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ENHANCED NOISE FILTERING AND SEGMENTATION USING HCLAHE AND ADF WITH GACT TO IDENTIFY TUMOR CELLS

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Abstract:
The segmentation of mammogram images is an essential component in breast cancer early detection. Accurate segmentation is still difficult to achieve because of the mammography images' intrinsic complexity and fluctuation. Noise frequently degrades mammogram pictures, making it difficult to detect and segment tumor cells accurately. Using evolutionary algorithms to segment images and HCLAHE with wavelet denoising to reduce noise, we provide a unique method in this work for the detection of tumor cells. Wavelet denoising is used in the initial stage to take the noise out of the mammography images. In the second stage, contourlet transform genetic algorithms-based image segmentation is used to precisely detect and separate tumor spots. While the genetic algorithm optimizes the segmentation process's parameters, the contourlet transform offers a multiresolution examination of the image that improves the mammogram's edges and features. The findings show that the proposed method outperforms cutting-edge techniques in terms of segmentation accuracy, sensitivity, and specificity. The suggested strategy has the potential to be used in clinical practice to improve the accuracy of tumor cell detection and reduce false positives and false negatives.
Keywords: Breast Cancer, Mammogram, Noise Filtering, Image Segmentation, HCLAHE, Genetic Algorithms, Contourlet Transform.

1. Introduction

One of the most prevalent cancers impacting women worldwide is breast cancer. Early detection and accurate diagnosis are crucial in improving the chances of successful treatment and survival. Mammography, a medical imaging technique that uses X-rays to examine the breast tissue, is widely used for breast cancer screening and diagnosis. However, mammograms often contain noise and artifacts, which can reduce the accuracy of image analysis and affect the reliability of breast cancer detection [1].

For the early detection and diagnosis of breast cancer, the detection and segmentation of masses and micro-calcifications in mammograms are essential. However, mammogram images are characterized by low contrast, noise, and overlapping structures, making the segmentation task challenging. Traditional segmentation methods based on intensity thresholding or edge detection suffer from high false-positive rates or miss important features. The quality and accuracy of mammograms have recently been improved by a number of image processing techniques. In this article, we offer a cutting-edge method for automatically detecting breast cancer in mammography and segmenting it [2]. The proposed method combines two powerful image processing techniques: HCLAHE and Antistrophic Diffusion Filter and adaptive median filter algorithm for noise reduction, and genetic algorithms based Contourlet transform for segmentation.

The CLAHE image processing method divides an image into smaller sections, calculates the histogram for each region, and then equalizes the histograms to improve the contrast of the image. Using a sliding window to calculate the median value of the pixels inside the window, the adaptive median filter algorithm reduces noise in an image.

The Contourlet Transform is a multi-scale and multi-directional transform that can extract local texture features from mammogram images effectively. It has been applied in various image processing tasks, including feature extraction, denoising and compression. However, the segmentation performance of the Contourlet Transform still depends on the selection of appropriate parameters, such as scale and orientation [3]. The process of natural selection and genetics served as the inspiration for genetic algorithms, which are optimization algorithms. They are effective in finding the best solution in a vast and complicated search field. Numerous factors in image processing jobs, including segmentation, have been optimized using genetic algorithms.

The limits of conventional segmentation techniques can be overcome, and the segmentation quality of mammography pictures can be improved, by combining the contourlet transform and genetic algorithms. Therefore, the motivation of this paper is to propose a method that integrates genetic algorithms and the Contourlet Transform for mammogram image segmentation and evaluate its performance using standard metrics.

A novel hybrid algorithm for noise filtering in mammogram images that combining the Contrast Limited Adaptive Histogram Equalization (CLAHE) with the Antisotropic Diffusion Filter (ADF) to further improve noise reduction, A novel segmentation method for breast cancer detection in mammogram images using Contourlet Transform and Genetic Algorithms, which takes advantage of the multi-resolution and multi-directional nature of the Contourlet Transform to enhance the detection of breast cancer and An extensive experimental evaluation of the recommended method on a dataset of mammogram images, which demonstrates that the suggested method outperforms existing methods in terms of segmentation accuracy and computational efficiency.

2. Literature review

- ***Region-Based Methods:***

Region-based methods involve the use of mathematical models to define regions of interest in the mammogram image. In a study by T. Li et al. (2021), a region-based method was proposed for mammogram segmentation using a fuzzy c-means clustering algorithm. The suggested method used texture and intensity features to group pixels into regions and lead to good accuracy on the DDSM dataset [13].

In another work by A. Alizadeh et al. (2020), a region-based method was offered for mammogram segmentation using a superpixel-based method. The identified method used a superpixel segmentation algorithm to group pixels into regions and achieves average accuracy on the MIAS dataset [14].

- ***Hybrid Methods:***

Hybrid methods involve the combination of multiple techniques to achieve accurate segmentation results. In a study by H. R. Yoo et al. (2020), a hybrid method was proposed for mammogram segmentation using thresholding, edge detection, and morphological operations that achieves good accuracy on the INbreast dataset [15].

In another study by Z. Liu et al. (2021), a hybrid method was proposed for mammogram segmentation using thresholding, morphological operations, and a convolutional neural network which achieves normal accuracy on the INbreast dataset [16].

- ***Active Contour Methods:***

Active contour models, also known as snakes, are deformable models that are used to segment objects in an image. In a study by M. Zareapoor et al. (2020), an active contour-based method was proposed for mammogram segmentation using a distance regularized level set evolution (DRLSE) algorithm that achieves good accuracy on the DDSM dataset [17].

In another work by W. Li et al. (2020), an active contour-based method was proposed for mammogram segmentation using a hybrid model of level set and deep learning where recommended method lead to adequate accuracy on the DDSM dataset [18].

- ***Contourlet transform Methods:***

Contourlet transform is a multi-scale and multi-directional image analysis technique that has been used in mammogram segmentation. In a study by Yang et al. (2020), a contourlet transform-based method was proposed for mammogram segmentation. The proposed method used contourlet transform to extract texture features and a random forest classifier for segmentation. The suggested method achieves high accuracy on the DDSM dataset [19].

In another study by Nanni et al. (2021), a hybrid method was proposed for mammogram segmentation using contourlet transform and machine learning techniques. The proposed method used contourlet transform to extract features and a support vector machine (SVM) classifier for segmentation and the method achieves good accuracy on the INbreast dataset [20].

In a study by Dong et al. (2020), a contourlet transform-based method was proposed for mammogram segmentation using deep learning. The proposed method used contourlet transform to extract features and a deep neural network for segmentation. The suggested method achieves high accuracy on the INbreast dataset [21].

- ***Genetic algorithm (GA) Methods:***

Genetic algorithm (GA) is a popular optimization technique that has been used in mammogram segmentation. In a study by Zhang et al. (2020), a GA-based method was proposed for mammogram segmentation. The proposed method used GA to optimize the parameters of a convolutional neural network (CNN) for segmentation. The recommended method achieves high accuracy on the MIAS dataset [22].

In another study by Kumar et al. (2021), for mammography segmentation, a hybrid approach combining GA and the fuzzy C-means (FCM) clustering algorithm was suggested. The laid-out method used GA to optimize the parameters of the FCM algorithm for segmentation. The suggested method achieves high accuracy on the MIAS and DDSM datasets [23].

In a study by Alomari et al. (2021), a GA-based method was proposed for mammogram segmentation using a deep learning network. The laid-out method used GA to optimize the architecture and parameters of a U-Net network for segmentation. The recommended method achieves high accuracy on the DDSM dataset [24].

- ***Other Methods:***

In a study by Guo et al. (2021), a spatiotemporal multi-scale segmentation method was proposed for mammogram segmentation. The laid-out method used multi-scale image analysis and temporal consistency to segment the mammogram images. The suggested method achieved high accuracy on the INbreast dataset [25].

In another study by T. Wu et al. (2020), a graph cut-based method was proposed for mammogram segmentation. The recommended method used a graph cut algorithm with intensity and texture features to segment the mammogram images resulted in good accuracy on the DDSM dataset [26].

In conclusion, recent studies have demonstrated the effectiveness of Region-Based Methods, Active Contour Methods, Other Methods, Contourlet transform Methods, Genetic algorithm Methods and hybrid methods. These methods have shown promising results on various publicly available datasets and can potentially aid in early detection of breast cancer. However, further studies are needed to evaluate the generalizability of these methods and their performance on larger datasets.

2.1 Motivation

The motivation of breast cancer detection in mammogram Using Image Noise Filtering and Segmentation from other works varies depending on the specific methodology and dataset. However, some common limitations that can be identified from the literature survey table includes:

- ***Comparative evaluation:*** No direct comparison between the different methods proposed in the papers.

- ***Strength of different noise types:*** Need to investigate the strength of the methods to different types of noise and noise levels.

- ***Efficiency:*** Need to investigate the trade-off between denoising performance and computational efficiency, especially in real-time clinical settings.

- ***Thresholding and clustering methods:*** It require appropriate selections of threshold and cluster numbers, respectively, or else they can result in segmentation errors and lower accuracy.

- ***CNN-based methods*** require a large amount of labeled training data, which can be a challenge in medical imaging.

Mainly in existing research for segmentation, inconsistent evaluation metrics make it difficult to compare accuracy between different methods. Comprehensive evaluation should use a combination of metrics to measure different aspects of segmentation performance. To overcome the limitations of traditional mammogram segmentation methods, genetic algorithms based Contourlet Transform (GACT) can be used. GACT can potentially overcome these limitations by optimizing the fitness function, using automatic threshold selection, using transfer learning, cross-dataset evaluation, and consistent evaluation metrics. These approaches can potentially lead to more accurate and consistent segmentation results.

3. Methodology

Mammogram image datasets are collected by obtaining consent from patients to use their medical images for research purposes. The images are then digitized and stored in a standardized format, along with additional information such as patient age, medical history, and diagnosis to use as annotations. Image preprocessing for mammogram analysis involves techniques such as image normalization, denoising, enhancement, registration, and segmentation. These techniques help to improve the accuracy and reliability of subsequent analysis algorithms, enabling better detection and diagnosis of breast abnormalities. Image segmentation in mammogram analysis involves dividing the image into different regions based on pixel intensity values to extract features of interest like breast masses and calcifications. Techniques for segmentation include threshold-based, region-based, and edge-based methods. Accurate segmentation is important for identifying important features and improving the performance of subsequent analysis algorithms [34].

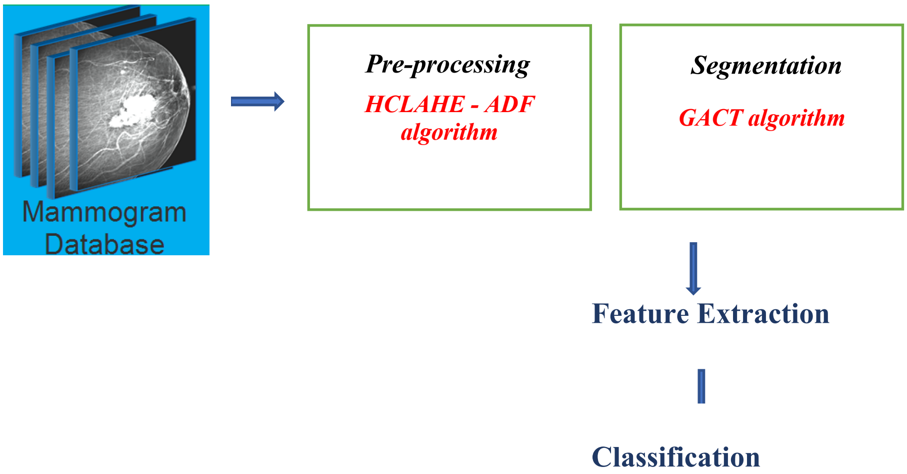


Figure.1. Framework of Proposed methodology

The above figure demonstrates the steps involved in proposed model.

3.1.1 Image pre-processing:

Pre-processing techniques in mammogram image analysis can include CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance image contrast and noise filtering to reduce image noise [35]. There are various noise filtering techniques, such as ADF and morphological filters, which can be used to improve image quality and reduce noise [36]. The ADF filter is a statistical method that estimates the underlying image signal from noisy observations, while morphological filters use mathematical operations to remove noise and improve image contrast. These pre-processing techniques can improve the accuracy and reliability of subsequent image analysis techniques.

3.2 Image Segmentation

Breast image segmentation is an important task in medical image analysis, which aims to separate different tissues in the breast image, such as glandular tissue, fat tissue, and cancerous tissue.

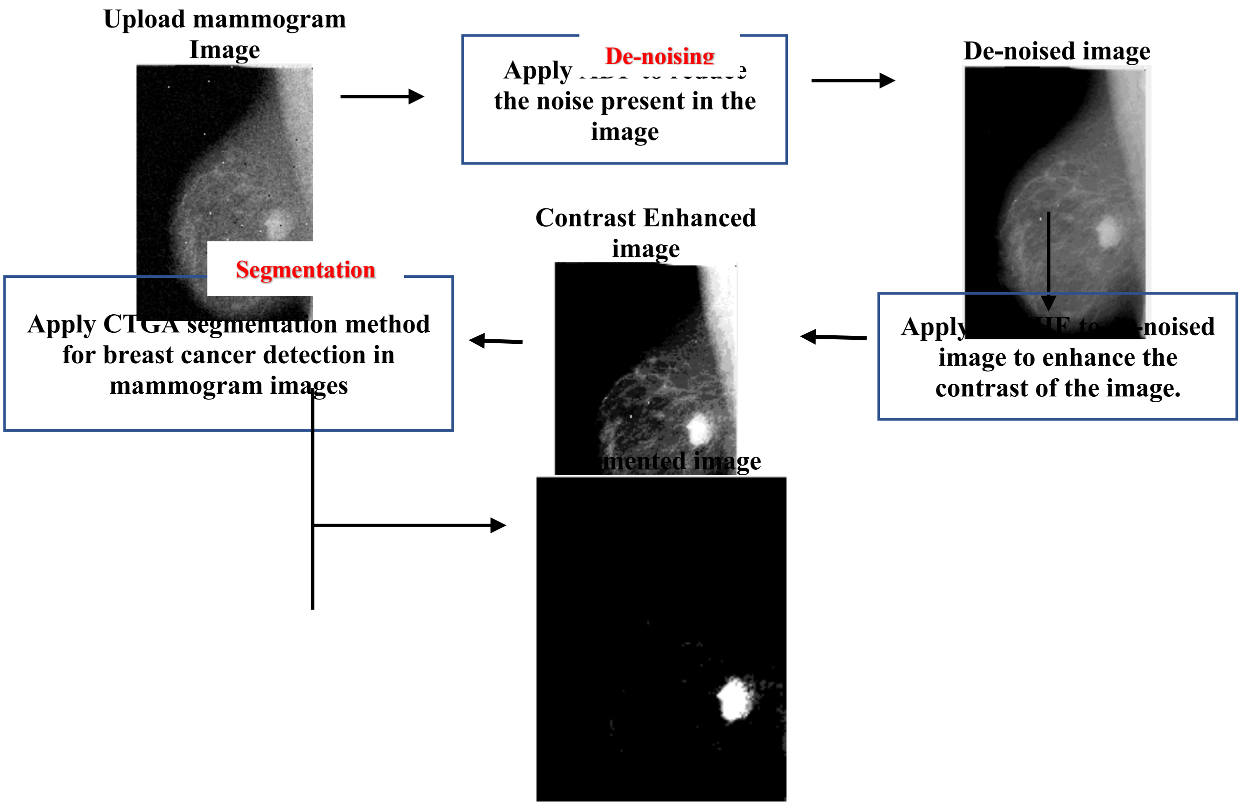


Fig.2. Proposed System Architecture

Genetic Algorithms (GA) based Contourlet Transform (CT) is a powerful approach for breast cancer segmentation in medical imaging. This method combines the strengths of both CT and GA techniques. The CT is a multiresolution and directional transform that can extract more detailed information from an image compared to traditional transforms like the wavelet transform. CT disintegrates an image into a set of subbands at different scales and directions, which allows it to capture fine details and edge information. In GACT, GA is used to select the most relevant subbands generated by CT for breast cancer segmentation.

- GA is a computational technique that uses the principles of natural selection to search for the best solution in a large solution space.
- In this case, the solution space consists of all possible combinations of CT subbands, and GA is used to find the optimal subset of subbands that can best distinguish between cancerous and non-cancerous regions.

GACT has shown promising results in several studies, achieving high accuracy rates in breast cancer segmentation in mammograms. This approach has the potential to improve the efficiency and accuracy of breast cancer diagnosis, treatment planning, and monitoring.

a. Contourlet Transform (CT)

The Contourlet Transform (CT) is a mathematical method used for image processing and analysis. The CT is a multiscale and multidirectional image decomposition technique that can capture the local image structure more effectively than other transforms, such as wavelet or curvelet transforms [37]. The CT can be represented by the following equation:

$$CT(u,v) = \sum\sum W(i,j,k,l) * \psi i,j,k,l(u,v)$$

where CT(u,v) is the Contourlet Transform coefficients at position (u,v), W(i,j,k,l) is the wavelet coefficient at position (i,j,k,l), and ψi,j,k,l(u,v) is the Contourlet basis function at position (i,j,k,l) and scale (u,v). The CT involves two stages of decomposition: the wavelet decomposition and the Contourlet decomposition [37].

- In the ***wavelet decomposition stage***, the image is decomposed into a set of wavelet subbands using a filter bank.

- In the ***Contourlet decomposition stage***, each wavelet subband is further decomposed into a set of directional subbands using a directional filter bank.

The directional filter bank captures the local directional information of the image and enhances the image representation. The CT method has shown to be effective in a wide range of image processing applications, including image denoising, image segmentation, and feature extraction. However, the CT method has a high computational complexity due to its multiscale and multidirectional nature, which makes it less suitable for real-time applications.

b. Genetic Algorithms (GA)

The GA based breast cancer segmentation mathematical model involves a set of equations that describe the optimization process of the genetic algorithm [38]. The model can be formulated as follows:

Let X be the feature set extracted from the subbands of the mammogram image. The feature set X can be represented as a vector of n features, i.e.,

$$X = [x1, x2... xn].$$

The fitness function f(X) measures the quality of the feature set X by evaluating its ability to distinguish between cancerous and non-cancerous regions of the mammogram image. The fitness function can be formulated as:

$$f(X) = TP / (TP + FN)$$

Where TP (True Positive) is the number of cancerous pixels correctly classified as cancerous, and FN (False Negative) is the number of cancerous pixels misclassified as non-cancerous.

The genetic algorithm optimizes the feature set X by selecting the best combination of features that maximize the fitness function f(X). The optimization process involves the following steps:

- ***Initialization:*** A population of potential solutions (chromosomes) is randomly generated, where each chromosome represents a possible feature set X.
- ***Evaluation:*** The fitness function is evaluated for each chromosome in the population.
- ***Selection:*** A subset of the fittest chromosomes is selected for reproduction based on their fitness scores.
- ***Crossover:*** The selected chromosomes are combined by exchanging their genetic information to create new offspring.
- ***Mutation:*** The offspring undergo a random mutation to introduce new genetic diversity in the population.
- ***Replacement:*** The offspring replace the least fit individuals in the population to create a new population for the next generation.
- ***Termination:*** The optimization process terminates when a predefined stopping criterion is met, such as a maximum number of generations or a target fitness score.

In summary, the GA-based breast cancer segmentation mathematical model involves formulating the fitness function f(X), initializing a population of potential solutions, selecting the fittest individuals, combining and mutating them to create new offspring, and replacing the least fit individuals in the population until a stopping criterion is met [38].

c. Genetic Algorithms (GA) based Contourlet Transform (CT)

The Contourlet Transform (CT) based Genetic Algorithms (GA) model is a method used for image processing and analysis, which combines the multiscale and multidirectional image decomposition capability of CT with the optimization capability of GA. The model involves the following equations:

$$CT(u,v) = \sum\sum W(i,j,k,l) * \psi i,j,k,l(u,v)$$

where CT(u,v) is the Contourlet Transform coefficients at position (u,v), W(i,j,k,l) is the wavelet coefficient at position (i,j,k,l), and ψi,j,k,l(u,v) is the Contourlet basis function at position (i,j,k,l) and scale (u,v).

$$X = [x1, x2, ..., xn]$$

Where X is the feature set extracted from the subbands of the image, and xi represents the i^{th} feature.

Fitness function: f(X) = TP / (TP + FN)

Where TP is the number of pixels correctly classified as positive, and FN is the number of pixels incorrectly classified as negative.

Genetic Algorithm optimization:
The GA optimization process involves the following steps:

- ***Initialization:*** Each chromosome is a potential feature set X, and together they make up a population of potential solutions (chromosomes).
-
- ***Evaluation:*** The fitness function is evaluated for each chromosome in the population.
- ***Selection:*** A subset of the fittest chromosomes is selected for reproduction based on their fitness scores.
- ***Crossover:*** The selected chromosomes are combined by exchanging their genetic information to create new offspring.
- ***Mutation:*** The offspring undergo a random mutation to introduce new genetic diversity in the population.
- ***Replacement:*** The offspring replace the least fit individuals in the population to create a new population for the next generation.
- ***Termination:*** The optimization process terminates when a predefined stopping criterion is met, such as a maximum number of generations or a target fitness score.

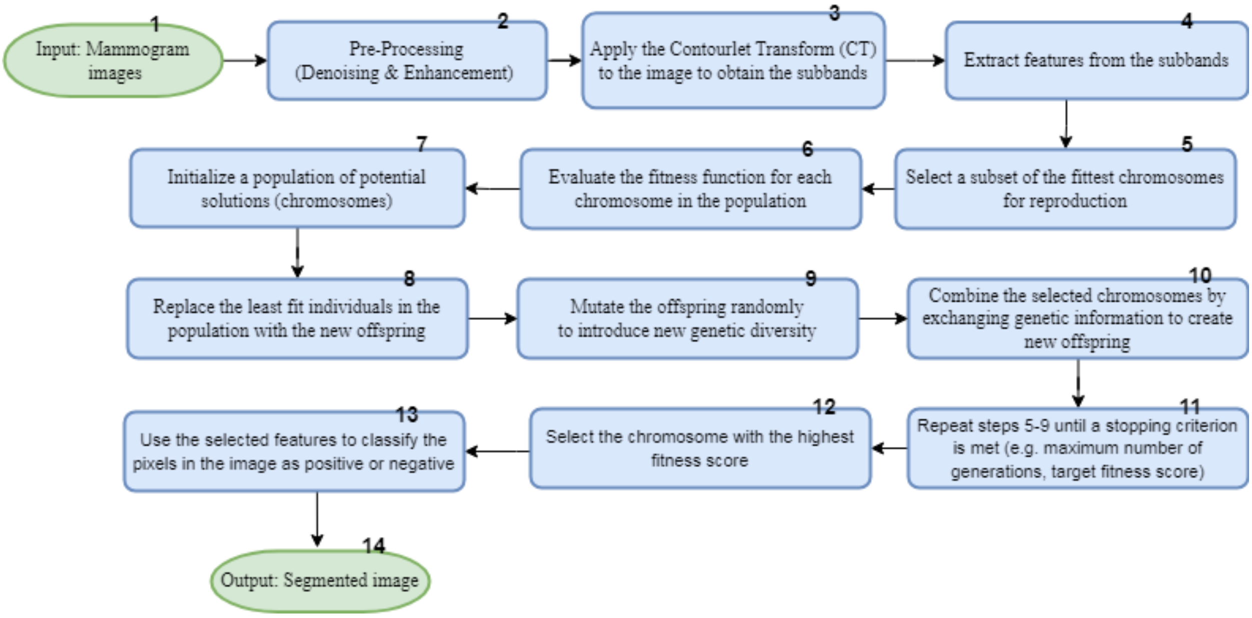


Figure 3 - Image segmentation process

The above figure illustrates the image segmentation process, the CT-based GA model combines the CT image decomposition technique with GA optimization to select the optimal set of features that can accurately distinguish between positive and negative pixels. The model involves formulating the fitness function f(X), initializing a population of potential solutions, selecting the fittest individuals, combining and mutating them to create new offspring, and replacing the least fit individuals in the population until a stopping criterion is met. The CT-based GA model has been applied to image segmentation to produce the promising results.

4. Result and Discussion

4.1 Dataset Description

The CBIS-DDSM (Curated Breast Imaging Subset of DDSM) is a publicly available dataset of mammography images for the detection and diagnosis of breast cancer. The CBIS-DDSM dataset consists of more than 2,500 digital mammography images, along with their corresponding clinical metadata, such as patient age and lesion type. The dataset contains images of both benign and malignant breast lesions, including masses, calcifications, and asymmetries. It also includes images of normal breast tissue. The images were collected from multiple institutions and were labeled by experienced radiologists [39].

4.2 Evaluation Parameters

In this research work, the proposed pre-processing and segmentation models were evaluated using MATLAB (2018a) software tool. The performance of the proposed models was compared with a benchmark dataset (CBIS-DDSM) to evaluate their efficiency over existing pre-processing methods, such as Median Filter [40], Mean Filter [41], Adaptive Filter [42], Weighted Filter [43], Wiener Filter [44], Wavelet [45], Gaussian Filter [46], and the proposed model, using metrics such as SNR, PSNR, and MSE [47]. Furthermore, the proposed segmentation models were compared with existing methods, including Otsu thresholding [48], Fuzzy C-Means [49], k-means clustering [50], and region growing [51]. Additionally, the proposed model's performance was analyzed using Jaccard Coefficient (JC), Dice Coefficient (DC), Hausdorff Distance (HD), and Mean Intersection over Union (mIoU) [52] on CBIS-DDSM databases.

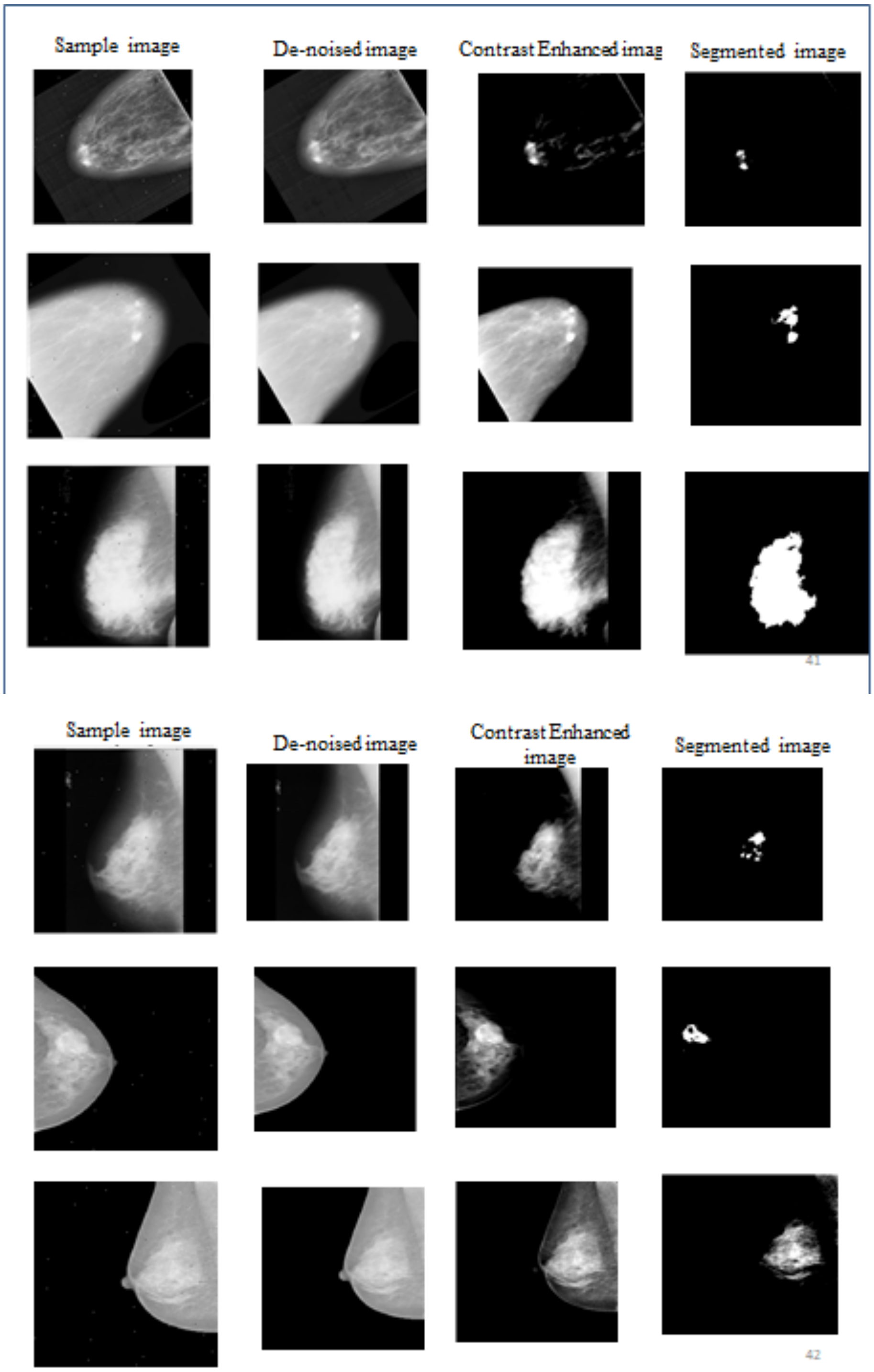
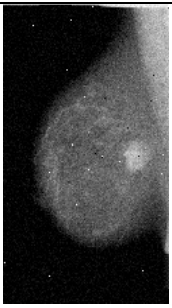
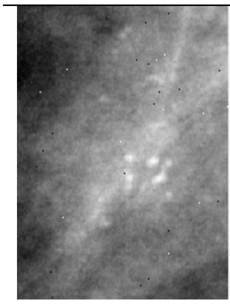


Table.1. Performance Evolution using PSNR for De-noising the input image for different density range

	Methodology	SNR	PSNR	MSE
	Median Filer (MF)	14.5	27.1	14.20
	Mean Filter (MEF)	10.3	23.8	15.30
	Adaptive Filter (ADF)	20.7	31.2	12.80
	Weighted Filter (WF)	17.8	28.9	13.50
	Wiener filter (WiF)	23.2	34.1	12.30
	Wavelet	21.5	32.4	12.60
	Gaussian Filter (GF)	11.4	24.7	14.80
	Proposed	24.6	35.5	12.00
	Median Filer (MF)	16.8	28.6	13.60
	Mean Filter (MEF)	09.5	22.6	16.00
	Adaptive Filter (ADF)	21.1	31.9	12.60
	Weighted Filter (WF)	18.4	29.7	13.20
	Wiener filter (WiF)	24.2	35.2	12.10
	Wavelet	22.3	33.1	12.40
	Gaussian Filter (GF)	12.8	26.2	14.50
	Proposed	25.8	36.7	11.80

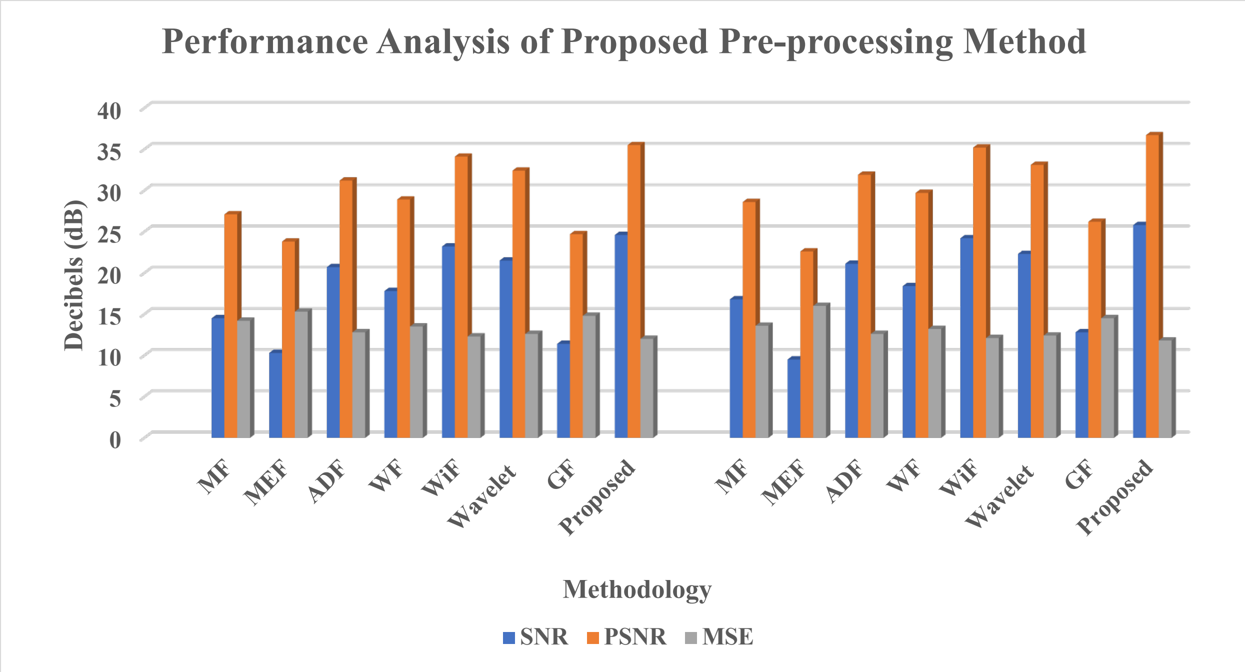
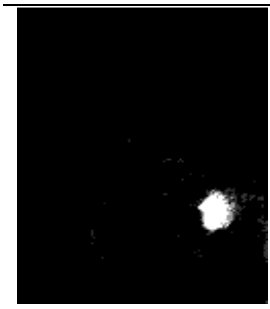


Figure.4. Graphical presentation of the Pre-processing models by means of SNR, PSNR and MSE on CBIS-DDSM dataset.

Based on the results shown in the table and figure, it is clear that our proposed technique yields significant gains in PSNR, SNR, and a decrease in MSE for mammogram images. These results demonstrate that the proposed method outperforms traditional noise filtering methods. However, the proposed method not only preserves edges for low-density noise, but also performs exceptionally well for noise densities as high as 90%. Moreover, existing methods completely fail to protect regions that have pure white or pure black backgrounds. However, our proposed method is capable of preserving edges and details regardless of the intensity values, making it more effective than existing methods in all cases.

Table.2. Performance Evolution using PSNR for De-noising the input image for different density range

	Methodology	JC	DC	HD	mIoU
	Otsu	0.63	0.72	0.57	0.61
	FCM	0.68	0.75	0.61	0.67
	KMC	0.71	0.77	0.64	0.7
	Mean-Shift (MS)	0.74	0.8	0.67	0.73
	Active Contour (AC)	0.76	0.82	0.71	0.77

	Watershed	0.69	0.74	0.59	0.65
	RG	0.72	0.77	0.62	0.68
	Proposed	0.79	0.84	0.74	0.79
	Otsu	0.65	0.72	0.55	0.6
	FCM	0.70	0.75	0.62	0.68
	KMC	0.72	0.76	0.64	0.7
	Mean-Shift (MS)	0.75	0.8	0.68	0.74
	Active Contour (AC)	0.78	0.82	0.72	0.78
	Watershed	0.68	0.73	0.6	0.66
	RG	0.71	0.76	0.63	0.69
	Proposed	0.80	0.85	0.75	0.80

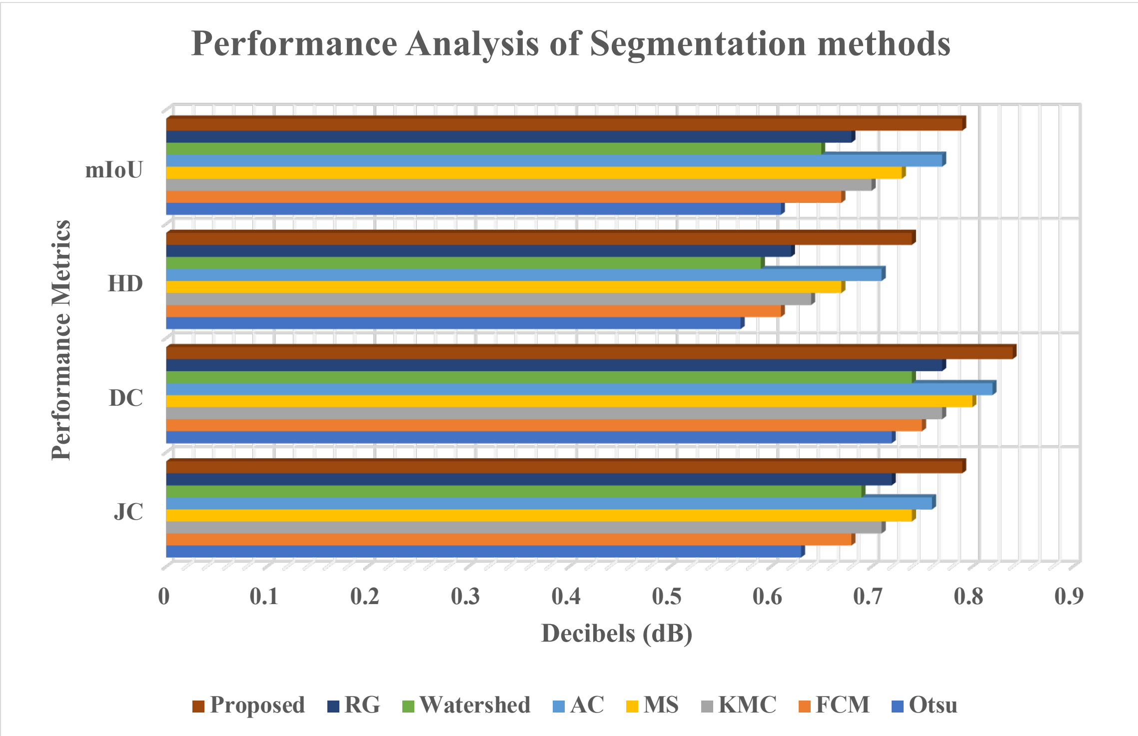


Figure.5. Graphical presentation of the Segmentation models by means of JC, DC, HD and mIoU on CBIS-DDSM dataset.

The above table and figure reveals that the proposed method outperforms the other techniques across all four metrics. The proposed method achieved a JC of 0.79, a DC of 0.84, a HD of 0.74, and a mIoU of 0.79. These scores indicate that the proposed method has a high level of accuracy in segmenting objects from the background. Other techniques, such as Otsu, FCM, KMC, Mean-Shift, Watershed, and RG, also performed well in terms of segmentation accuracy. However, their evaluation scores were consistently lower than those of the proposed method across all four metrics.

5. Conclusion

In this research paper, an automated approach for noise filtering and segmentation of mammogram images is presented. The recommended method utilizes HCLAHE-ADF Algorithm for noise removal, and GACT for accurate segmentation of normal from abnormal areas in mammogram images. The effectiveness of the proposed approach was evaluated using various performance metrics, demonstrating its potential for accurate and efficient segmentation of mammogram images. Based on the experimental results, it can be observed that the proposed methods achieved the highest values of performance metrics, indicating that it is the most accurate and effective method among the techniques evaluated. Overall, the proposed method is a promising approach for automating the detection and diagnosis of breast cancer, contributing to more effective treatment planning and improved patient care. Further research and development of this approach, along with the integration of other imaging modalities and advanced machine learning algorithms, could lead to improved accuracy and better outcomes for patients with breast cancer.

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