Journal of Ubiquitous Computing and Communication Technologies (ISSN: 2582-337X)
www.irojournals.com/jucct/

A Comprehensive Analysis of Preprocessing Techniques for Thermal Breast Image Processing

Parameswari C.[1], Rajalakshmi G.[2], Rathnamala S.[3], Sivakumar G.[4], Hemajeyasri P.[5], Sivasabitha K.[6]

Sethu Institute of Technology, Virudhunagar, India.

E-mail: [1]parameswari.virudu@gmail.com, [2]gurusamyrajalakshmi89@gmail.com, [3]rathnamala@sethu.ac.in, [4]sivait23@gmail.com, [5]hemajeyasri12122003@gmail.com, [6]sivasabithak15@gmail.com

Abstract

Comprehensive and effective breast cancer screening programs are essential diagnostic instruments for early detection, which are then followed by rigorous intervention initiatives. A promising method for conducting non-invasive testing is the combination of remote sensing and thermal imaging technologies. Convolutional neural networks (CNNs) are capable of effectively identifying aberrant histological characteristics shared by most breast cancers; however, their application in breast cancer diagnosis is surprisingly limited. An overview of preprocessing techniques for thermal breast image processing is given in this paper. Several preprocessing techniques, including median filtering, wavelet transform, Wiener filtering, and histogram equalization, have been independently investigated in earlier research. There are very few all-inclusive techniques that methodically combine several conventional and statistical techniques to combine contrast enhancement and noise reduction in mammography images in the best possible way. Furthermore, there hasn't been much research done on using CNNs as preprocessing filters as opposed to classifiers. By developing a multi-step preprocessing pipeline that combines conventional filtering methods (Median, Wiener), DWT-based transformation techniques, and enhancement techniques (histogram equalization and dynamic edge sharpening), this study closes this knowledge gap. This study

DOI: https://doi.org/10.36548/jucct.2024.2.002
Received: 21.04.2025, received in revised form: 23.05.2025, accepted: 11.06.2025, published: 24.06.2025

uses a detailed signal-to-noise ratio (SNR) analysis across frequency orientations to evaluate their combined impact on image quality.

Keywords: Breast Cancer, Thermography, CNN, Preprocessing, Noise Reduction, Contrast Enhancement.

1. Introduction

In medical imaging, precise image interpretation is essential for both diagnosis and treatment planning. Mammography, the primary method of screening for breast cancer, requires excellent image quality and clarity for the early detection of abnormalities, despite the fact that images often display multiple abnormalities that impair their clarity. These procedures allow radiologists to conduct their research through the expected results of noise reduction, improved contrast effects, and critical information detection. Over time, scientific research has produced a variety of preprocessing techniques that increase the diagnostic precision and utility of mammography images. This study provides a critical evaluation of basic preprocessing methods for improving mammograms.

This paper compares and contrasts the use of different image processing techniques in mammography image preprocessing. These techniques include adaptive histogram equalization, wavelet transformation, histogram equalization, upper cap and lower cap transformation, Gaussian filtering, mean filtering, Wiener filtering, and signal-to-noise ratio (SNR) analysis. Research on their relative effectiveness in mammography is lacking, despite the fact that each has distinct advantages and disadvantages when it comes to enhancing image quality. A methodical preprocessing pipeline that combines traditional and data-driven techniques must be created to aid in medical image analysis and diagnosis. Metrics like SNR must be used to quantitatively assess its performance. This study's main objective is to methodically evaluate and compare these preprocessing methods in order to make judgments regarding their effects on mammography imaging's overall image clarity, contrast enhancement, and noise reduction.

Comparing the effectiveness of different preprocessing combinations using empirical results and SNR values is a secondary goal in order to determine which ones are most effective in enhancing mammography diagnostic accuracy. The current study will assist radiologists and image processing specialists in identifying efficient preprocessing pipelines for better visualization of breast tissue abnormalities. Pre-incident breast cancer detection and more accurate diagnosis are made possible by the use of appropriate preprocessing techniques, which will ultimately improve patient survival.

1.1 Thermography

Heat breast imaging offers a practical substitute for mammograms, which are uncomfortable and expose people to radiation, in order to detect breast cancer. Using infrared cameras, this method detects heat from the body's surface, particularly the breast. By examining thermal patterns, this technique can even identify anomalous temperatures in precancerous conditions that would indicate the presence of tumors or other questionable conditions. Because thermal imaging enables repeated measurement, it also facilitates better patient monitoring. Additionally, it provides helpful information about the breast's vascular dynamics, which helps doctors identify possible underlying causes. When all else is equal, breast thermal imaging is a significant advancement in breast cancer diagnosis since it can identify the disease at the most likely optimal time for treatment.

2. Related Work

Early breast cancer detection requires strong screening processes for intervention to be successful. Thermal imaging remote sensing technology offers a wonderful method of conducting non-invasive tests [1]. Detection of pathological histological characteristics of most breast cancers could be done effectively with the help of CNNs, but their application in breast cancer diagnosis is surprisingly limited [2]. This article provides a bird's-eye view of the evolution of breast cancer detection with emphasis on thermal imaging and CNN application, thermal imaging features, data availability, radar types of features, and CNN program for auto-typing [3]. In addition, destiny research suggestions are provided where example datasets are needed, e.g., thermal-image segmentation strategy optimization, convolutional kernel optimization, and small fashion generation [4]. Finally, the incorporation of thermal imaging with CNNs holds significant promise to improve early detection of breast cancer, increase impaired outcomes, and reduce mortality rates. CNNs offer better results in terms of accuracy if coupled with other networks [7].

The detection process of breast cancer receives improved quality with this approach, making it possible for medical imaging technology to detect and treat breast cancer more effectively. HE (Histogram Equalization) and Median filters provide improved performance values compared to Mean and Wiener filters [10]. These filters provide steady peak values of Signal-to-Noise ratio along with extremely low error signals. This couple indicates the best following of actual model construction process [12]. Low mean square error (MSE) values are obtained after image enhancement with this technique as it retains precise image data and removes distortion [16]. HE and Median filters exhibit minimal image content variation and noise sensitivity as they possess efficient control over numerous regional image features [17]. These medical imaging techniques handle very well when it comes to edge preservation and have high robustness in PSNR values and MSE results and sensitivity towards noise and prominent features in breast cancer screening tasks [18]. These dual competencies make these techniques most preferable solutions. Medical imaging applications prefer enhanced image quality solutions because of these marks on the sides of the breast [19]. The position of these marks depends on the size of breasts. Uniform processing is done on the entire image in Gaussian filtering, while heterogeneous filtering uses region selection in some of the regions of thermographic images [20]. A vessel structure reconstruction method was proposed by the authors as a preprocessing technique. Three CNN models, namely CNN-SL, CNN-HD, and CNN-SF, were constructed by incorporating conceptual modules in the baseline CNN architecture to test and evaluate conceptual module performance in breast cancer detection with thermal images [22]. The models utilized sigmoid functions to provide probability distributions, which were utilized for classifying inputs as cancer or normal classes at the implementation's final stage [23].

We had trained and tested on the popular DMR-IR dataset with its static and dynamic protocols [25], [27]. The static protocol has 177 normal patient images and 42 cancer patient images, and the dynamic protocol includes 1,900 images of 95 normal patients, as well as 840 images of 42 patients having adverse conditions [26]. To overcome bias and improve generalization due to the asymmetrical distribution of data, we implemented data augmentation practices [29]. Methods that changed illumination and rotation were employed in the research as part of methodology [28]. Data augmentation is significant in deep learning classification tasks since it augments the size of the dataset, enhances feature discovery, and improves classification accuracy [30]. Using these approaches, our AM CNN models achieved improved results, accompanied by a detailed examination of their utility in the detection of breast cancer from thermal images [31].

Table 1. Comparison of Various Methodologies

Reference	Database	Feature Extraction	Classifier	Accuracy
[5]	DMRIR	Histogram Equalization	CNN	88%
[6]	DMRIR	Wavelet Denoising, Adaptive wavelet denoising	CNN	90%
[8]	MIAS	Gabor filter	KNN, SVM	85% for Maligant, 100% for Normal
[9]	Image capture by FLIR	Adaptive Histogram Equalization	NN	100%
[11]	DMRIR	Rotation, RGB to Gray image	CNN-HD CNN-SF	CNN-HD: 99.49% CNN-SF: 99.34%
[13]	MEDLINE	RGB to Gray image, Histogram Equalization	SVM	92%
[14]	mini-MIAS	Histogram Equalization, Median filter	CAD	97%
[15]	DMRIR	Histogram Equalization, Median filter	CNN	92.47%
[21]	DMRIR	Gaussian filter, Histogram Equalization	CNN	90.48%
[24]	DMRIR	Gaussian filter	CNN	84%

Table 1 presents the accuracy of various methodologies on different datasets, where DMRIR and FLIR datasets offer thermographic images, and MIAS, mini-MIAS, and MEDLINE offer mammographic images for processing.

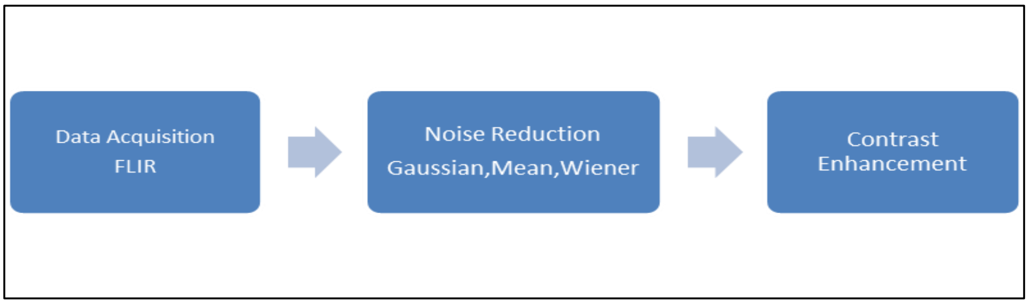


Figure 1. Preprocessing Methodologies

3. Methodology

3.1 Data Acquisition

The DMR Visual Lab's FLIR SC-620 camera was used to collect the data. With a resolution of 640 by 480 pixels and a pixel spacing of 45 micrometers, the FLIR SC-620 camera operates. Breast nodules were captured by the camera system and then classified as normal, benign, or malignant by the visual system. Even though changes in breast tissue could be seen as fat, adipose tissue, or fibrosis, the diagnosis used imaging algorithms in conjunction with archived image analysis at a resolution of 1024 x 1024 pixels. Table 2 shows the distribution of images.

Table 2. Dataset

Total images	**Healthy**	**Unknown**	**Sick**
324	186	5	133

3.2 Image Preprocessing

Three primary preprocessing steps are needed for digital image enhancement for imaging applications: noise reduction, contrast enhancement, and RGB to grayscale conversion. Grayscale conversion of the RGB color space improves post-operation efficiency and data focus by streamlining image processing and data storage. Since random pixel intensity shifts from noise impair image quality by hiding important information, the noise reduction technique uses grayscale transformation to minimize distortions and imperfections in the image. During background noise reduction processes, common techniques for noise reduction that maintain important image features include mean filtering and Gaussian smoothing. Contrast enhancement, the last preprocessing step after noise reduction, tries to make image features more visible and clear. Techniques for contrast enhancement alter an image's pixel intensity distribution and improve the contrast between regions and overall image quality. RGB to grayscale conversion, noise reduction, contrast enhancement, and other preprocessing steps can be applied methodically to digital images to optimize them for further analysis. This will provide a more meaningful and accurate interpretation of visual information in a range of applications, from computer vision to medical imaging and beyond.

3.3 Noise Reduction

The success of digital image quality enhancement for experiments largely relies on noise reduction algorithms. The present work explored simple noise reduction methods that comprised Gaussian filtering, mean filtering, Wiener filtering, wavelet collapse, and more. The evaluation process involved comparison of noise suppression effectiveness among techniques, image storage information and computation needs, taking into account limitations in techniques to enable researchers and practitioners to choose appropriate approaches to noise reduction for their own imaging problems. Beyond this, we provide practical insights and potential areas of future research to further the work in digital imaging and in developing solid noise reduction techniques. Mean filtering can filter out perceptual noise and improve ripples removal effectively during reduction, preserving edges. Wiener filtering gives a reasonable balance between signal retention and noise reduction. Gaussian blur is smoother and faster in removing noise but potentially causes loss of detail in the image. The use of median filtering, in combination with wavelet filtering and Wiener filtering, improves system performance to reduce noise.

3.4 Median Filter

A nonlinear digital filtering method called a median filter is frequently used to eliminate noise from a signal or image. A fixed-size window is moved over the data, the values inside the window are sorted, and the median value of the sorted list is substituted for the central value.

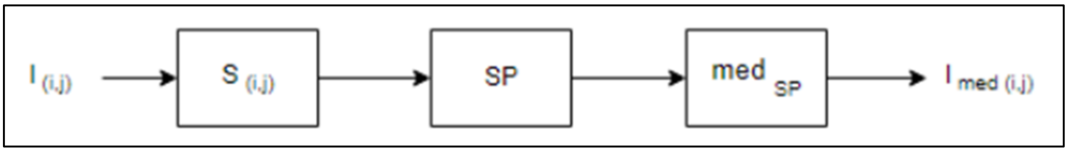


Figure 2. Median Filter

This procedure eliminates noise while maintaining edges. The input image initially goes through the selective window procedure in Fig. 2. Because the image has a large window size in this process, it must move across the image's window size. It makes use of Equation 1 for that.

$$S_{ij} = I[\,i{:}i+2,\ j{:}j+2] \quad (1)$$

Where,

$S_{(i,j)}$ is a Selective window image with i,j

i and j are the coordinates of the window

$I_{(i,j)}$is the Input image with the window size

Then the selective window size is sorted in an ascending order with equation 2.

$$S_p = [\ S_1 <= S_2 <= S_3 <= \ldots\ldots <= S_n] \quad (2)$$

Where,

S_p is a sorted selective window size.

$S_1, S_2, S_3 \ldots S_n$ is each pixel in the window

After sorting median of the selective window is calculated with the equation 3

$$med = med_{sp}\ S\ [n+1/2] \quad , odd$$
$$(S\ [n/2]+S[n+1/2])\ /\ 2, even \quad \} \quad (3)$$

Where,

Med_{sp} is Median of sorted array of selective window size

n is No. of window element in the selective window size

$I_{med(i,j)}$ is output image with replaced median

Due to its efficiency in preserving edges and eliminating impulsive noise, a straightforward median filter was used in this investigation. Although fuzzy median and adaptive filters might offer even better noise reduction in some situations, they were left out of the current study to create a consistent baseline against which more conventional methods could be evaluated.

3.5 Wavelet Denoising

Wavelet denoising, also called as wavelet thresholding, is a technique for eliminating noise from a signal or image while keeping important elements like edges. The noisy signal is transformed into the wavelet domain, the wavelet coefficients are subjected to a threshold to remove noise, and the signal is then reconstructed using the altered wavelet coefficients.

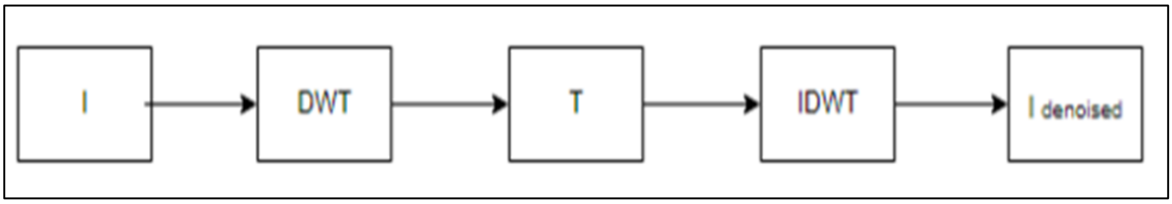


Figure 3. Process of Wavelet Denoising

Wavelet denoising is demonstrated in Fig. 3. Equation 4 is used to process the image through the discrete wavelet transform function in the initial step.

$$DWT = DWT(I) \tag{4}$$

Where,

DWT is Discrete Wavelet Transform

I is the input image

After the completion of the DWT, the threshold is calculated, for this equation 5

$$T = Threshold\ (DWT, \lambda) \tag{5}$$

Where,

T is the output of the threshold value

λ is the coefficient of discrete wavelet

Then the inverse discrete function is calculated, in the equation 6

$$IDWT = IDWT\ (T) \tag{6}$$

Where,

IDWT is Inverse Discrete Wavelet Transform

$I_{denoised}$ is the Output of the denoised image.

3.6 Wiener

In order to take advantage of the multi-resolution frequency representation for adaptive noise suppression, Wiener filtering was chosen. By eliminating high-frequency and low-frequency noise components while maintaining image characteristics crucial for diagnostic interpretation, the sequence enhances denoising performance. Because it minimizes the mean square error between the estimated and actual signals while taking into account each signal and noise characteristic, the Wiener filter is the most dependable method for denoising signals. It is effective in a variety of settings, such as image processing or audio enhancement tasks, because it adjusts to local statistics.

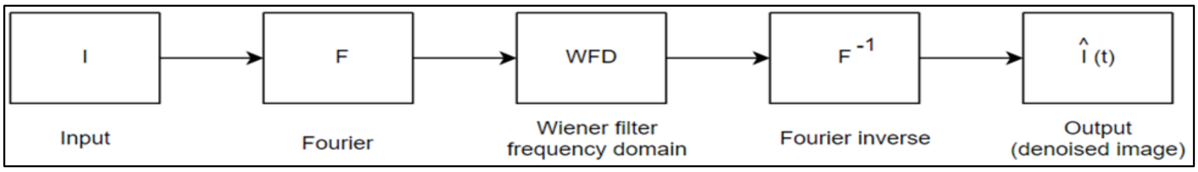


Figure 4. Wiener

Use the Fourier Transform to convert the original signal from the time domain to the frequency domain. The filtered signal is then converted back to the time domain using the Inverse Fourier Transform, yielding the noise-reduced signal using equation 7.

$\hat{\imath}(t) = F^{-1}((S_{II}(f) / (S_{II}(f) + S_{nn}(f)))*(F\{I(t)\})$ ----7

Where

I (t) is Input noise signal

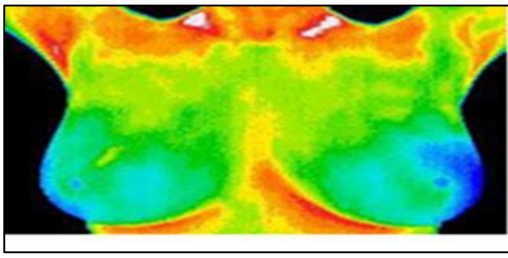
F {i(t)}→Fourier of noisy signal I (t)

F-1 is Inverse of Fourier function

$(S_{II}(f) / (S_{II}(f) + S_{nn}(f)$ is Wiener filter in the frequency domain

î (t) is output denoised symbol

The input image is displayed in Fig. 5, and the processed image output with a Gaussian blur filter is shown in Fig. 6.



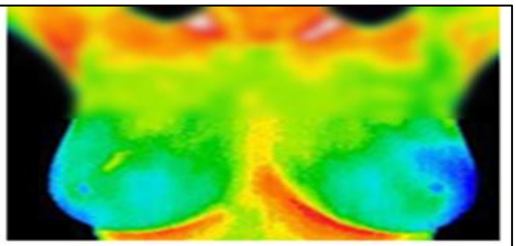
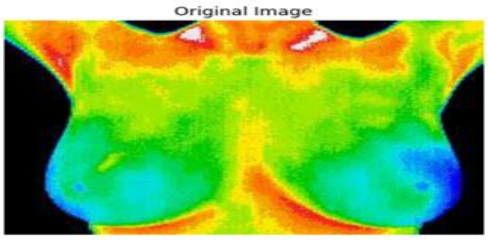


Figure 5. Input Image **Figure 6.** Gaussian Blur



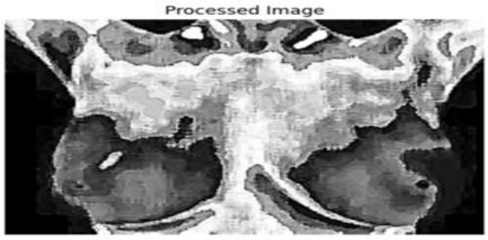
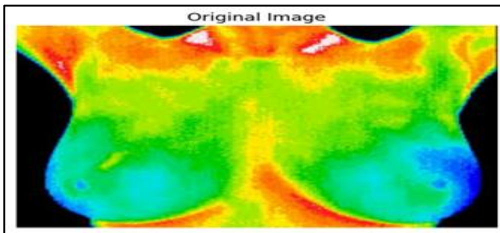


Figure 7. Input Image **Figure 8.** Median Blur

The input image is displayed in Fig. 7. The processed image output with the median blur filter is shown in Fig. 8.



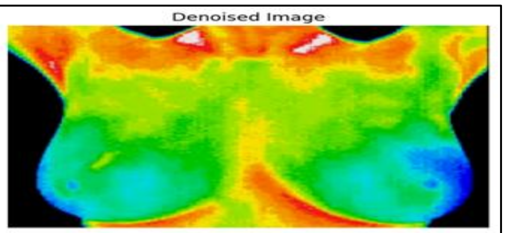
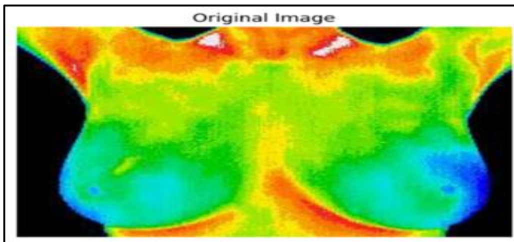


Figure 9. Input Image **Figure 10.** Wavelet Denoising

The input image is displayed in Figure 9, and the processed output with the wavelet-denoised image is shown in Figure 10.



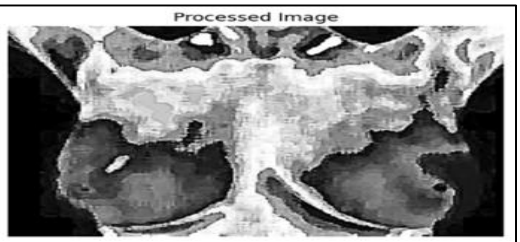


Figure 11. Input Image **Figure 12.** Wiener

Figure 11 displays the input image, and Figure 12 displays the Wiener-processed image output.

3.7 Contrast Enhancement

Contrast enhancement is the operation that raises the contrast of light and dark regions of an image for a general improvement in clarity and visibility. This may be done with histogram equalization, adaptive contrast stretching, and local contrast enhancement. Histogram equalization (AHE) is a type of histogram equalization that is applied locally as opposed to globally. It breaks the image into tiny regions and equalizes the histogram within each area independently. It achieves great local contrast and detail retention, particularly in regions of varying light or complicated textures. High contrast is selected using histogram equalization because uniform pixel intensity redistribution over the range is highly effective and simple. It improves the level of detail in the image and enhances visual quality by modifying the level of intensity, producing a balanced and visually pleasing image style.

3.8 Histogram Equalization

By redistributing intensity levels to create a more uniform histogram, histogram equalization enhances a picture's contrast. By successfully resolving low contrast and uneven lighting, this global adjustment enhances photo details throughout the image, improving visual quality.

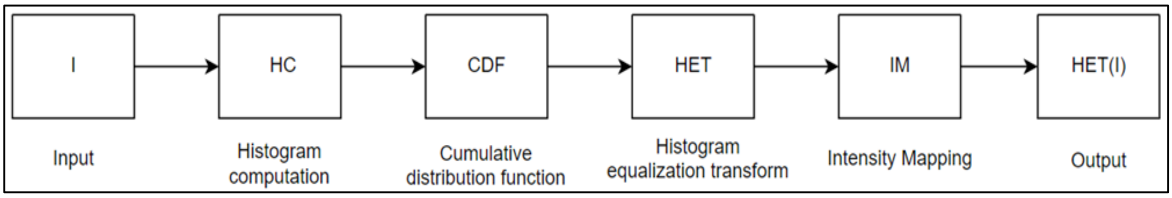


Figure 13. Histogram Equalization

HET (I) = IM (((CDF(I) – min (CDF(I))) / (M* N-1)) (L-1)) ------8

In order to distribute the pixel intensities over the full range of available intensity levels (usually 256 for an 8-bit image), the cumulative distribution function (or CDF) of the image's histogram must be calculated and normalized. The intensity mapping function IM, which scales the CDF values between the minimum CDF value and the total number of pixels minus one, adjusted by the number of intensity levels L, is used to map each intensity level in order to accomplish this normalization. As a result, HET(I) is transformed to more evenly distribute pixel intensities, improving the image's contrast.

Where,

L is Number of intensity levels (Commonly 256 for 8-bit pixel images).

I is Input image.

HC (I) is Histogram computation of image

CDF (I) is Cumulative distribution function (CDF) of the histogram

min (CDF(I)) is Minimum value of the CDF.

M, N is Dimensions of the image I (width and height).

HFT (I) is Histogram equalization transformation of image I.

IM(x) is Intensity mapping function that maps to the output intensity level.

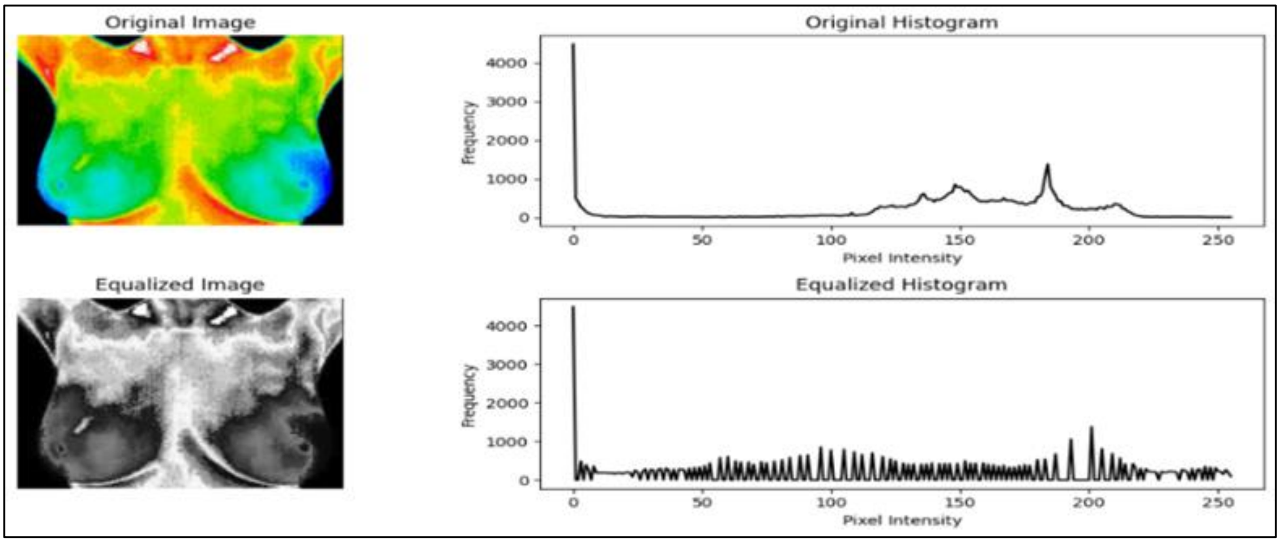
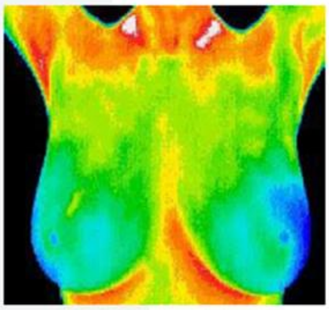


Figure 14. Histogram Equalization for Thermography

The entire histogram equalization procedure is displayed in.14. We start by providing the original image as an input image. The original histogram image is then generated. Following this procedure, an equalized image will be produced, and at last, the equalized histogram will be shown.



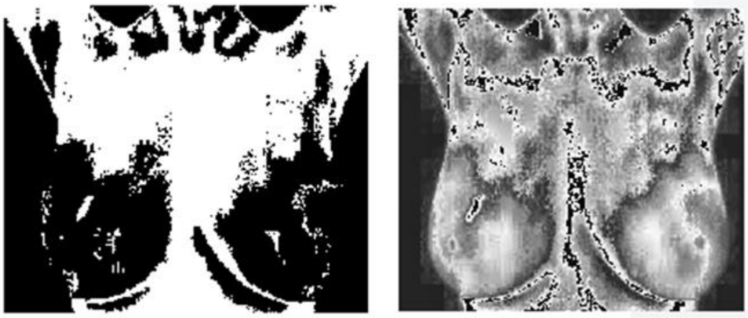
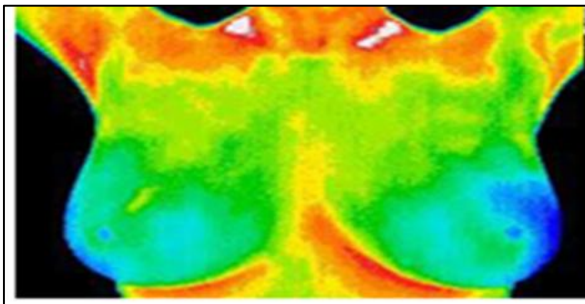


Figure 15. Input Image **Figure 16.** Adaptive Histogram Equalization

The input image is displayed in Fig. 15. A processed adaptive histogram equalized image is shown in Fig. 16.

3.9 Image Sharpening

Using digital images to enhance clarity and define the figure's edges is known as dynamic imaging. It makes the edges appear sharper and more defined by enhancing the contrast there. Sharpening can be accomplished with a variety of algorithms and filters, including high-pass filtering, non-sharp masking, and Laplacian filters. Sharpening is typically used to enhance visual and sensory quality in digital image editing, photography, and medical imaging.



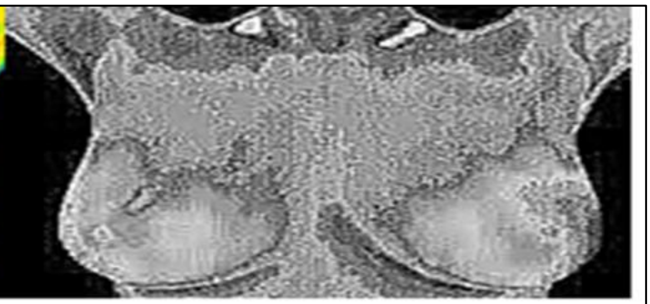


Figure 17. Input Image **Figure 18.** Image Sharpening Output Image

The input image is displayed in Fig. 17, and the processed image with sharpened output is displayed in Fig. 18.

4. Experimental Results

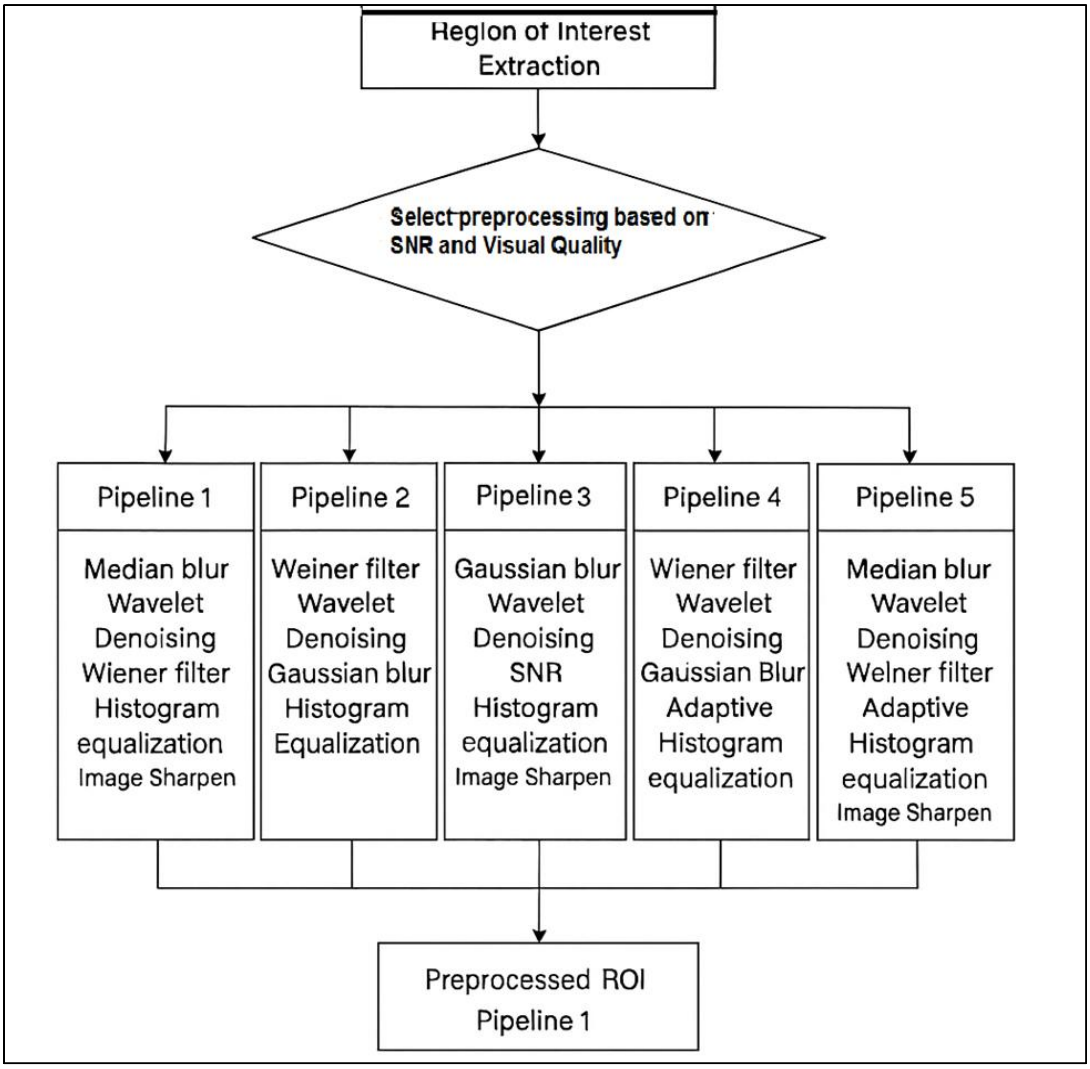


Figure 19. The Entire Steps of Preprocessing

The full preprocessing steps with the five suggested pipelines are shown in Figure 19, and pipeline 1 is ultimately chosen based on comparisons with the factors covered in the previous chapter. Each system has its own filter, and Table 3 lists the five pretreatment techniques that were employed. This figure illustrates a standardized method for enhancing image quality by combining extraction techniques in a methodical manner. Any set of distinct preprocessing techniques indicates that the filtering system's implementation is adaptable and flexible. By carefully choosing and setting up these filters, we hope to meet the unique requirements of the input data and produce the intended result, which will improve the image quality.

Table 3. Comparison of Different Pipelines for Dataset Preprocessing

Pipeline 1	Pipeline 2	Pipeline 3	Pipeline 4	Pipeline 5
Median blur	Weiner filter	Gaussian blur	Weiner filter	Median blur
Wavelet Denoising	Wavelet Denoising	Wavelet Denoising	Wavelet Denoising	Wavelet Denoising
Weiner filter	Gaussian Blur	SNR	Gaussian Blur	Weiner filter
Histogram equalization	Histogram Equalization	Histogram equalization	Adaptive Histogram equalization	Adaptive Histogram equalization
Image Sharpening	Image Sharpening	Image Sharpening	Image Sharpening	Image Sharpening

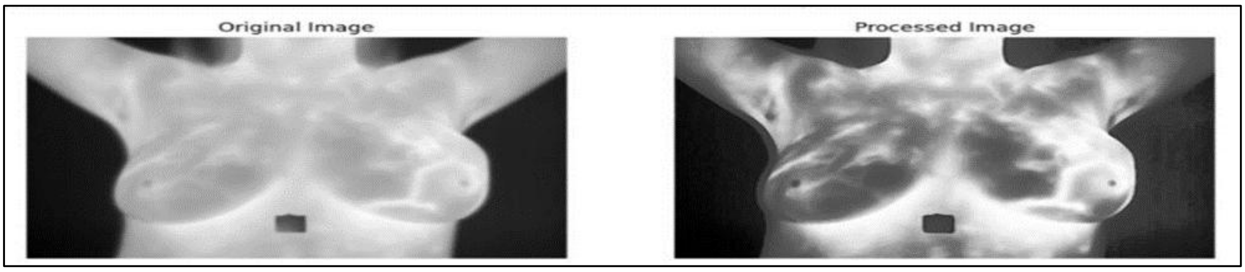


Figure 20. Pipeline 1

The median filter is a digital filtering technique that uses non-linear operations to eliminate noise from signals or images. After sorting the data using a fixed window size, the median value of the sorted list is used to replace the central value. The filtering technique's noise removal mechanism keeps the edges sharp.

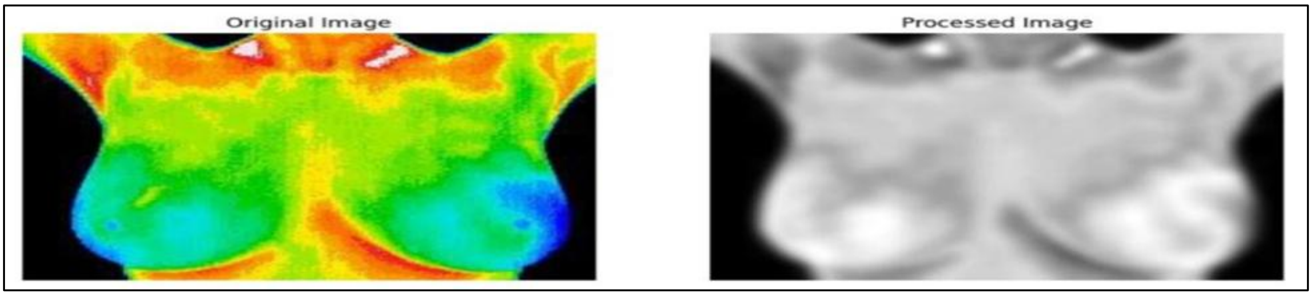


Figure 21. Pipeline 2

An image undergoes a series of sequential steps to enhance its quality when processed through Fig. 21. First, the Wiener Filter uses adaptive filtering based on local variance to minimize the mean squared error between the estimated and true image, hence reducing noise. The next step is Wavelet Denoising, which reduces noise in high-frequency areas of the image by breaking it up into distinct frequency components and then reconstructing the image to minimize blur. The image is then further smoothed by applying a Gaussian Blur filter, which creates a softening effect by applying a Gaussian function to the pixel values. Then, by redistributing intensity values to produce a uniform histogram, Histogram Equalization improves image contrast and highlights details. Lastly, a high-pass filter is used to improve details and apply Image Sharpening to enhance edges, creating a clearer and more vibrant image. This set of procedures creates a processed image that is aesthetically pleasing by lowering noise, enhancing contrast, and sharpening the image.

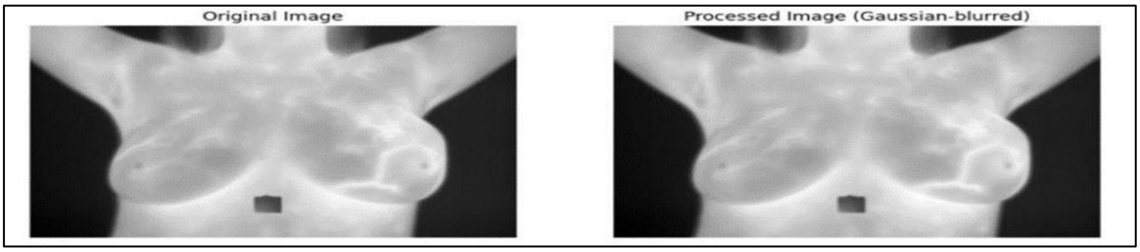


Figure 23. Pipeline 3

An image goes through sophisticated procedures intended to improve its overall quality when it is processed through Fig. 23. The image is first smoothed and horizontal noise is reduced by applying Gaussian Blur, which averages pixel values using a Gaussian function. The image is then broken down into multi-frequency components by wavelet denoising, which preserves crucial process information while enabling targeted noise reduction in high-frequency areas. By increasing signal intensity in relation to background noise, the Signal-to-Noise Ratio (SNR) enhancement step enhances image clarity. Interesting features are easier to identify. Then, as it extends the highest intensity values, histogram equalization modifies the intensity distribution to improve overall contrast and highlight details at various light levels. Lastly, to highlight details and create edges, layered image processing is used. This comprehensive approach uses methods like these to effectively reduce noise, improve the signal, sharpen the image, and improve contrast, giving it high quality, a pleasing appearance, and the ability to be further analyzed.

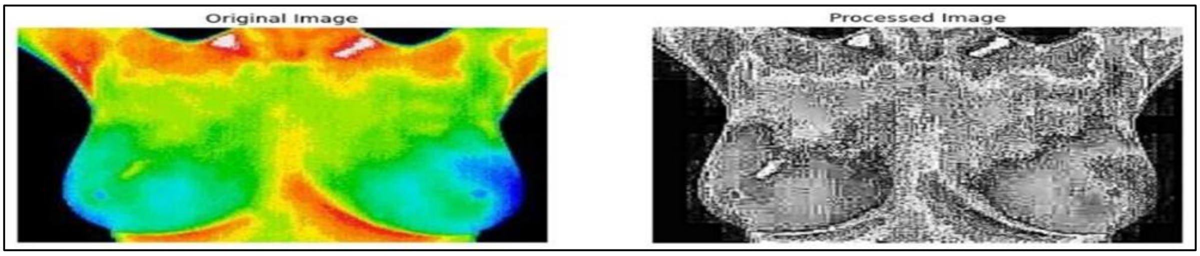


Figure 24. Pipeline 4

As illustrated in Fig. 24, the Wiener filter is first used to minimize noise while maintaining edges. Depending on the image detail and noise properties, parameters are adjusted. Wavelet Denoising is then used to further reduce noise in various frequency bands while preserving image detail. A Gaussian Blur is then applied to smooth out any remaining noise and detail and level it out. The blur radius is adjusted to achieve the desired effect. The contrast is then enhanced by adaptive histogram equalization, which works well for highlighting dark and light regions and improving image clarity overall by locally redistributing intensity values. Lastly, use methods like sharp masking, cautious parameter adjustment, and artifact avoidance to complete image sharpening. Gradually improve the image while striking a balance between detail enhancement and noise reduction, making sure each step works well with the others.

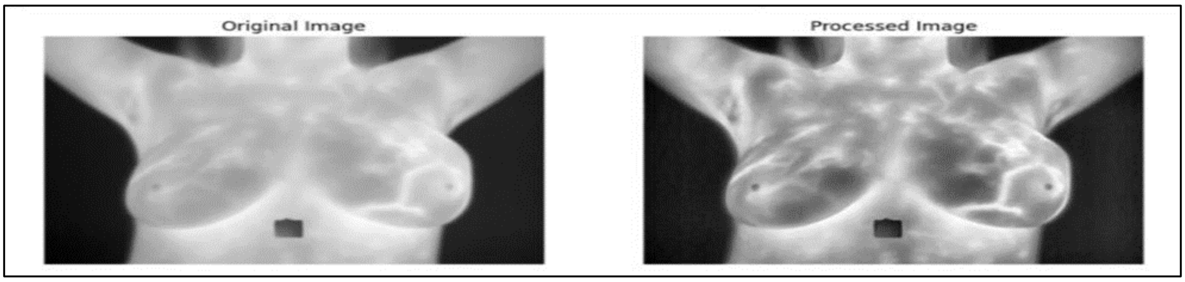


Figure 25. Pipeline 5

The nonlinear digital filtering method referred to as the median filter works to remove noise from images and signals. A window of a certain fixed size translates over the data to sort its values and replace the middle value with the median value of the sorted array. The filtering method preserves edges since it removes noise from the image.

The strategic combination of median filtering, wavelet transformation, Wiener filtering, histogram equalization, and dynamic image enhancement forms the selected Pipeline 1, as presented in Table 3. This pipeline utilizes a combined strategic approach of varied techniques to address various aspects of image enhancement encompassing both noise reduction and enhancement of contrast, along with obtaining sharpness improvement. The initial median filtering step effectuates effective noise removal while keeping useful edge information, which facilitates better processing in subsequent stages. Using wavelet transformation and multi-resolution analysis, the system effectively removes noise from various frequency bands without deforming image properties. Wiener filtering introduces improved noise characteristic estimation to the noise reduction process, which yields a higher signal-to-noise ratio. The use of histogram equalization results in improved visual appearance and information visibility by altering pixel intensity distribution for increased contrast, whereas enhanced image sharpness efficiently generates lively images via the enhancement of image edges' contrast. This pipeline derives its power through its adoption of a systematic strategy that addresses noise reduction, differentiation, and sharp improvement all at once to improve image quality. Each component within the series is carefully selected to complement other elements, creating a harmonious visual interest to facilitate image processing for information. Pipeline 1 shows flexibility in graphics and use, qualifying for graphics work and other activities. Empirical evidence and comparative analysis confirm the efficacy of the method that yields higher quality images and improvement results.

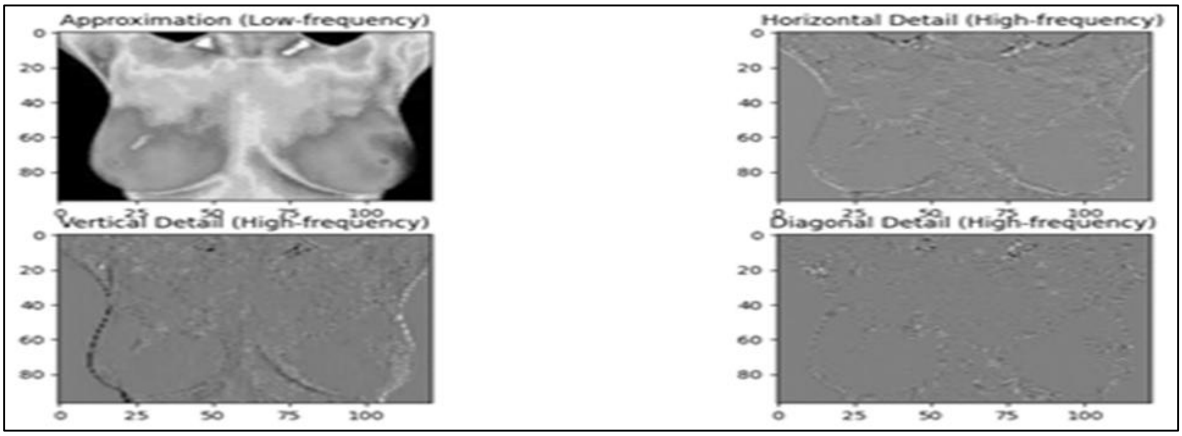


Figure 26. SNR

By contrasting signal intensity (image content) with background noise, Fig. 26 illustrates the significance of the signal-to-noise ratio (SNR) in image processing. Different frequency components are included in SNR analysis: diagonal details skew SNR analysis by measuring noise levels in relation to signal strength at various orientations, horizontal details measure SNR horizontally, vertical details estimate SNR vertically, and approximation estimates overall SNR. Every element helps to improve image clarity and reduce noise.

5. Conclusion and Future Work

Pipeline 1 integrates median filtering, wavelet transformation, Wiener filtering, histogram equalization, and dynamic image enhancement methods to effectively improve image quality. With an effective combination of techniques, it solves significant image processing goals: reduction of noise, contrast, and sharpness of the image by leveraging the strengths of each method. Median and Wiener filters together reduce noise without deleting important features, and wavelet transformation offers multi-resolution analysis. Histogram equalization improves contrast, and sharpening methods enhance visual acuity. The pipeline is robust and flexible in various image enhancement processes, as supported by empirical evidence and comparative study. Although the standalone image enhancement methods utilized in this paper are traditional, the originality of this research is in the strategic combination and empirical study of multi-stage pipelines for mammographic image preprocessing. In contrast to previous research that examines individual filters or transformations exclusively, this paper presents a rigorous comparison that has the potential to advise practitioners on successful low-complexity enhancement combinations for diagnostic imaging applications.

Further research may include optimizing the computational time complexity of the pipeline to be used in real time. Integration with adaptive or deep learning-based enhancement methods can also enhance performance, particularly on datasets with low-quality or extremely complex images. Evaluating Pipeline 1 across various domains such as medical images, satellite imagery, and low-light photographs can also increase its applicability. Optimizing every module based on domain-specific requirements can also lead to improved image enhancement outcomes.

References

[1] Gurusamy, Rajalakshmi, Parameswari Chandrasekaran, Yamuna Devi Manickam Malu, Madhusudhanan Sampath, and Nesarani Abraham. "DeepCNNMed: Enhancing Medicinal Plant Identification Through Deep Convolutional and Hybrid Neural Networks." Brazilian Archives of Biology and Technology 68 (2025): e25240881.

[2] Alshehri, Alia, and Duaa AlSaeed. "Breast cancer diagnosis in thermography using pre-trained vgg16 with deep attention mechanisms." Symmetry 15, no. 3 (2023): 582.

[3] Hounmenou, Castro Gbememali, Kossi Essona Gneyou, and GLELE KAKAÏ RL. "A formalism of the general mathematical expression of multilayer perceptron neural networks." (2021).

[4] Ma, Chao, Stephan Wojtowytsch, and Lei Wu. "Towards a mathematical understanding of neural network-based machine learning: what we know and what we don't." arXiv preprint arXiv:2009.10713 (2020).

[5] Sulistiyanti, S. Ratna, Thomas Sri Widodo, Adhi Susanto, and Gede Bayu Suparta. "Noise filtering on thermal images acquired by modified ordinary digital camera." In 2010 International Conference on Electronics and Information Engineering, vol. 2, pp. V2-462. IEEE, 2010.

[6] Chen, Guangyi, Wenfang Xie, and Yongjia Zhao. "Wavelet-based denoising: A brief review." In 2013 fourth international conference on intelligent control and information processing (ICICIP), IEEE, (2013): 570-574.

[7] Ariateja, Dananjaya, Igi Ardiyanto, and Indah Soesanti. "A review of contrast enhancement techniques in digital image processing." In 2018 4th International Conference on Science and Technology (ICST), IEEE, (2018): 1-6.

[8] Mohamed, Sara EL, Wael A. Mohamed, Mohamed B. Abdelhalim, and Khaled EL Ahmed. "Advanced enhancement techniques for breast cancer classification in mammographic images." The Open Biomedical Engineering Journal 16, no. 1 (2022).

[9] Ansari, Sheeba, and Suresh Salankar. "An Overview on Thermal Image Processing." RICE (2017): 117-120.

[10] Cui, Haoyang, Yongpeng Xu, Jundong Zeng, and Zhong Tang. "The methods in infrared thermal imaging diagnosis technology of power equipment." In 2013 IEEE 4th International Conference on Electronics Information and Emergency Communication, IEEE, (2013): 246-251.

[11] Alshehri, Alia, and Duaa AlSaeed. "Breast cancer detection in thermography using convolutional neural networks (cnns) with deep attention mechanisms." Applied Sciences 12, no. 24 (2022): 12922.

[12] Civilibal, Soner, Kerim Kursat Cevik, and Ahmet Bozkurt. "A deep learning approach for automatic detection, segmentation and classification of breast lesions from thermal images." Expert Systems with Applications 212 (2023): 118774.

[13] Sadoughi, Farahnaz, Zahra Kazemy, Farahnaz Hamedan, Leila Owji, Meysam Rahmanikatigari, and Tahere Talebi Azadboni. "Artificial intelligence methods for the diagnosis of breast cancer by image processing: a review." Breast Cancer: Targets and Therapy (2018): 219-230.

[14] Fisseha, Rahel Desta. "Preprocessing of Mammography Image For Improving Accuracy & Efficiency of Cad In Early Detection of Breast Cancer."

[15] Mukhmetov, O., D. Igali, A. Mashekova, Yong Zhao, E. Y. K. Ng, S. C. Fok, and S. L. Teh. "Thermal modeling for breast tumor detection using thermography." International Journal of Thermal Sciences 161 (2021): 106712.

[16] Tayel MB, ElbagouryAM. "An efficient and reliable method for regional analysis of breast thermographicimages". GSJ. 2020 Sep;8(9).

[17] Ekici, Sami, and Hushang Jawzal. "Breast cancer diagnosis using thermography and convolutional neural networks." Medical hypotheses 137 (2020): 109542.

[18] Mammoottil, Mathew Jose, Lloyd J. Kulangara, Anna Susan Cherian, Prabu Mohandas, Khairunnisa Hasikin, and Mufti Mahmud. "Detection of Breast Cancer from Five-View Thermal Images Using Convolutional Neural Networks." Journal of Healthcare Engineering 2022, no. 1 (2022): 4295221.

[19] Gonçalves, Caroline Barcelos, Jefferson R. Souza, and Henrique Fernandes. "CNN architecture optimization using bio-inspired algorithms for breast cancer detection in infrared images." Computers in Biology and Medicine 142 (2022): 105205.

[20] Mukhmetov, O., D. Igali, A. Mashekova, Yong Zhao, E. Y. K. Ng, S. C. Fok, and S. L. Teh. "Thermal modeling for breast tumor detection using thermography." International Journal of Thermal Sciences 161 (2021): 106712.

[21] Gopakumar, Swathi, K. Sruthi, and Shivasubramani Krishnamoorthy. "Modified level-set for segmenting breast tumor from thermal images." In 2018 3rd international conference for convergence in technology (I2CT), IEEE, (2018): 1-5.

[22] Dar, Rayees Ahmad, Muzafar Rasool, and Assif Assad. "Breast cancer detection using deep learning: Datasets, methods, and challenges ahead." Computers in biology and medicine 149 (2022): 106073.

[23] Lee, Carol H., D. David Dershaw, Daniel Kopans, Phil Evans, Barbara Monsees, Debra Monticciolo, R. James Brenner et al. "Breast cancer screening with imaging:

recommendations from the Society of Breast Imaging and the ACR on the use of mammography, breast MRI, breast ultrasound, and other technologies for the detection of clinically occult breast cancer." Journal of the American college of radiology 7, no. 1 (2010): 18-27.

[24] Mohamed, Esraa A., Essam A. Rashed, Tarek Gaber, and Omar Karam. "Deep learning model for fully automated breast cancer detection system from thermograms." PloS one 17, no. 1 (2022): e0262349.

[25] Dey, Subhrajit, Rajarshi Roychoudhury, Samir Malakar, and Ram Sarkar. "Screening of breast cancer from thermogram images by edge detection aided deep transfer learning model." Multimedia Tools and Applications 81, no. 7 (2022): 9331-9349. [26] Abdel-Nasser, Mohamed, Antonio Moreno, and Domenec Puig. "Breast cancer detection in thermal infrared images using representation learning and texture analysis methods." Electronics 8, no. 1 (2019): 100.

[27] Acharya, U. Rajendra, Eddie Yin-Kwee Ng, Jen-Hong Tan, and S. Vinitha Sree. "Thermography based breast cancer detection using texture features and support vector machine." Journal of medical systems 36 (2012): 1503-1510.

[28] Borchartt, Tiago B., Aura Conci, Rita CF Lima, Roger Resmini, and Angel Sanchez. "Breast thermography from an image processing viewpoint: A survey." Signal processing 93, no. 10 (2013): 2785-2803.

[29] Araújo, Marcus C., Rita CF Lima, and Renata MCR De Souza. "Interval symbolic feature extraction for thermography breast cancer detection." Expert Systems with Applications 41, no. 15 (2014): 6728-6737.

[30] Ekici, Sami, and Hushang Jawzal. "Breast cancer diagnosis using thermography and convolutional neural networks." Medical hypotheses 137 (2020): 109542.

[31] Parameswari, C., and S. Siva Ranjani. "RETRACTED ARTICLE: Prediction of atherosclerosis pathology in retinal fundal images with machine learning approaches." Journal of Ambient Intelligence and Humanized Computing 12, no. 6 (2021): 6701-6711.