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A novel approach for enhancing mammographic images

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Abstract: In order to reduce the risk factor connected with the disease, pre-clinical identification of breast cancer is essential, and mammography is one of the finest screening methods. In this study work, we propose a brand-new method for improving poor-quality mammography pictures. Contrast limited adaptive histogram equalisation (CLAHE) and morphological operations (MOs) are two image processing methods we recommend using. The median filter, low pass Gaussian filtering, MOs, and wavelet decomposition are the next steps in the suggested technique after removing noise. Applying our suggested method to mammogram images from the Mammographic Image Analysis Society (MIAS) dataset to assess how effective it is. We use the peak signal noise ratio (PSNR), mean square error (MSE), and root mean square error (RMSE) as three common picture quality measures to assess our method. These measurements allow us to evaluate the improvement in image quality brought about by our suggested strategy quantitatively.

Keywords: CLAHE; contrast limited adaptive histogram equalisation; guided image filtering; mammograms; morphological operations; medical image processing.

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1 Introduction

The second most frequent disease in women after lung cancer, breast cancer is a serious health problem for them. Mammography is a crucial medical imaging method for early breast cancer detection. However, mammography is difficult because it requires images with fine details and high contrast as well as minimal noise, little patient movement, and ideal inspection conditions (Valarmathi and Robinson, 2016; Wang et al., 2017). It is crucial to employ specialised mammography imaging equipment made for this purpose in order to provide high-quality mammogram pictures. Using x-ray tubes with low energy output, such as those with tungsten anodes running at low kilovoltage (30kVp or less) or rhodium or molybdenum anodes, is one example of this.

The use of such specialised equipment guarantees the highest quality mammography pictures and enables the identification of even minute anomalies that may be suggestive of breast cancer (Huang and Zhu, 2012; Mammographic Mass Characteristics, 2017).

To guarantee picture quality, proper patient placement and breast compression are just as crucial as the equipment. The full imaging process, including all parts of the mammographic imaging system must be operating correctly in order to guarantee high-quality mammogram images. The mammographic x-ray machine itself, the camera, the photographic processor, the screens, the film, and the view boxes or digital displays used to view the pictures are all included in this. Any defects or malfunctions in these components can negatively impact the image quality and potentially compromise the detection of breast cancer. Therefore, it is crucial that all components are regularly maintained and inspected to ensure optimal functionality (Biltawi et al., 2012; Abdel-Zaher and Eldeib, 2016).

Therefore, a combination of advanced technology and proper technique is essential for accurate mammography screening and early detection of breast cancer. It is crucial to ensure the quality of images in mammography as it is a critical factor in detecting abnormalities and reducing the risk of breast cancer. There is the need to figure out the abnormalities for early detection of breast cancer, like calcification, masses, sizes, etc. Small clusters of micro-calcification can lead to poor contrast in mammograms. Noise removal is also required in the case of mammograms as noises can lead to false assumptions of microcalcification.

The paper illustrates the working of contrast limited adaptive histogram equalisation (CLAHE) and morphological operations for enhancing the input image. The

proposed work concentrates on improving the quality of input images further to the extent that results in higher PSNR values and lowers MSE and RMSE figures.

State of art

Tripathy and Swarnkar (2020) has used the contrast improvement index (CII) and the to evaluate the effectiveness of the picture-enhancing algorithm on 322 mammogram images from MIAS dataset. The effect of the proposed model and methods used, particularly ROI and HE, are measured and compared using the contrast improvement index (CII), which also serves to reduce computing costs. Experimental results strongly imply that the CLAHE method can increase overall computer-aided diagnostic (CAD) system detection effectiveness and improve it greatly. The proposed framework can enhance image variance and eliminate the pectoral muscle without compromising any of the image's content.

According to Shwetha et al. (2020), a few of the methods employed include the median, mean, Weiner, modified Gabor, homomorphic, contrast limited adaptive equalisation, anisoid diffusion, guided filter and bilateral filter. The author also revised the Gabor filter, a linear texture analysis filter that determines whether there is any clear frequency participation in mammography in a particular direction in a localised area surrounding the region of examination. Mean square error (MSE), RMSE, PSNR, VAR, SSIM, and SD are calculated for each of these filters. The highest PSNR of the group is generated using the modified Gabor filter.

Zebari et al. (2020) used wavelet decomposition approach for image enhancement to emphasise the ROI and picture backdrop to produce a significant contrast between them to solve the problem of Over and under-segmentation problems. This seeks to advance the trainable segmentation model and threshold based for calculating Region of Interest. This research works for designing and developing segmentation, which can be detected in the breast region and eliminate the noise from mammographic image.

Wang et al. (2020) used 100 mammograms from the mammography database of women in Northeast China to show that DTCWT can more precisely describe the directional features of ROI containing microcalcification. The study suggests an extraction technique based on the fusion of textural characteristics and dual-tree complex wavelet transform (DTCWT). To denoise and enhance the image, pre-processing is done using an improved adaptive median filtering algorithm. The four techniques – grey-scale transformation, histogram equalisation, wavelet transform, NSCT, and the suggested method – are used to enhance the image. The best strategy has been shown to be a combination of strategies.

Mehmood et al. (2021) used MIAS database and Contrast limited adaptive equalisation for contrasting image in breast cancer detection. CLAHE is used for enhancing mammograms to contrast images and to view hidden details. The best results are getting for small contrast medical images on using CLAHE.

Patel and Hadia (2021) used MIAS database, median filter for denoising the image and CLAHE+ AHE for contrast enhancement in image enhancement. By modifying the characteristics using CLAHE, adaptive histogram equalisation (AHE) increases contrast of greyscale images. For improving quality of images, adaptive waited median filter is applied with the median filter.

Kavitha et al. (2021) used Optimal Multilevel threshold segmentation with DL included with capsule network model for Pre-Processing, MIAS and DDSM databases and nonlinear filter called Adaptive fuzzy filter for denoising images. OMLTS-DLCN model performs AFF to remove the existence of noise in mammographic images. It gives the best results for mammographic images.

Zebari et al. (2021) used MIAS, DDSM, INbreast, and BCDR databases for comparing accuracy, and Wavelet based enhancement feature extraction model for denoising the image. This method, which is based on wavelet transform, is applied on ROI extracted images to remove noise from the image. With the increase in ratio of peak signal and noise, the accuracy is increased by selecting a suitable or strong threshold setting to reduce noise while preserving image quality.

Cai et al. (2021) used MIAS Database, Wang-Mendel algorithm for denoising the image, and 16-bit Lookup table for Contrast Enhancement. This research used Wang-Mendel algorithm, based on Fuzzy technique, for noise reduction, and 16b lookup table for contrasting images. Wang Mendel algorithm is a useful technique based on fuzzy theory that uses fuzzy separation to remove noise.

Almalki et al. (2022) used mammographic images which suffer from low contrast images and contain salt and pepper noise. He has overcome these problems by using image enhancement techniques like median filter and CLAHE. This research works to enhance mammographic images by improving the overall segmentation and classification.

Mohamed et al. (2022) used image enhancement techniques for improving captured image for the accuracy of the diagnosis. The algorithms included in this paper are edge enhancement, median filtering, erosion, contrast-limited adaptive equalisation and dilation. However, these algorithms have already been used in much research, the results might not reach optimum value used on the methods and image property that are been used for the classification and feature extractions.

Avcı and Karakaya (2023) used Fiji ImageJ and MATLAB for image processing. The paper employed the mini MIAS database. Pre-processing techniques like thresholding and filtering were used to remove labels from mammography pictures. To remove areas of black-and-white photographs that contained labels and numbers, erosion and dilation morphological techniques are used. The pre-processing technique involved several fusions of median filter, CLAHE and masking algorithms. In the literature, the most recommended segmentation method, the k means clustering is used. Methods of feature extraction used here include GLCM feature extraction and GLRLM algorithm. LOOCV was used here to obtain models.

2 Research methodology

The research methodology for the enhancement paper on mammogram images involves enhancing the contrast and reducing noise of low-quality input images for the detection of abnormalities by radiologists (Janani et al., 2015; Bitenc et al., 2015). Enhancement of mammogram images can be achieved using various techniques, which can be broadly classified into four categories: conventional, region-based, feature-based, and fuzzy enhancement techniques.

This study focuses on region-based enhancement techniques, particularly the implementation of contrast limited adaptive histogram equalisation (CLAHE) and

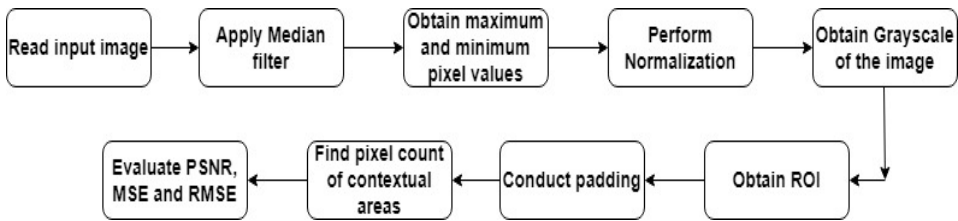
morphological operations such as opening, dilation, erosion, and closing. In addition, the research proposes an innovative method to enhance the region of interest (ROI) in mammogram images.

To justify the obtained results, performance metrics such as peak signal noise ratio (PSNR), MSE, and root mean square error (RMSE) are calculated. Greater PSNR values and lower MSE and RMSE values signify improved mammography images.

CLAHE is a technique designed to enhance contrast and eliminate noise, thereby enhancing the calibre of mammographic pictures. This method uses a non-linear grey transform to increase the contrast ratio. Mammogram pictures can also be further enhanced using other techniques, such as wavelet decomposition, filtering, and mathematical morphology. To conduct the research, mammogram images were gathered from the Mammographic Image Analysis Society (MIAS) dataset and subjected to the enhancement techniques mentioned earlier. The resulting images were assessed based on performance metrics, and the effectiveness of the proposed method in enhancing mammogram images was compared to that of CLAHE and morphological operations.

Figure 1 shows the flowchart describing the methodology adopted for the implementation of CLAHE for an enhancement of input mammogram image.

Figure 1 Figure shows the flowchart adopted to implement CLAHE



Morphological operations are considered best for binary images and can be applied on greyscale images (Wu et al., 2013). There are many morphological operations used to enhance the mammogram images such as opening, closing, erosion, and dilation.

Figure 2 shows the flowchart illustrating methodology adopted for implementing different morphological operations (opening, dilation, erosion, and closing) for enhancement of input mammogram image.

Figure 2 Figure shows the flowchart adopted to implement morphological operations

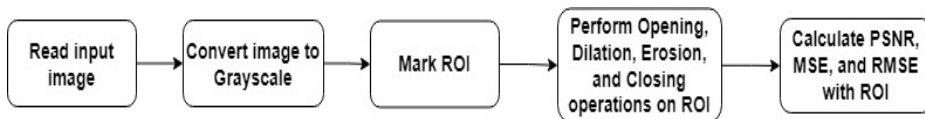
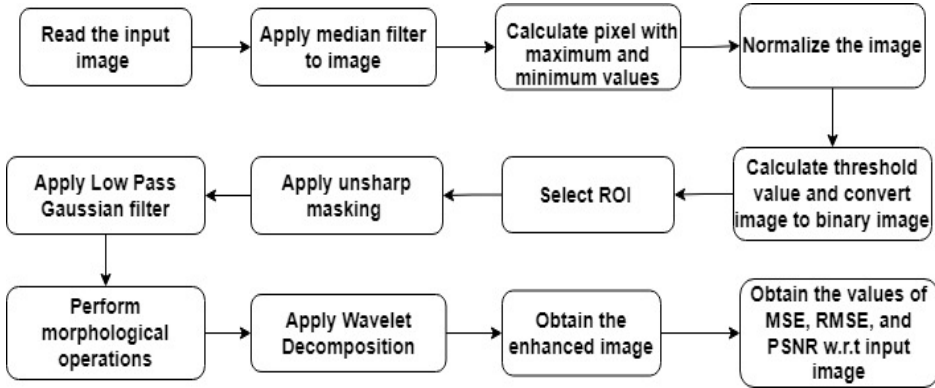


Figure 3 shows the flowchart depicting the proposed methodology intended to perform enhancement of an input mammogram image. The proposed technique consists of different phases and each phase has a specific function.

Figure 3 Figure shows the flowchart adopted to implement the proposed work



3 Implementation and results

This section elaborates the implementation conducted on a couple of mammogram images from the MIAS dataset using CLAHE, morphological operations, and the proposed technique.

CLAHE technique is implemented on mammographic images for its enhancement. CLAHE is a contrast enhancement technique that uses AHE to improve the contrast and remove noise in the image. This method enhances the contrast ratio by non-linear grey transform.

Morphological operations such as opening, dilation, erosion, and closing are used to remove noise and other artefacts from mammographic images. These operations are used to identify the region of interest (ROI) and to remove unwanted elements in the image. The innovative method proposed in the research work combines the use of CLAHE and morphological operations to further enhance the ROI and improve the quality of the mammographic image.

Proposed methodology implements combination of processes like filtering, thresholding, and morphological mention in Figure 3. The proposed approach intends to increase a picture's quality, resulting in a more enhanced image with better visual clarity and detail.

The numerical values of PSNR, MSE, and RMSE are calculated to justify the obtained results. Higher values of PSNR and lower values of MSE and RMSE indicate a more enhanced mammographic image, which can help radiologists in the detection of breast cancer. Figure 4 shows the Input mammogram image – mdb001.pgm.

Case 1:

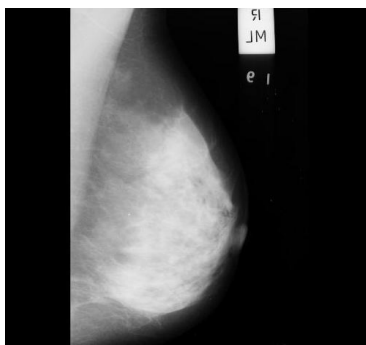
Figure 4 Input mammogram image – *mdb001.pgm**CLAHE*

Figure 5 shows the enhancement conducted on the input image *mdb001.pgm* as per the methodology illustrated in Figure 1 for CLAHE.

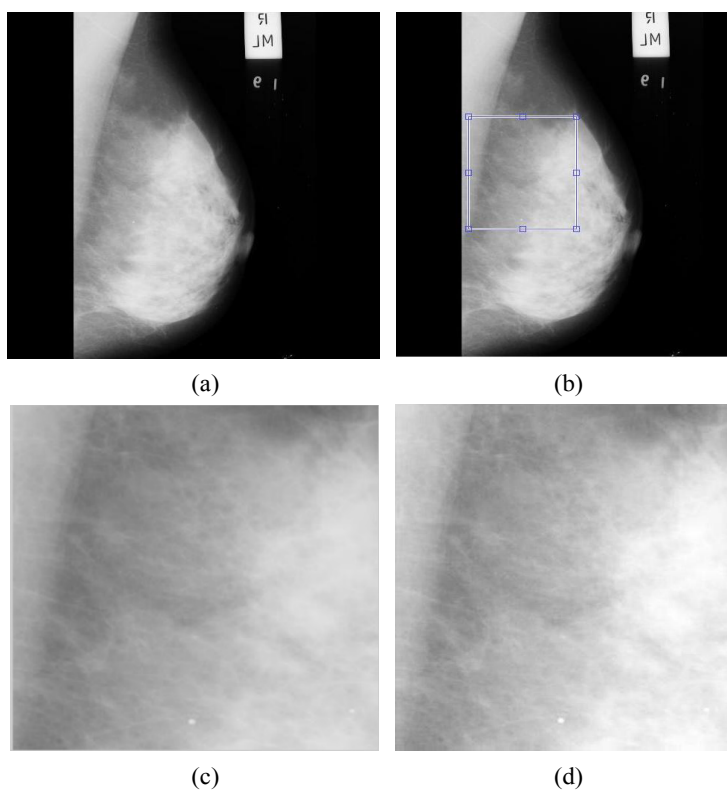
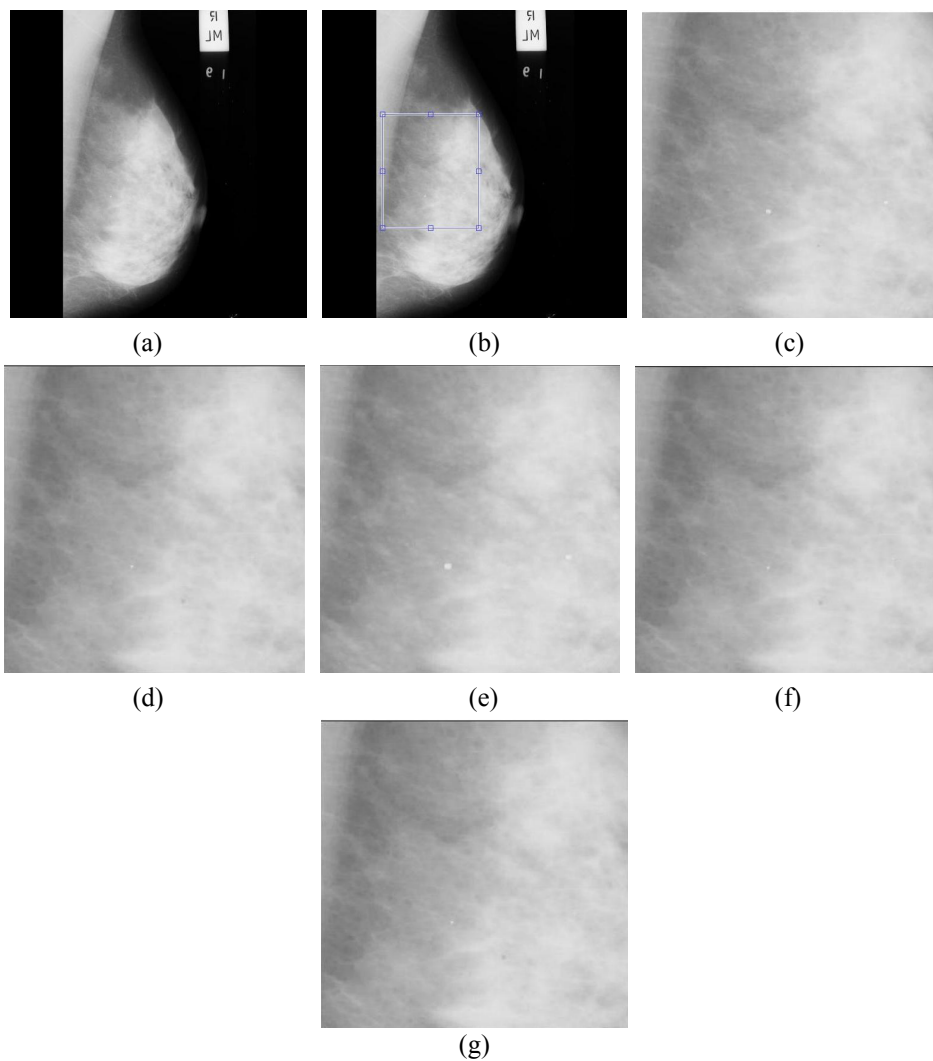
Figure 5 (a) Original input image; (b) image with marked ROI; (c) resized ROI image and (d) CLAHE image (see online version for colours)*Morphological operations*

Figure 6 shows the enhancement conducted on the input image *mdb001.pgm* as per the methodology illustrated in Figure 2 for morphological operations.

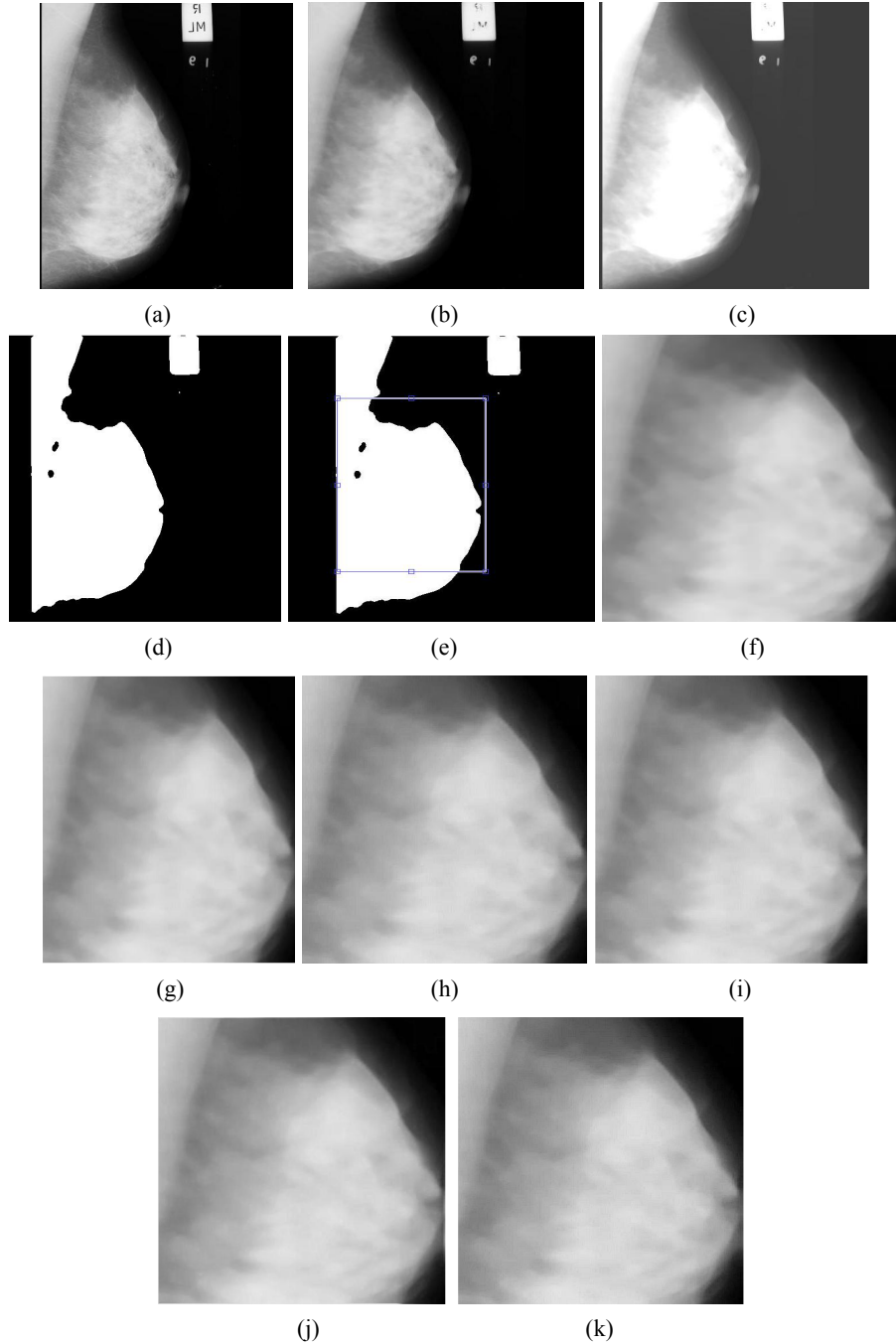
Figure 6 Figure shows the images obtained during the execution of four morphological operations: (a) input image; (b) image with marked ROI; (c) resized cropped image; (d) resized opened image; (e) resized dilated image and (f) resized eroded image and (g) resized closed image (see online version for colours)



Proposed work

Figure 7 shows the enhancement conducted on the input image *mdb001.pgm* as per the methodology illustrated in Figure 3 depicting the proposed model.

Figure 7 Figure displays the images obtained during the application of proposed work on ROI: (a) input image; (b) median filtered image; (c) normalised image; (d) converted binary image; (e) binary image with; (f) ROI marked on marked ROI the median filter image; (g) image obtained after; (h) unsharp masked image; (i) high pass cropping Gaussian filter image; (j) image obtained from morphological operations and (k) final obtained image (see online version for colours)

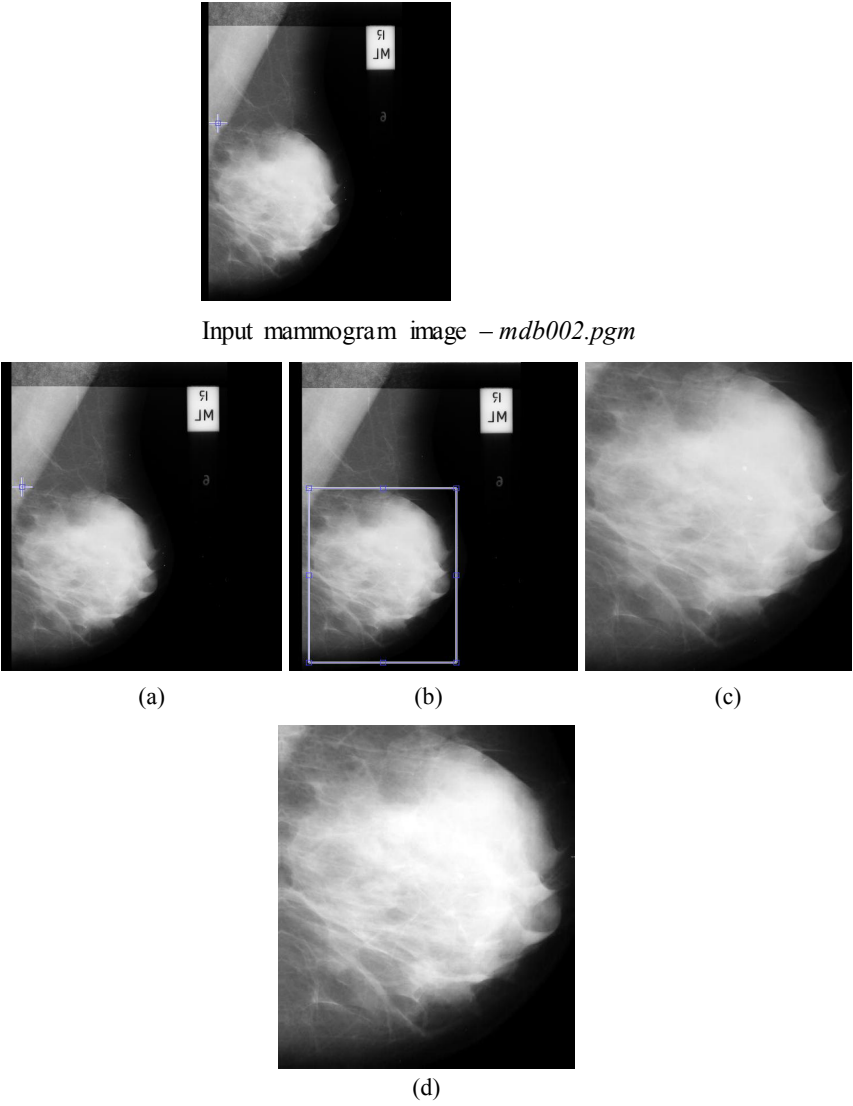


Case 2:

CLAHE

Figure 8 shows the enhancement conducted on the input image *mdb002.pgm* as per the methodology illustrated in Figure 1 for CLAHE.

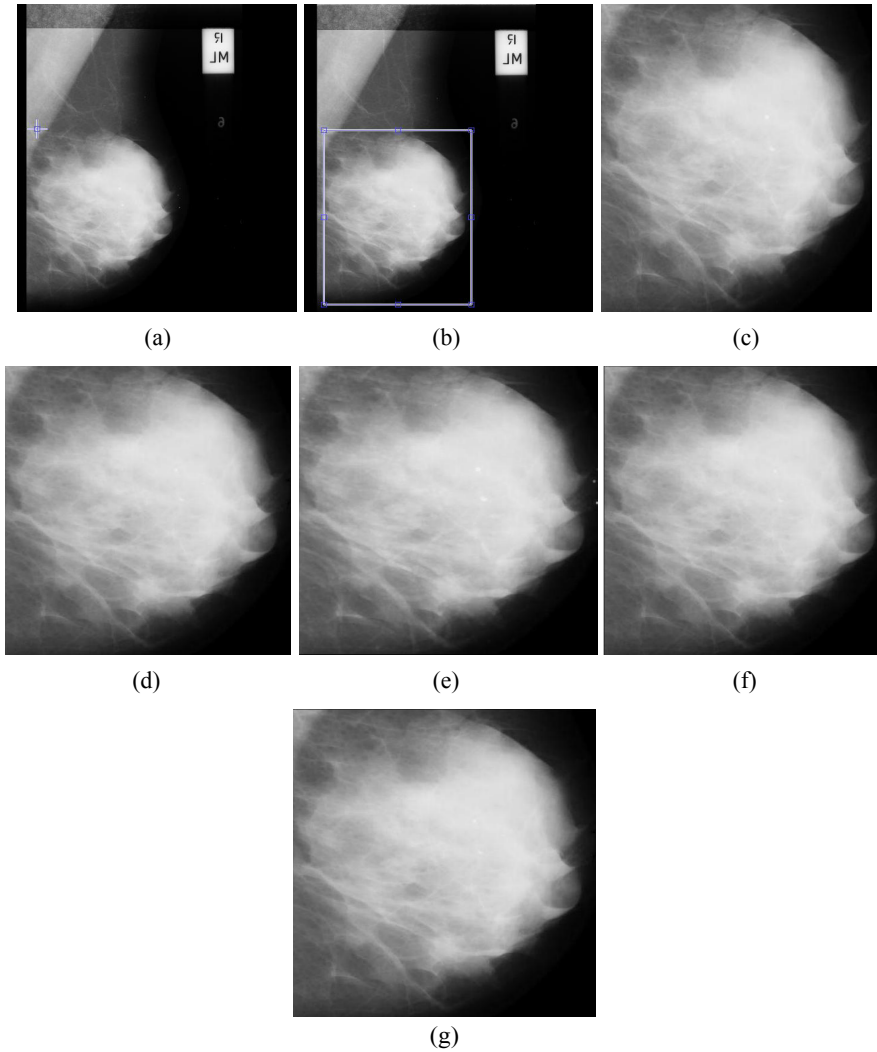
Figure 8 Figure shows the images obtained during different stages of CLAHE: (a) original input image; (b) image with marked ROI; (c) resized ROI image and (d) CLAHE image (see online version for colours)



Morphological operations

Figure 9 shows the enhancement conducted on the input image *mdb002.pgm* as per the methodology illustrated in Figure 2 for morphological operations.

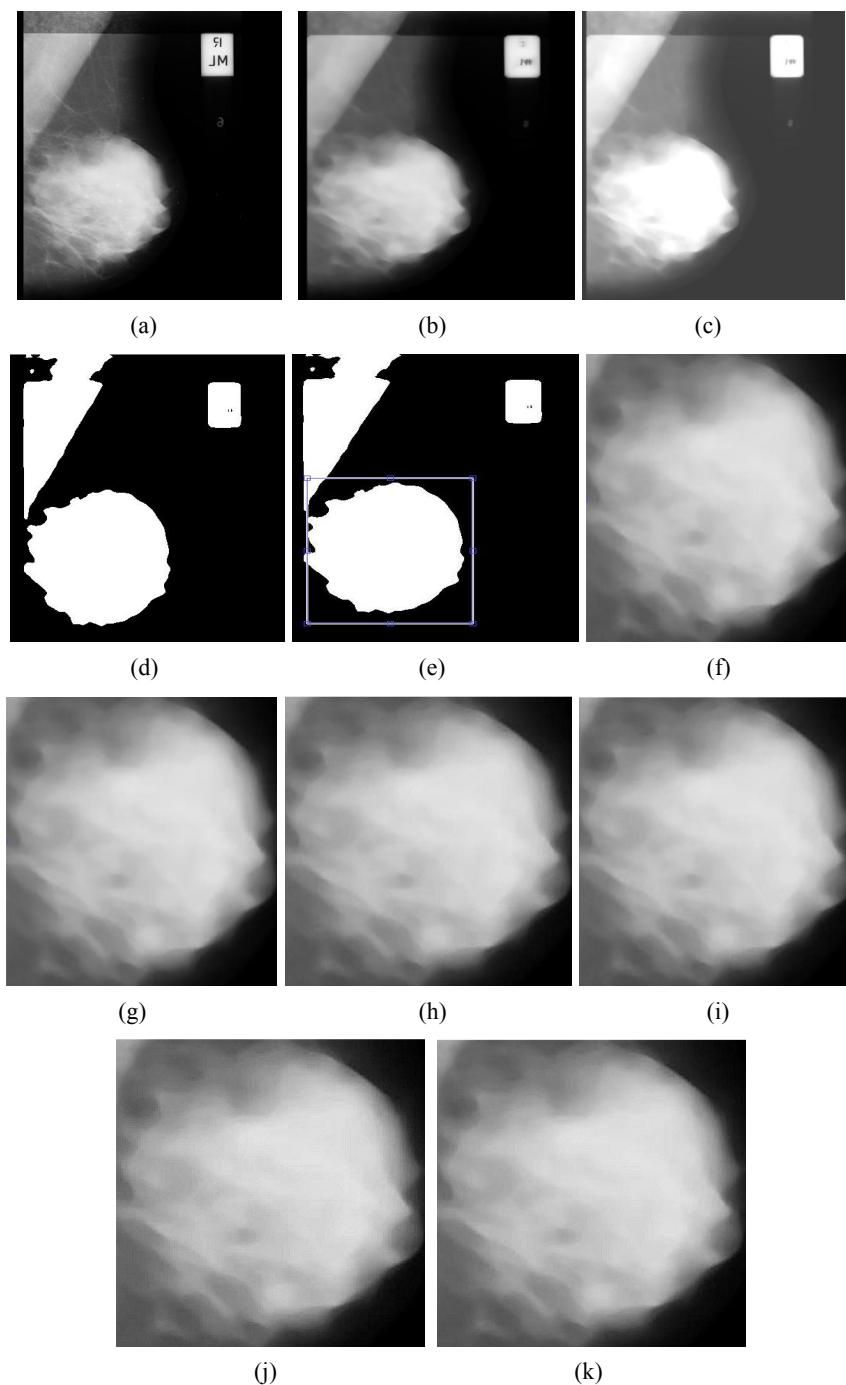
Figure 9 Figure shows the images obtained during the execution of four morphological operations: (a) input image; (b) image with marked ROI; (c) resized cropped image; (d) resized opened image; (e) resized dilated image; (f) resized eroded image and (g) resized closed image (see online version for colours)



Proposed work

Figure 10 shows the enhancement conducted on the input image *mdb002.pgm* as per the methodology illustrated in Figure 3 depicting the proposed model.

Figure 10 (a) Input image; (b) median filtered image; (c) normalised image; (d) converted binary image; (e) binary image with; (f) ROI marked ROI marked on median filter image; (g) image obtained after; (h) unsharp masked image; (i) high cropping pass Gaussian filter image; (j) image obtained from morphological operations and (k) final obtained image (see online version for colours)



4 Result and discussion

After the proper implementation of flowcharts as mentioned in the research paper in Section 3, 10 mammogram images have been considered for testing and proving worthy of the proposed method over CLAHE and Morphological operations from the MIAS database. The readings mentioned in Tables 1–3 depict the values of MSE, RMSE, and PSNR obtained using CLAHE, Morphological operations, and the proposed method respectively. The most crucial parameter signifying the degree of enhancement achieved is PSNR. PSNR is a normalised version of the MSE.

Table 1 depicts the readings of MSE for the 10 mammogram images under study using CLAHE, Morphological operations, and the proposed method. The MSE attained by the proposed method is comparatively lower as compared to CLAHE and different operations of MOs. The lower value of MSE in all the executed cases indicates that the proposed method outperformed the conventional methods of enhancement.

Table 1 Readings of MSE for the 10 mammogram images under study using CLAHE, morphological operations, and the proposed method

<i>Image</i>	<i>CLAHE</i>	<i>Opening (MO)</i>	<i>Dilation (MO)</i>	<i>Erosion (MO)</i>	<i>Closing (MO)</i>	<i>Proposed method</i>
mdb001.pgm	5.3888	2.8899	2.89	3.7021	3.9841	0.08807
mdb002.pgm	3.3282	2.8321	2.8424	3.2955	3.5371	0.8402
mdb003.pgm	2.446	2.6445	2.647	2.6908	3.2155	0.7506
mdb004.pgm	2.4972	2.5987	2.5881	2.9986	3.5169	0.9265
mdb005.pgm	6.4266	2.3496	2.3587	2.9805	3.16	1.4039
mdb006.pgm	7.3982	2.9605	2.7433	0.9659	1.4798	0.9385
mdb007.pgm	5.8470	7.9444	3.0943	0.6838	1.5803	0.6686
mdb008.pgm	7.4910	9.5009	3.4247	0.7727	1.6216	0.7545
mdb009.pgm	5.8394	6.9395	2.9024	0.8570	2.4959	0.8238
mdb010.pgm	8.3213	9.8080	3.0404	0.6313	1.6997	0.6215

Figure 11 shows the comparative graph representing readings of MSE obtained for the 10 mammogram images as per Table 1.

Table 2 depicts the readings of RMSE for the 10 mammogram images under study using CLAHE, Morphological operations, and the proposed method.

Table 2 Readings of RMSE for the 10 mammogram images under study using CLAHE, morphological operations, and the proposed method

<i>Image</i>	<i>CLAHE</i>	<i>Opening (MO)</i>	<i>Dilation (MO)</i>	<i>Erosion (MO)</i>	<i>Closing (MO)</i>	<i>Proposed Method</i>
mdb001.pgm	2.3214	1.7	1.7	1.9241	1.996	0.9385
mdb002.pgm	1.8243	1.6829	1.6859	1.8153	1.8807	0.9166
mdb003.pgm	1.564	1.6262	1.627	1.6404	1.7932	0.8664
mdb004.pgm	1.5802	1.6121	1.6088	1.7317	1.8753	0.9625
mdb005.pgm	2.5351	1.5328	1.5358	1.7264	1.7776	1.1848

Table 2 Readings of RMSE for the 10 mammogram images under study using CLAHE, morphological operations, and the proposed method (continued)

<i>Image</i>	<i>CLAHE</i>	<i>Opening (MO)</i>	<i>Dilation (MO)</i>	<i>Erosion (MO)</i>	<i>Closing (MO)</i>	<i>Proposed Method</i>
mdb006.pgm	2.7200	1.7206	1.6563	0.9828	0.9688	1.2165
mdb007.pgm	2.4181	2.8186	1.7591	0.8269	0.8177	1.2571
mdb008.pgm	2.7370	3.0824	1.8506	0.8791	0.8686	1.2734
mdb009.pgm	2.4165	2.6343	1.7036	0.9258	0.9076	1.5798
mdb010.pgm	2.8847	3.1318	1.7437	0.7945	0.7884	1.3037

Figure 11 Figure shows the comparative graph representing readings of MSE obtained for the 10 mammogram images (see online version for colours)

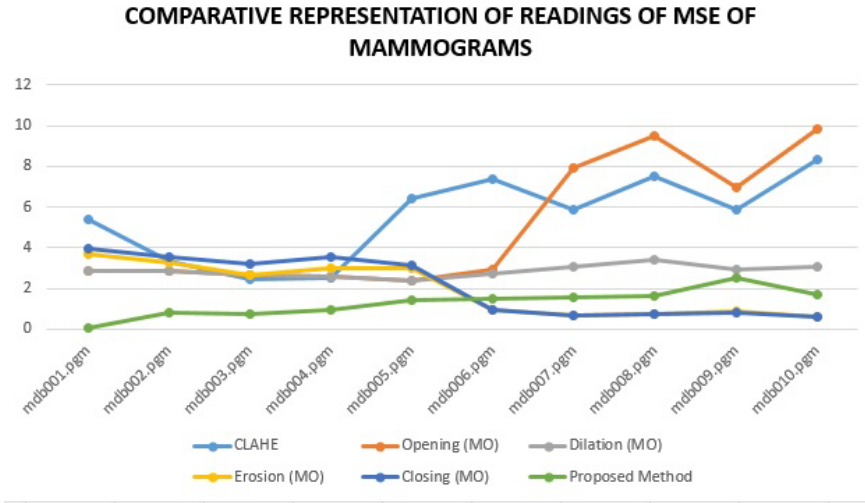


Figure 12 shows the comparative graph representing readings of RMSE obtained for the 10 mammogram images as per Table 2.

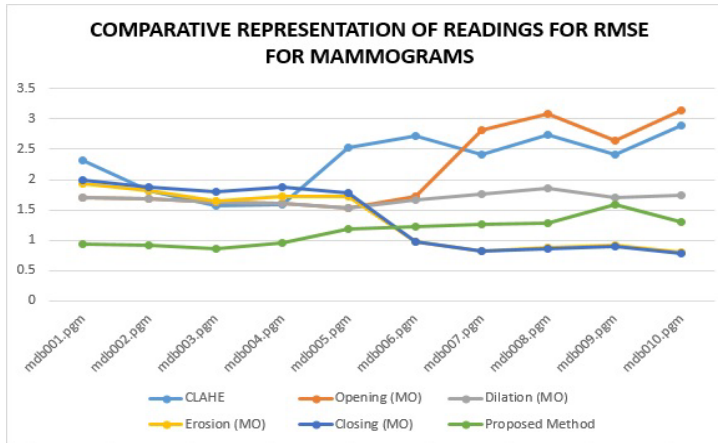
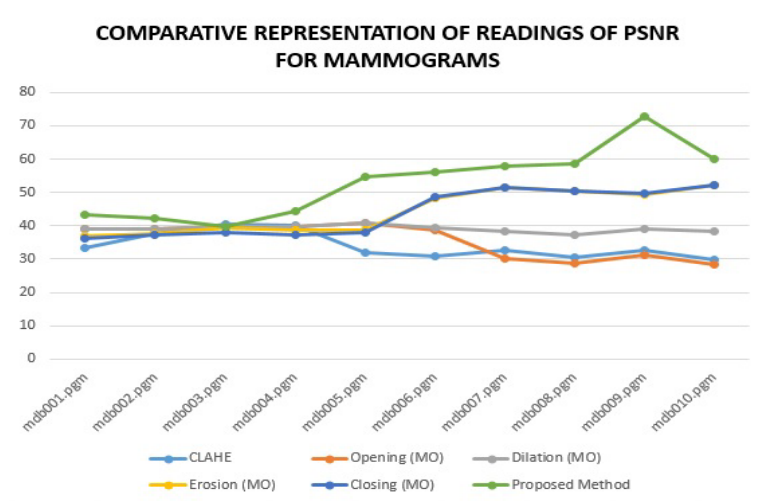
Table 3 depicts the readings of PSNR for the 10 mammogram images under study using CLAHE, Morphological operations, and the proposed method.

Table 3 Readings of PSNR for the 10 mammogram images under study using CLAHE, morphological operations, and the proposed method

<i>Image</i>	<i>CLAHE</i>	<i>Opening (MO)</i>	<i>Dilation (MO)</i>	<i>Erosion (MO)</i>	<i>Closing (MO)</i>	<i>Proposed Method</i>
mdb001.pgm	33.5	38.91	38.91	36.76	36.12	43.218607
mdb002.pgm	37.69	39.09	39.06	37.77	37.16	42.212452
mdb003.pgm	40.36	39.68	39.68	39.53	37.99	39.897966
mdb004.pgm	40.18	39.84	39.87	38.59	37.21	44.326238
mdb005.pgm	31.97	40.71	40.68	38.64	38.14	54.564064
mdb006.pgm	30.75	38.70	39.37	48.43	48.68	56.019828

Table 3 Readings of PSNR for the 10 mammogram images under study using CLAHE, morphological operations, and the proposed method (continued)

Image	CLAHE	Opening (MO)	Dilation (MO)	Erosion (MO)	Closing (MO)	Proposed Method
mdb007.pgm	32.79	30.13	38.32	51.43	51.63	57.891226
mdb008.pgm	30.64	28.58	37.44	50.37	50.58	58.643895
mdb009.pgm	32.80	31.30	38.88	49.47	49.81	72.753945
mdb010.pgm	29.73	28.30	38.47	52.13	52.26	60.038225

Figure 12 Figure shows the comparative graph representing readings of RMSE obtained for the 10 mammogram images (see online version for colours)**Figure 13** shows the comparative graph representing readings of PSNR obtained for the 10 mammogram images as per Table 3.**Figure 13** Shows the comparative graph representing readings of PSNR obtained for the 10 mammogram images (see online version for colours)

5 Conclusion

The investigation and staging of primary breast cancer can be greatly aided by contrast-enhanced spectral mammography (CESM). The main goal is to increase the diagnostic precision of conventional mammography when combined with iodinated contrast agents, particularly in cases when the parenchymal background image is more thick in the patient. The focus of the study paper was on improving the low-quality photos, particularly those in areas of interest (ROI). In particular for women with thicker parenchymal background patterns, the paper investigates the improved diagnostic accuracy of mammography, offering more precise tumour size and diagnosis of multifocal illness. The research paper computed the value of three performance evaluation metrics (MSE, RMSE, and PSNR) and have been implemented on ten mammogram images from the MIAS dataset. The conducted research work indicates that the value of PSNR has been maximum for the proposed technique as compared to CLAHE and Morphological operations. In the future, one can also have an insight into architectural distortion, which is also seen and considered to be the important early detection factor and is often ignored (Kamra et al., 2016).

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