Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.12 n.58, p. 424-433. March/April, 2026.

DOI: https://doi.org/10.5935/jetia.v12i58.3106

RESEARCH ARTICLE OPEN ACCESS

QUALITY ENHANCEMENT TECHNIQUES FOR BREAST CARCINOMA IN EPITHELIAL TISSUE IDENTIFICAATION PROCESS

K. Bharathi*[1], A. S. Arunachalam[2]

[1*]Research scholar, Department of Computer Science & Information Technology, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, India.

[2]Professor, Department of Computer Science & Information Technology, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, India.

[1]https://orcid.org/0009-0007-0285-8368, [2]https://orcid.org/0000-0002-7765-2205

Email: *bvvarsha491@gmail.com, arunachalam1976@gmail.com

ARTICLE INFO

Article History

Received: December 11, 2025

Reviewed: January 1, 2026

Accepted: January 15, 2026

Published: March 31, 2026

Keywords:

Image Enhancement,
Gaussian noise Removal,
Speckle noise Removal,
Wiener Filter,
Median Filter.
Gaussian Filter

ABSTRACT

Breast Cancer is considered to be the deadliest disease among women due to the carcinoma in epithelial tissue development in breast. The cause of the disease many vary due to many circumstances, but identification procedure followed are mostly similar. The clinical way of identifying the cancer effected tissues in breast are followed in advance stages or pre advanced stages, which is due to the lack of adequate knowledge about breast cancer. The treatment given during the final stages are mostly not feasible solution and eventually ends with negative result. Digital Image Processing (DIP) technique coupled with Data Mining and Machine learning algorithms are most recently used breast cancer identification procedure. The identification procedure followed using those techniques are not only accurate, it also gives very fast analyzing report based on the historical record. This research article proposes pre-processing technique, which is a part of the overall research work of breast cancer identification procedure. The Mammography images collected from the source may contains many irrelevant information as well as missing values. The article gives a clear idea of pre-processing techniques followed as well as filtering techniques implemented to enhance the quality of the collected breast cancer Mammography images.

I. INTRODUCTION

The Breast carcinoma images are collected from various sources are to be cleaned before taking the images into the analyzing stage. The initial noise removal techniques are applied for removing the irrelevancy presence in the collected images. The unclear and unwanted objects present in the images re removed unconditionally to prevent the inaccurate prediction results. The pre-processing plays a major role in increasing the probability chance of accuracy as well as for improving the quality of the collected images [1], [2]. The raw breast cancer Mammography images are taken to the preprocessing stage, where initial cleaning process is carried out for improving the final accuracy. The dimensions of the images are normally determined with pixel representations, which is common in all digital images. DIP gives a benefit of easy transformation, processing and storing the image into human understandable record for easy prediction. The DIP gives a clear and enhanced quality images for easy identification and prediction process. In recent years many diagnostics centers and radiologist started to deploy the DIP technology in the medical applications [3]. Some of the advantages of using DIP in medical image processing are listed below

i) Easy Image enhancement / restoration
ii) Medical image visualization
iii) Artistic effects after processing
iv) Industrial inspection for testing purpose
v) Law enforcement for legal rules

Imaging technology plays a major role in medical field to diagnose patents internal organs without clinical cut or operations. This fields also helps major surgent to clearly visualize the inner and deep wounds without opening the body. The DIP helps in finding the carcinoma in epithelial tissue growth very clearly and gives clearcut idea of the severity level of infection or growth. This research article focuses on cleaning the irrelevancy in collected Mammography breast cancer images with the usage of DIP processing techniques, which makes the breast cancer identification accurately. The processed images after the preprocessing stages are taken for applying the filtering methodology for enhancing the quality of the pre-processed images. The segmentation techniques followed after the pro-processing helps the specialist to identify the severity level of the growth in early stage of breast cancer [4]. The image enhancement procedure is followed after the pro-processing technique to enhance the quality of the processed images. The noise present in the images is also removed before the segmentation stage. The noise removing techniques removes all the cancer affected parts from the mammography breast cancer images. Machine learning and deep learning algorithms are used further to analyze the severity of the cancer growth in the breast [5]. The research article is organized as follows. Section 1 gives an introduction to the area of image processing and breast cancer affects. The significance of the research work is also discussed in this section. Section 2 gives complete literature review about the latest research work undergone in the area of breast cancer detection using digital image processing. Section 3 clearly explains the materials and methods for implementing the proposed research work. Section 4 gives a detailed explanation about the obtained results for the breast cancer pre-processing stage with clear future goals. The final part of the research article explains the conclusion part, where the future work is explained.

II. REVIEW OF LITERATURE

The initial clinical observations contained the intricate connection between hormone therapy and breast cancer progression, wherein testosterone-based hormone therapy has been examined using clinical case evaluations and observational assessments (Clinical Case Review and Hormonal Impact Analysis, CCRHIA), as well as found useful information regarding the behavior of cancer in transmen, but the study in [6] was limited by the small number of subjects and inability to statistically validate it. Extensive epidemiological surveys by population-level statistical cancer modeling (Population Cancer Statistics Modeling, PCSM) at [7]) yielded a broad global cancer incidence and mortality pattern, yet lacked predictive and diagnostic diagnostic usefulness of its applications. In [8], tumor size-based survival estimation models (Tumor Size Survival Prediction Model, TSSPM) showed a high level of prognostic evaluation based on tumor sizes, and there was no integration of the molecular or imaging based biomarkers. In [9], longitudinal randomized screening trials that used mammography-based population screening evaluation (Randomized Mammography Screening Evaluation, RMSE) confirmed the efficacy of early screening at 25 years, but had the drawbacks of the possibility of over diagnosis and inability to adapt to contemporary imaging modalities. The move to automated diagnosis started with the earlier computer-aided diagnosis systems based on feature extraction and pattern recognition (Computer-Aided Diagnosis for Early Detection, CAD-ED) in [10] which did a better job of detecting early signs but had issues of high false-positive rates and hand-crafted feature dependency.

In [11], multi-class classification (AIS-MCC) based on the Artificial Immune System was also proposed as a bio-inspired classification method in cancer classification but it had a significant drawback in its computational complexity and scalability. Classification with a decision-tree-based learner with optimized continuous attribute compression using the C4.5 Decision Tree Algorithm (C4.5-DTA) in [12] was more interpretable of the classification but had overfitting and could not handle noisy medical data. Interpretable Fuzzy Rule Extraction (Fuzzy Classification Rule Mining, FCRM) in [13] based on the use of fuzzy logic was found to enhance clinical transparency, but with high rule explosion and lower accuracy on large datasets. Multi-classifier ensemble models with statistical and machine learning classifiers (Multi-Classifier Diagnostic System, MCDS) in [14] were more resilient to data sets although they did not have dynamic feature selection and deep representation learning. Approximately classification rule learning (Rule Induction using Approximate Classification, RIAC) in [15] gave interpretable diagnostic rules, but did not perform well on high dimensional medical features. LS-SVM based support vector classifier improvement of support vectors as used in [16] in diagnosis increased the speed of classifications and accuracy, but was sensitive to choice of kernels and lacked sensitivity to imbalanced clinical data. Reduced Feature Set Optimization (RFSO)-based classification with feature-reduction in [17] showed better computational efficiency, but it had a risk of information loss in terms of diagnostic sensitivity.

Swarm intelligence and neural learning with Wavelet Neural Network optimized by Swarm Intelligence (SI-WNN) in [18] was found to be highly effective in enhancing the accuracy of mammogram-based detection however, with high sensitivity to parameters and costly computation. The initial use of deep learning was with probabilistic generative models based on Deep Belief Networks (DBN) in [19] that were effective at learning hierarchical features, but with long training times and vanishing gradient problems. The superior detection accuracy was achieved in [20] with advanced convolutional modeling based on Deep Convolutional Neural Networks (DCNN-MI) with the use of big labeled datasets and low interpretability. Artificial Intelligence-based Interval Cancer Prevention Systems (AI-ICPS) in [21] optimized the screening process in large scale economies, lowering the number of cancer cases missed in national programs, but still, needed constant real-world validation of the system and other ethical issues like automated decision-making. In [22], genomic-level diagnosis with Deep Learning-based Non-coding RNA Disease Association Prediction (DL-ncRNA-DAP) was found to early detect metaplastic breast cancer but had little biological interpretability and could not find enough data. Lastly, early detection through preprocessing, as proposed by Image Preprocessing Optimization (ML-IPPO) [23], focused on, but did not implement, noise reduction and contrast enhancement to amplify the classification accuracy of advanced deep learning architectures, but it did not have end-to-end optimization.

III. MATERIALS AND METHODS

Some methods are implemented in the chosen picture data set within the image processing application domains for image preprocessing. The overall aim of this process is to develop a means for enhancing lung images that may be utilized for further diagnosis. The chosen digital MRI has proved to be the most effective technique for early detection of lung cancer. The MRI images taken in real-time for this study were provided by Gemini Scans. The images are categorized into MRI pairs, each of which is a patient's left and right lungs. The data set includes photos that belong to two categories: malignant and beige.

An image enhancement technique is a method of processing an image so that the final product is far more appropriate for a given application than the original image. With the aid of the MATLAB software, the stored digital image is improved. Figure 1 shows the suggested strategy.

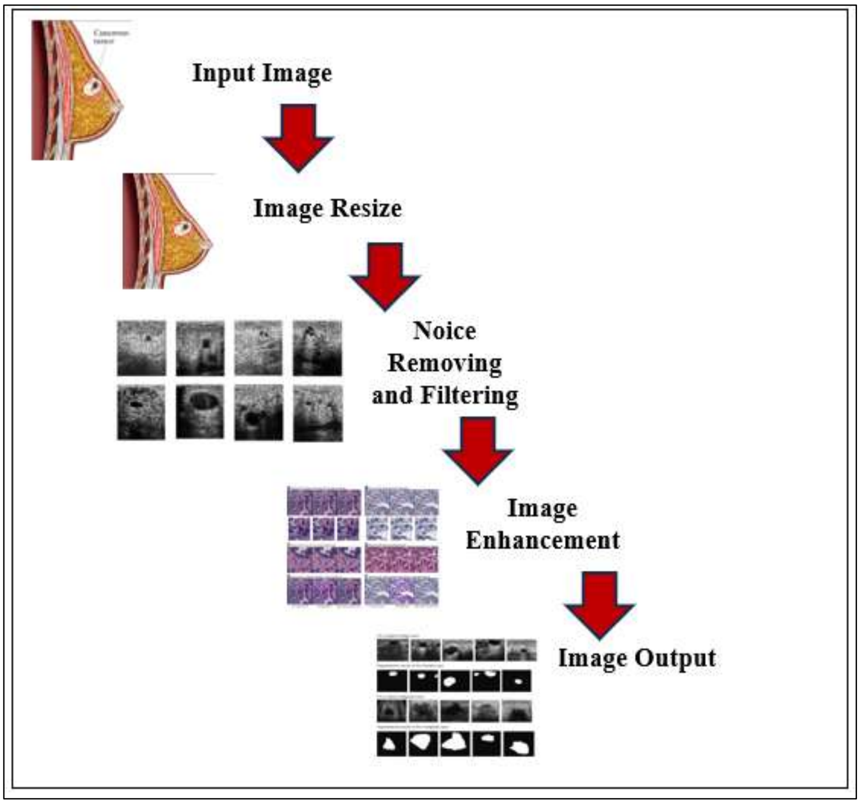


Figure 1: Preprocessing Methodology.
Source: Authors, (2026).

The preprocessing method recommends the following processes: concurrent, noise elimination, filtering, and enhancement of contrast.

1. The real-time MRI image is supplied by the Gemini scan center.
2. The colour image is converted to a greyscale image.
3. Various sizes are enhanced on the photos.
4. Several methods of filtering are utilized to remove noise from the grey image.
5. The Adaptive Histogram Equalization filtering method enhances the contrast of the image.
6. The enhanced output image is the one that was obtained.

III.1 PRE-PROCESSING

Due to various noises present in them, the raw images collected from the scan center and websites are not fit to be processed directly. Therefore, it is pre-processed prior to examination. Labelling, artefact removal, enhancement, and segmentation form a crucial step in MRI. Preprocessing involves image resizing, conversion, reduction of noise, and improvement of quality, which results in an image that enables the precise identification of minute details.

Gray Scale Conversion: Filtering techniques such as power spectra and blur filters are adjusted for eliminating noise. It is obvious that the Wiener filter is divided into two different components: the inverse filtering component and the noise smoothing component. Besides employing inverse filtering (high pass filtering) for de-convolution, it even employs a compression operation (low pass filtering) to remove noise.

Image resizes: For enlarging and shrinking the given image size in pixel form, image scaling is a significant role to play in image processing methods. Image down-sampling and image up-sampling are the two forms of image interpolation needed while resizing the data to the size of the output display or to a specific communication channel. Presenting the final visual information might involve an approximate representation of the original high-resolution, even when it is more efficient to send low-resolution versions to the client. In most applications, ranging from consumer products to critical positions in the security, defence, and medical sectors, a correct scaling of image information is a required initial step. In this section, the nearest neighbour algorithmic method was employed as part of the image scaling method. The nearest neighbour method's use accelerates the image processing process towards the end. The method which may be used to assess the speed of resizing is marred by the fact that the final image often has block artefacts, which are hardly perceptible to the human eye but also cause significant deterioration in error calculations applied to compare approaches. Bi-linear and bi-cubic interpolation are two other commonly used methods.

Noise Removal: Random variation of color data or intensity in images formed by scanners or medical devices is referred to as image noise. By and large, image noise is regarded as an unwanted secondary product of image formation. A measure of the doubt or lack of sureness about a signal resulting from random changes in the signal is loosely referred to as noise. The variability has diverse etiology.

Visual noise is to be found in all medical imaging. A noisy image looks mottled, grainy, textured, or snowy. There are several types of noise, and the most common one in medical imaging is detailed below.

Salt and pepper: As part of image noise removal methods, salt and pepper image conversion is widely used. It occurs in the form of black and white pixels which appear randomly. When there are short transients, such as improper switching, salt and pepper noise seeps into images. It is sometimes called "spike noise" or "impulsive noise."

Gaussian: The Gaussian distribution, also known as statistical noise, is statistical noise with a normal distribution probability density function (PDF). Each pixel in the image will be changed from its original value by a (usually) small amount when there is Gaussian noise.

Shot or Poisson: The most common noise in the brighter regions of an image is referred to as short noise, or Poisson noise. Photon shot noise is another name for the statistical quantum fluctuations that an image sensor normally generates, which vary the number of photons detected at a given exposure.

Speckle: The image quality of active radar and synthetic aperture radar is degraded by speckle noise, a grainy disturbance present in both [16]. Ultrasonic medical devices are generally the source of this type of noise.

III.2 FILTERING METHODS

To enhance an image, filters are used primarily to either repress the high frequencies of the image, which smooths the image, or its low frequencies, which enhances or detects the edges of the image. An image can be filtered, for example, to emphasize specific characteristics or remove others. There are numerous ways to do this, and the most effective may depend on the image and the purpose for which it is being used. There are several applications for image filtering, including edge detection, noise filtering, sharpening, and smoothing.

Wiener: Inverse filtering and noise smoothing are best traded off by wiener filtering. It reverses the blurring and removes the extra noise simultaneously. When the mean square error is considered, the Wiener filtering is the best. In other words, it minimizes the overall mean square error in the process of noise smoothing and inverse filtering. The Wiener filter linearly estimates the original image. A stochastic model forms the basis for the technique. The Wiener filter in the Fourier domain can be written as below, based on the orthogonality principle:

$$f(x,y) = \frac{H*(f_1,f_2)S_{xx}(f_1,f_2)}{H(f_1,f_2)2S_{xx}(f_1,f_2)+S_{nn}(f_1,f_2)}$$

Median: It impacts a rectangular area through the use of the median filter. When filtering images, it adjusts photo sizes by certain conditions stated below. The median position within the 3-by-3 neighbourhood about each pixel from the input pictures is held by every output pixel. zeros play the image edges' place instead. The value of the current pixel at (x,y), the point on which S is currently centered, is substituted with a single value that is the output of the filter. The notation employed is as follows.

$Z_{min} = \text{ Minimum pixel value in } \mathrm{S_{xy}}$
$Z_{max} = \text{ Maximum pixel value in } \mathrm{S_{xy}}$
$Z_{med} = \text{ Median pixel value in } \mathrm{S_{xy}}$
$Z_{xy} = P\text{ixel value at co} - \text{ordinates } (\mathrm{x,y})$
$S_{max} = \text{Maximum allowed size of } \mathrm{S_{xy}}$

Edges are not blurred and images are preserved when non-repellent noise is removed from two-dimensional signals by smoothing it out with median filtering. This renders it extremely suitable for enhancing MRI images. To determine which pixels in an image have been affected by impulsive noise, the median filter applies spatial processing. By contrasting each pixel within the image to its surrounding pixels, the median filter identifies which pixels are noise. Both the neighborhood size and comparison threshold are alterable. Impulse pixels are those that are dissimilar to most of their neighbors and are not physically coincident with those comparable to them. The median pixel value of the nearby pixels that passed the noise labelling test is then used to replace these noise pixels.

Gaussian: The most important element of both theory and applications is the Gaussian filter. One common image filtering approach is Gaussian filtering, which is a WAP with weight defined as

$$W_{ij}\alpha \exp\left(\| x_i - x_j \|\right), i \neq j$$

$W_{ij} = 0$, in which L_2 controls the range of the steep decline. In fact, Gaussian smoothing is a local filtering method. Gaussian filter is a prominent image denoising technique which oversmoothed images at the expense of most detail loss, especially the sharpness of edges. Gaussian smoothing, or low-pass filtering, retains the low-frequency aspects of the image, which do not significantly change, but eliminates high-frequency features, including noise and edges. In other words, everything that is smaller than the feature of the image gets blurred by the filter.

Contrast Enhancement: The contrast is the difference between the maximum and minimum pixel intensities. The formula for expanding the image histogram to increase contrast is

$$g\ (x,y) = \frac{f(x,y) - fmin}{fmax - fmin} * 2^{bpp}$$

The equation requires greyscale levels multiplied by the lowest and highest pixel intensity. As our example picture is 8 bpp, the grey levels would be 256. The minimum value is 0 and the maximum value is 225. So the 0 is the minimum and 225 is the maximum. In this case, the formula is

$$g\,(x, y) = \frac{f(x, y) - 0}{225 - 0} * 255$$

f(x,y), where f is the intensity value of every pixel. In a picture, we will calculate this formula for every f(x,y). The capability of the image is enhanced as the equations are used. The main objectives of the contrast enhancement system are two-fold: equalisation and removal of unwanted objects, such as noise and blocking objects, with a locally adaptive histogram [22]. Specifically, block-based processing involves local adaptation, overlapping adjacent blocks minimises blocking artefact, and spatiotemporally adaptive filtering eliminates noise. Without considering the image boundary, the block-overlapped histogram equalisation algorithm's details are summarised as follows. Figure 3 explains the correspondence between the full image and the (m,n) block. The corresponding B x B block is subjected to histogram equalisation, and the centre pixel intensity of the block is adjusted according to the equalisation. We just add the last column of the new block and remove the first column of the old block to compute the histogram of the next block, or (m, n+1) block.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

Image resizing: Alter the image size (in pixels). In both the horizontal and vertical directions, picture down sampling, or resampling at a lower rate, reduces a 512x512 image to 256x256, which is a factor of 2. An enlarged image is produced from a smaller one by image upsampling, or resampling at a higher rate (512x512 -> 1024x1024).

Shrink the image size and turn everything into 1D. A two-dimensional image can be reduced in two steps: first along the x direction and then along the y direction. Pixels are reduced by a factor of a < 1; fat pixels are size 1/a; the (rescaled) target image size is aw (1/a) = w = the original size (though pixel size differs) A "tiny pixel" has size 1/a, and a rescaled target image has size aw (1/a) = w = original size. Image stretching is achieved by the factor of a > 1. Figure 2(a1,2,3,4) has the original Mammography breast cancer images for the preprocessing that was carried out for this research work. Preprocessing techniques are employed, such as image scaling, noise reduction, filtering, and contrast enhancement. Figures 2(b1) to 2(b4) shows the representation of the images resized into 128x128 size. Figure 2(c1) to 2(c4) represented in the table shows the images resized into 256 x 256. Finally, the resizing of 512 x 512 size is represented in figure 2(d1) to 2(d4).

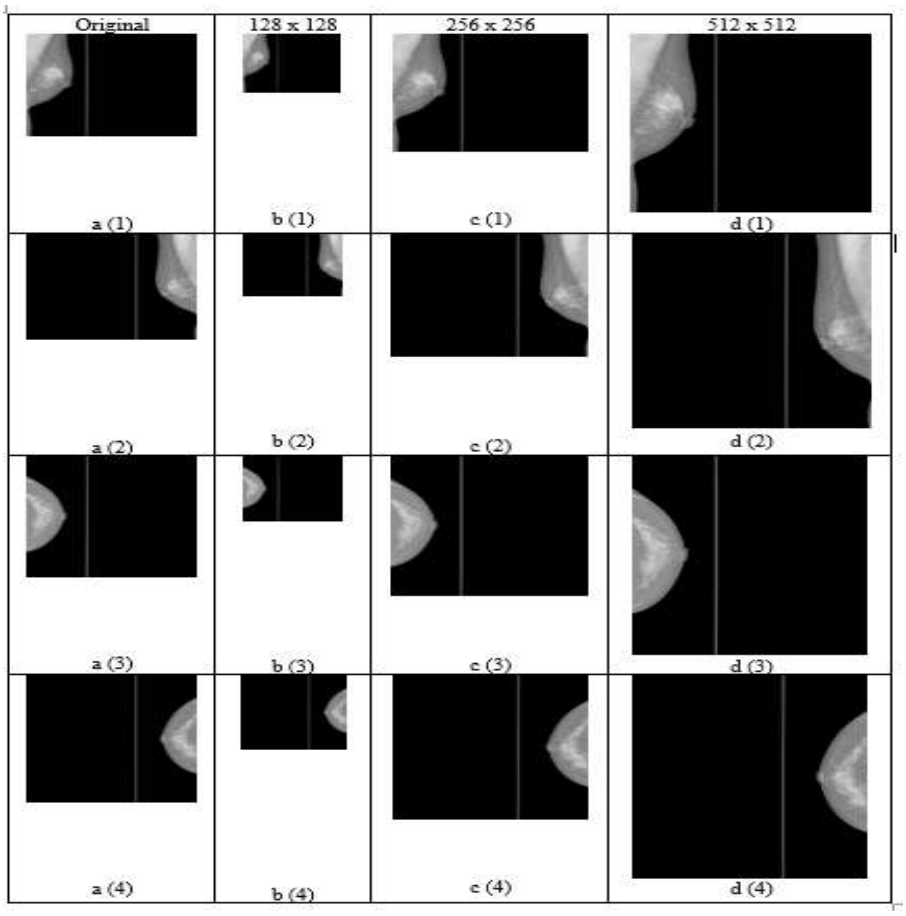


Figure 2: Results of Image Sizes.
Source: Authors, (2026).

The images present in the figure 2 are taken from two different patents, which is shown from the different dimensions. The pixel range of the original images are huge in numbers, which can make the proposed model to take more running time. The preprocessing technique followed in this research article can give a proper solution in reducing the size of the image without changing the clarity of the images.

Table 1: Image Pixel Count.

Image Size	Image Name	Space Occupied (KB)	No. of Pixels
227X222	a (1)	118.24	118,336
	a (2)	107.49	125,296
	a (3)	76.11	76,176
	a (4)	68.78	68,644
128x128	b (1)	2.55	324
	b (2)	2.33	289
	b (3)	1.93	256
	b (4)	1.75	121
256x256	c (1)	8.16	1024
	c (2)	7.50	961
	c (3)	5.85	729
	c (4)	4.46	576
512x512	d (1)	21.82	2809
	d (2)	19.99	2601
	d (3)	15.63	2025
	d (4)	11.56	1444

Source: Authors, (2026).

Table 1 presents the number of pixels at every step of the preprocessed image results. This table demonstrate the various dimensional images of the breast cancer affected patient with differences in pixel rates. The table also shows the variation from the original images as well as the resized images. Also, table 1 indicates how much memory space was utilized in storing the photos of varying sizes.

Figure 3: Pixel Rate of original image.
Source: Authors, (2026).

Figure 3 gives a detailed view of the utilized memory space of the original images and pixel generated with the images. The simulations carried out to examine the pixel size as well as the memory utilized.

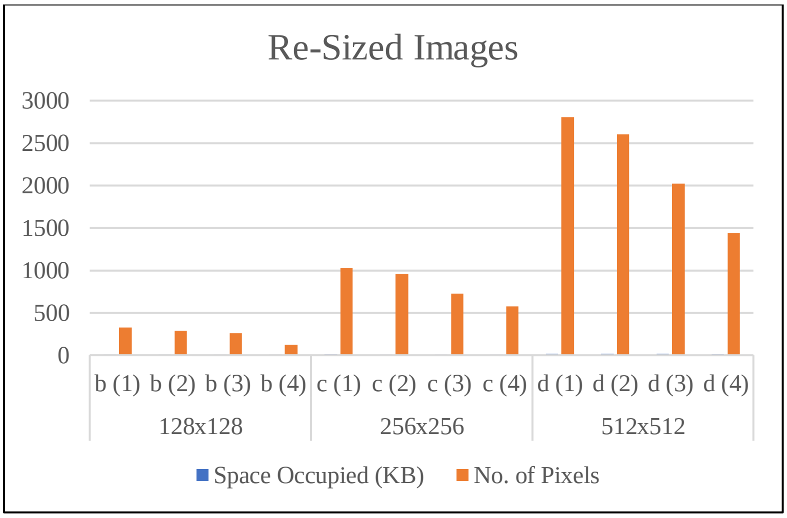


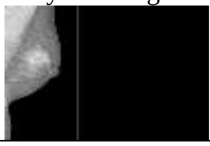
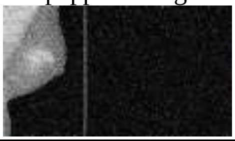
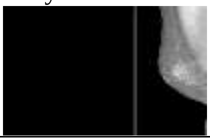
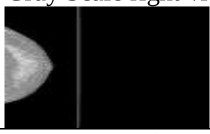
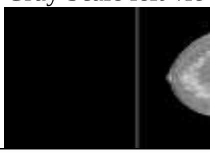
Figure 4: Pixel Rate of re-sized images.
Source: Authors, (2026).

Figure 4 gives a detailed view of the utilized memory space of the various stages breast cancer affected patient and pixel generated with the images. The similar initial inspection and simulations are carried out to examine the pixel size as well as the memory utilized. The figure gives a detailed view of better utilization.

IV.1 RESULT FOR SALT AND PEPPER NOISE REMOVAL

Dark pixels will be in light regions and light pixels in dark regions of an image contaminated with salt and pepper noise. This is because of dead pixels, transmission bit errors, and analogue to digital conversion problems. Dark frame elimination and interpolation at dark bright pixels can be applied to eliminate it.

Table 2: Salt And Pepper Noise Removal.

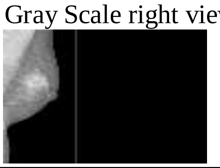
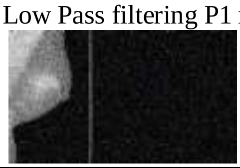
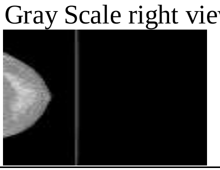
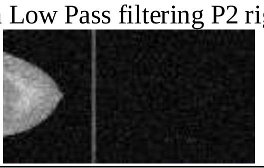
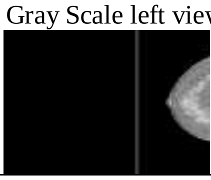
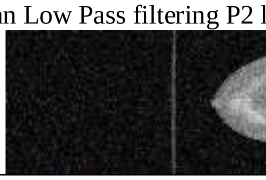
P1 Gray Scale right view 	Salt and pepper P1 right view 
P1 Gray Scale left view 	Salt and pepper P1 left view 
P2 Gray Scale right view 	Salt and pepper P2 right view 
P2 Gray Scale left view 	Salt and pepper P2 left view 

Source: Authors, (2026).

IV.2 RESULT OF GAUSSIAN LOW PASS FILTER

Every pixel in the image will be altered from its initial value by a (typically) little amount throughout the Gaussian noise removal process. As seen below, low pass filtering uses a compression technique to eliminate noise. This research explores the application of the Gaussian Low Pass Filter at the preprocessing step of image processing in breast cancer diagnosis. For suspicious region detection, discriminative feature extraction, and classification of the filtered images using the correct machine learning or deep learning algorithms, they are further processed. The final aim is to utilize automated image analysis to enhance diagnostic accuracy and help doctors in early breast cancer detection.

Table 3: Gaussian Low Pass Filter.

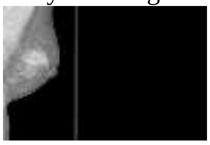
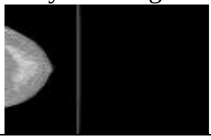
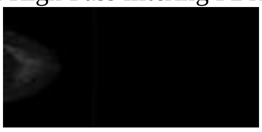
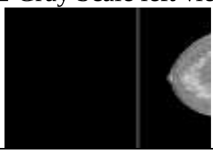
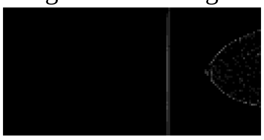
P1 Gray Scale right view 	Gaussian Low Pass filtering P1 right view 
P1 Gray Scale left view 	Gaussian Low Pass filtering P1 left view 
P2 Gray Scale right view 	Gaussian Low Pass filtering P2 right view 
P2 Gray Scale left view 	Gaussian Low Pass filtering P2 left view 

Source: Authors, (2026).

IV.3 RESULT OF GAUSSIAN HIGH PASS FILTER

Statistical noise with a normal distribution probability density function (pdf) also known as the Gaussian distribution is called Gaussian noise. Each pixel in the image will be changed from its original value by a (usually) small amount when there is Gaussian noise. As can be seen below, Gaussian High Pass employs inverse filtering to perform the de-convolution.

Table 4: Gaussian High Pass Filter.

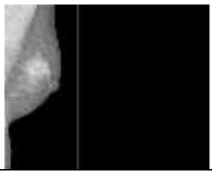
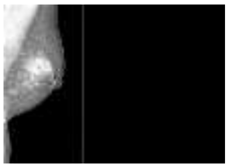
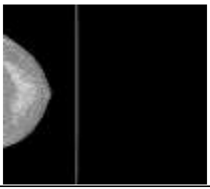
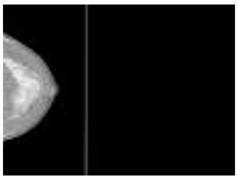
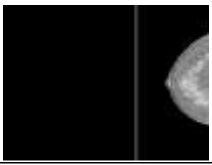
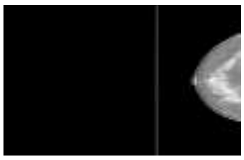
P1 Gray Scale right view 	Gaussian High Pass filtering P1 right view 
P1 Gray Scale left view 	Gaussian High Pass filtering P1 left view 
P2 Gray Scale right view 	Gaussian High Pass filtering P2 right view 
P2 Gray Scale left view 	Gaussian High Pass filtering P2 left view 

Source: Authors, (2026).

IV.4 RESULT OF HISTOGRAM EQUALIZATION

The contrast of a greyscale image can be adjusted through histogram equalisation. Most of the pixel values of the original image occur within the middle of the intensity range, which means the image has low contrast. The pixel values in the resulting image are spread evenly throughout the range. Histogram equalisation is a straightforward image-processing technique employed in medical imaging to generate better-quality black-and-white images. (Digital X-rays, CT scans, and MRIs)

Table 5: The performance of Histogram Equalization.

P1 right view Before Contrast Enhancement 	P1 right view After Contrast Enhancement 
P1 left view Before Contrast Enhancement 	P1 left view After Contrast Enhancement 
P2 right view Before Contrast Enhancement 	P2 right view After Contrast Enhancement 
P2 left view Before Contrast Enhancement 	P2 left view After Contrast Enhancement 

Source: Authors, (2026).

The Filtering Techniques Wiener Filter, Median Filter and Gaussian Low and High Pass Filter are deployed with various methods. The Result obtained can be clearly observed from Table VI. The observed results are very clear in explaining the size variation of image and techniques deployed can alter the image clarity.

Table 6: Filtering Techniques and Result Observed.

Method	Filtering Technique	Results Observed
128 X 128	Wiener Filter	Small size and Dark
	Median Filter	Small size and Bright
	Gaussian Low and High Pass Filter	Small size and Clear
256 X 256	Wiener Filter	Medium size and Dark
	Median Filter	Medium size and Bright
	Gaussian Low and High Pass Filter	Medium size and Clear
512 X 512	Wiener Filter	Large size and Dark
	Median Filter	Large size and Bright
	Gaussian Low and High Pass Filter	Large size and Clear

Source: Authors, (2026).

The implementation of filtering process enhancement techniques, overlapping histogram equalisation is adapted and used with histogram equalization as in Table VI.

V. CONCLUSION

The particular part of the research work focuses on the cleaning stage of the breast cancer Mammography images. The technique deployed in this part of the research work removes the irrelevancy in images as well as helps in improving the quality of the Mammography images. Various filtering techniques are implemented for enhancing the quality of the pre-processed mammography images. The sample breast cancer of two different patents is shown in the experimental results. The results are studied, compared against a normal pattern of noise, and evaluated as per quality. The aim of this research work is to focus on choosing appropriate filtering techniques and removing noise keeping in mind the phases of breast cancer images. Apart from reducing time, the preprocessing method considers the three varieties of filter types and searches for the best pixel outcome using the median filter. Furthermost, the preprocessed and enhanced images are taken for the next analyzing stage with proposed algorithm to identify the breast cancer affected parts from the Mammography images.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: K. Bharathi, A. S. Arunachalam.
Methodology: K. Bharathi, A. S. Arunachalam.
Investigation: K. Bharathi, A. S. Arunachalam.
Discussion of results: K. Bharathi, A. S. Arunachalam.
Writing – Original Draft: K. Bharathi, A. S. Arunachalam.
Writing – Review and Editing: K. Bharathi, A. S. Arunachalam.
Resources: K. Bharathi, A. S. Arunachalam.
Supervision: K. Bharathi, A. S. Arunachalam.
Approval of the final text: K. Bharathi, A. S. Arunachalam.

VII. REFERENCES

[1] Sheikh, Hamid R., and Alan C. Bovik. "Image information and visual quality".IEEE Transactions on image processing vol.15(2), pp: 430-444, 2006

[2] S. Charan, M. J. Khan, and K. Khurshid, "Breast cancer detection in mammograms using convolutional neural network," in 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET). IEEE, 2018, pp. 1–5.

[3] H. Cai, Q. Huang, W. Rong, Y. Song, J. Li, J. Wang, J. Chen, and L. Li, "Breast microcalcification diagnosis using deep convolutional neural network from digital mammograms," Computational and Mathematical Methods in Medicine, vol. 2019, pp. 1–10, 03 2019.

[4] L. Tsochatzidis, L. Costaridou, and I. Pratikakis, "Deep learning for breast cancer diagnosis from mammograms—a comparative study," Journal of Imaging, vol. 5, no. 3, p. 37, 2019.

[5] Y.-D. Zhang, S. C. Satapathy, D. S. Guttery, J. M. Górriz, and S.-H. Wang, "Improved breast cancer classification through combining graph convolutional network and convolutional neural network," Information Processing Management, vol. 58, no. 2, p. 102439, 2021. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306457320309328

[6] S. Tanini, A. D. Fisher, I. Meattini, S. Bianchi and J. Ristori, "Testosterone and breast cancer in transmen: Case reports, review of the literature, and clinical observation," Clinical Breast Cancer,vol.19,no.2,pp.e271–e275, 2018.

[7] R. L. Siegel, K. D. Miller and A. Jemal, "Cancer statistics," CA Cancer Journal for Clinicians, vol. 68, no. 1, pp. 7–30, 2018.

[8] S. A. Narod, "Tumour size predicts long-term survival among women with lymph node-positive breast cancer," Current Oncology, vol. 19, no. 5, pp. 249–253, 2012.

[9] A. B. Miller, C. Wall, C. J. Baines, P. Sun et al., “Twenty-five year follow-up for breast cancer incidence and mortality of the Canadian National Breast Screening Study: Randomised screening trial,” British Medical Journal, vol. 348, pp. 366, 2014.

[10] R. M. Rangayyan, F. J. Ayres and J. E. L. Desautels, “A review of computer-aided diagnosis of breast cancer: Toward the detection of early signs,” Journal of the Franklin Institute, vol. 344, no. 3/4, pp. 312–348, 2007.

[11] D. E. Goodman, L. C. Boggess and A. B. Watkins, “Artificial immune system classification of multiple-class problems,” Proceedings of the Artificial Neural Network in Engineering Systems, vol. 12, pp. 179–186, 2004.

[12] J. R. Quinlan, “Improved use of continuous attributes in C4. 5,” Journal of Artificial Intelligence Research, vol. 4, pp. 77–90, 1996.

[13] D. Nauck and R. Kruse, “Obtaining interpretable fuzzy classification rules from medical data,” Artificia Intelligence in Medicine, vol. 16, no. 2, pp. 149–169, 1999.

[14] G. I. Salama, M. B. Abdelhalim and M. A. Zeid, “Breast cancer diagnosis on three different datasets using multi classifiers,” International Journal of Computer and Information Technology, vol. 1, pp. 36–43, 2012.

[15] H.J. Hamilton, N. Shan and N. Cercone, “RIAC: Arule induction algorithm based on approximate classification,” Technical Report, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.7.7768&rep=rep1&type=pdf, 1996.

[16] K. Polat and S. Günes, “Breast cancer diagnosis using least square support vector machine,” Digital Signal Processing, vol. 17, no. 4, pp. 694–701, 2007.

[17] A. Mert, N. Z. Kılıç, E. Bilgili and A. Akan, “Breast cancer detection with a reduced feature set,” Computational and Mathematical Methods in Medicine, pp. 1–11, Article ID 265138, 2015.

[18] J. Dheeba, N. A. Singh and S. T. Selvi, “Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach,” Journal of Biomedical Informatics, vol. 49, no. 2, pp. 45–52, 2014.

[19] A. M. Abdel-Zaher and A. M. Eldeib, “Breast cancer classification using deep belief networks,” Expert Systems with Applications, vol. 46, pp. 139–144, 2016.

[20] Marouene Chaieb, Malek Azzouz, Mokhles Ben Refifa, and Mouadh Fraj. 2025. Deep learning-driven prediction in healthcare systems: Applying advanced CNNs for enhanced breast cancer detection. Comput. Biol. Med. 189, C (May 2025).

[21] Byng, D. et al. AI-based prevention of interval cancers in a national mammography screening program. Eur. J. Radiol. 152, 110321 (2022).

[22] Ahmad, S., Zafar, I., Shafiq, S. et al. Deep learning-based computational approach for predicting ncRNAs-disease associations in metaplastic breast cancer diagnosis. BMC Cancer 25, 830 (2025)

[23] Bharathidasan.G, A.S. Arunachalam, Pre Processing for Early Detection of Breast Cancer using Machine Learning, NeuroQuantology, Vol. 20(10), pp. 8423- 8435, 2022.