge gained here can help build more sophisticated preprocessing techniques in addition to improving experimental settings. Gaussian filtering and other classical enhancement techniques can serve as an initial step to enhance the quality of data supplied to deep learning pipelines, thereby reducing errors caused by noise

during model training; filter performance insights might also guide how noise-reduction techniques are integrated into deep learning models, making it possible for systems to adjust to various kinds of noise dynamically. Future research ought to include runtime and computational cost as well, to ensure that techniques are both accurate and workable for widespread diagnostic use.

Figure 10 shows better noise-reduction results compared with the other enhancement methods examined. In this study, various kinds of noise — Gaussian, Poisson, speckle, and salt-and-pepper — were denoised by several types of filters, demonstrating the effectiveness of different denoising methods on images distorted by various noise types. In a related study, salt-and-pepper noise of density 0.5 was applied to three distinct kinds of mammography images in the mini-MIAS database; this noise was eliminated using a Gaussian filter, which was shown to be successful in lowering noise without appreciably compromising image detail (21).

In another investigation, three kinds of noise were added to reduce noise in mammography images of microcalcification breast phantoms of different densities using mean, median, and Gaussian filters; the findings showed that, compared with the mean and median filters, the Gaussian filter performed best when denoising images with all three types of added noise (22) (Table 5).

Compared with the current study's results, a noticeable difference in PSNR level was found. These differences are attributable to several factors: (1) differences in databases used, the nature of the experimental data, and the number of samples; (2) differences in filter settings and evaluation criteria; and (3) differences in the level of added noise intensity and Gaussian sigma. These factors highlight the importance of

considering such elements when comparing findings across different investigations (Table 6).

Table 5. PSNR results of filters applied to mini-MIAS mammogram images for salt-and-pepper noise removal

Filter	mdb001lm	mdb110rl	mdb322rm
Wiener [3×3]	30.6853	30.0827	28.3819
Median [3×3]	38.4963	38.245	37.3703
Adaptive median [15×15]	47.8133	47.864	47.2503
Gaussian ($\sigma=0.06$)	32.1619	31.9525	31.0426
Mean [3×3]	30.6419	30.0141	29.2954

Table 6. Average PSNR values for different preprocessing filters (comparison study)

Image	Gaussian filter S&P	Gaussian	Speckle
PVAL/E	31.67	30.24	30.41
PVAL	31.53	30.24	30.17
PVAL/G	32.7	31.08	31.69
PVAL/H	34.16	31.9	34.2

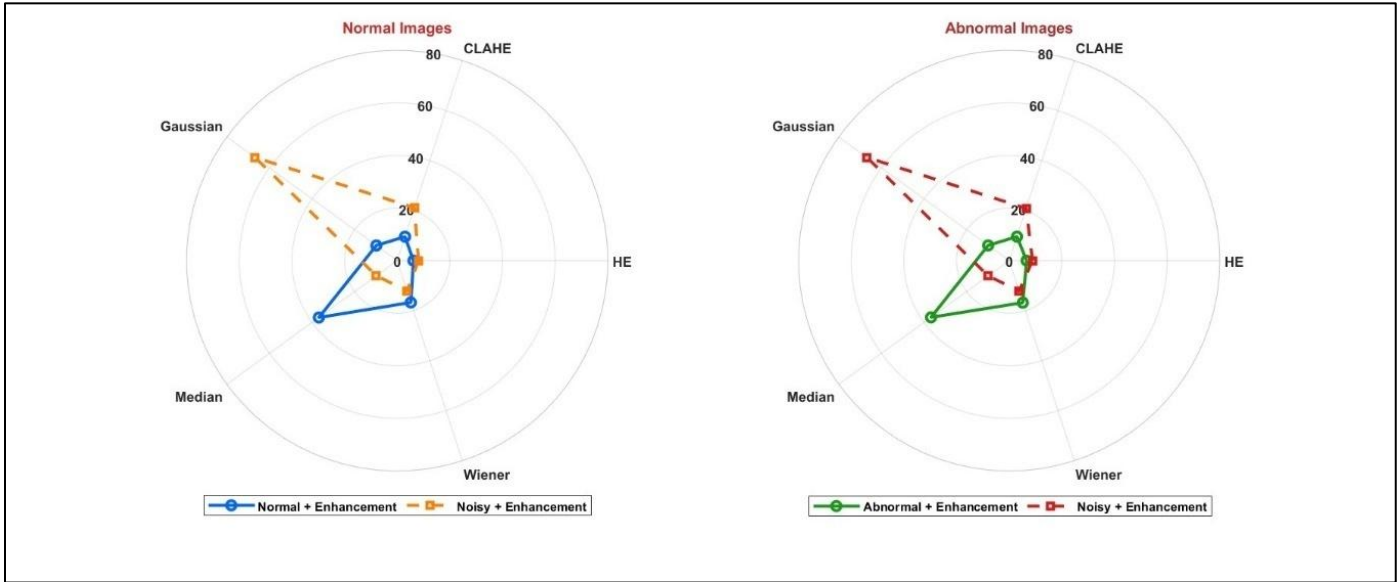


Figure 10. PSNR radar comparison across enhancement techniques for salt-and-pepper noise

CONCLUSION

The results clearly indicate that the best approach for denoising mammogram images is using Gaussian and median filters, which have the best performance and can significantly improve image quality — important for accurate diagnosis and further processing tasks. CLAHE was also effective for enhancing contrast, particularly in images with low-intensity noise; however, Wiener filters and histogram equalization demonstrated only a moderate level of efficacy. These results imply that Gaussian and median filters are more dependable options for improving noisy mammograms, and can significantly aid in improved visual evaluation and early detection of abnormalities.

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COMPETING INTEREST

The authors declare that they have no competing interests.

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REFERENCES

1. Arnold M, Morgan E, Rumgay H, Mafra A, Singh D, Laversanne M, et al. Current and future burden of breast cancer: global statistics for 2020 and 2040. *Breast*. 2022;66:15-23. <https://doi.org/10.1016/j.breast.2022.08.010>
2. Bhushan A, Gonsalves A, Menon JU. Current state of breast cancer diagnosis, treatment, and theranostics. *Pharmaceutics*. 2021;13(5):723. <https://doi.org/10.3390/pharmaceutics13050723>
3. Rashid SA, Bapir RN. Correlation of mammographic density and breast cancer characteristics. *Adv Med J*. 2022;7(2):139-47. <https://doi.org/10.56056/amj.2022.190>
4. Wang L. Mammography with deep learning for breast cancer detection. *Front Oncol*. 2024;14:1281922. <https://doi.org/10.3389/fonc.2024.1281922>
5. Dawood SN, Jamal AF. Tumor size measurements predicted by digital mammography, ultrasonography, and magnetic resonance imaging in primary invasive breast cancer disease. *Zanco J Med Sci*. 2024;28(2):341-50. <https://doi.org/10.15218/zjms.2024.032>
6. Kavuri A, Das M. Relative contributions of anatomical and quantum noise in signal detection and perception of tomographic digital breast images. *IEEE Trans Med Imaging*. 2020;39(11):3321-30. <https://doi.org/10.1109/TMI.2020.2991295>
7. Singh AR, Athisayamani S, Karim FK, Ibrahim AZ, Alshetewi S, Mostafa SM. An enhanced denoising system for mammogram images using deep transformer model with fusion of local and global features. *Sci Rep*. 2025;15(1):6562. <https://doi.org/10.1038/s41598-025-89451-w>
8. Mehdy MM, Ng P, Shair EF, Saleh NM, Gomes C. Artificial neural networks in image processing for early detection of breast cancer. *Comput Math Methods Med*. 2017;2017(1):2610628. <https://doi.org/10.1155/2017/2610628>
9. Sorin V, Sklair-Levy M, Glicksberg BS, Konen E, Nadkarni GN, Klang E. Deep learning for contrast enhanced mammography — a systematic review. *Acad Radiol*. 2025;32(5):2497-508. <https://doi.org/10.1016/j.acra.2024.11.035>
10. Almalki YE, Soomro TA, Irfan M, Alduraibi SK, Ali A. Impact of image enhancement module for

- analysis of mammogram images for diagnostics of breast cancer. *Sensors*. 2022;22(5):1868. <https://doi.org/10.3390/s22051868>
11. Bhateja V, Misra M, Urooj S. Non-linear polynomial filters for edge enhancement of mammogram lesions. *Comput Methods Programs Biomed*. 2016;129:125-34. <https://doi.org/10.1016/j.cmpb.2016.01.007>
 12. Rajaguru H, SR SC. Efficient denoising framework for mammogram images with a new impulse detector and non-local means. *Asian Pac J Cancer Prev*. 2020;21(1):179. <https://doi.org/10.31557/APJCP.2020.21.1.179>
 13. Almalki YE, Soomro TA, Irfan M, Alduraibi SK, Ali A. Computerized analysis of mammogram images for early detection of breast cancer. *Healthcare (Basel)*. 2022;10(5):801. <https://doi.org/10.3390/healthcare10050801>
 14. Avci H, Karakaya J. A novel medical image enhancement algorithm for breast cancer detection on mammography images using machine learning. *Diagnostics (Basel)*. 2023;13(3):348. <https://doi.org/10.3390/diagnostics13030348>
 15. Deng H, Deng W, Sun X, Liu M, Ye C, Zhou X. Mammogram enhancement using intuitionistic fuzzy sets. *IEEE Trans Biomed Eng*. 2016;64(8):1803-14. <https://doi.org/10.1109/TBME.2016.2624306>
 16. Boudouh SS, Bouakkaz M. Enhanced breast mass mammography classification approach based on pre-processing and hybridization of transfer learning models. *J Cancer Res Clin Oncol*. 2023;149(16):14549-64. <https://doi.org/10.1007/s00432-023-05249-1>
 17. Yoon WB, Oh JE, Chae EY, Kim HH, Lee SY, Kim KG. Automatic detection of pectoral muscle region for computer-aided diagnosis using MIAS mammograms. *Biomed Res Int*. 2016;2016(1):5967580. <https://doi.org/10.1155/2016/5967580>
 18. Chan HP, Helvie MA, Gao M, Hadjiiski L, Zhou C, Garver K, et al. Deep learning denoising of digital breast tomosynthesis: observer performance study of the effect on detection of microcalcifications in breast phantom images. *Med Phys*. 2023;50(10):6177-89. <https://doi.org/10.1002/mp.16439>
 19. Geng C, Paganetti H, Grassberger C. Prediction of treatment response for combined chemo- and radiation therapy for non-small cell lung cancer patients using a bio-mathematical model. *Sci Rep*. 2017;7(1):13542. <https://doi.org/10.1038/s41598-017-13646-z>
 20. Okoye K, Hosseini S. Analysis of variance (ANOVA) in R: one-way and two-way ANOVA. In: *R Programming: Statistical Data Analysis in Research*. Singapore: Springer; 2024. P. 187-209. https://doi.org/10.1007/978-981-97-3385-9_9
 21. Hamed G, Marey M, Amin SE-S, Tolba MF. A proposed model for denoising breast mammogram images. In: *2018 13th International Conference on Computer Engineering and Systems (ICCES)*. IEEE; 2018. <https://doi.org/10.1109/ICCES.2018.8639307>
 22. Okoh FO, Ocheje JA. Evaluating denoising performances of basic filters in the detection of microcalcifications on mammogram images. *Int J Sci Res Arch*. 2023;9(2):201-10. <https://doi.org/10.30574/ijrsra.2023.9.2.0544>