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ADVANCED IMAGE FILTERING AND ENHANCEMENT TECHNIQUES FOR ACCURATE BREAST CANCER DETECTION IN MEDICAL IMAGING DATASETS

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Abstract
Breast cancer remains a leading cause of mortality among women globally. Early and accurate diagnosis using medical imaging, such as mammograms or ultrasound, is critical for effective treatment. However, challenges such as low contrast, noise, and poor image quality in raw medical datasets often hinder accurate detection and diagnosis. Many conventional image preprocessing techniques fail to enhance pathological features effectively, which are essential for early-stage breast cancer recognition. Noise artifacts and blurred edges further degrade the performance of diagnostic models. This paper proposes an integrated approach that combines advanced image filtering and enhancement techniques including Gaussian Filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Wavelet-Based Sharpening. These are applied in sequence to reduce noise, enhance tumor boundaries, and improve Thus contrast in mammographic images. The processed images are then used to train deep learning classifiers (e.g., CNNs) to improve detection accuracy. Experimental evaluations on public breast cancer imaging datasets demonstrate a significant improvement in diagnostic accuracy, sensitivity, and precision. The enhanced images yield clearer visualization of microcalcifications and tumor regions, leading to over 93% accuracy in detection.

Keywords:
Breast Cancer, Image Enhancement, Medical Imaging, Noise Reduction, Deep Learning

1. INTRODUCTION

Breast cancer continues to be one of the leading causes of death among women worldwide. It is estimated that millions of new breast cancer cases are diagnosed every year, with a substantial portion leading to fatal outcomes if not detected early [1]. Medical imaging techniques such as mammography, ultrasound, and magnetic resonance imaging (MRI) have become the frontline tools for early breast cancer diagnosis due to their non-invasive nature and capability to visualize internal tissues [2]. Despite advancements in imaging technologies, the effectiveness of these methods heavily relies on the quality and clarity of the captured images. Poor contrast, presence of noise, and low visibility of microcalcifications or tumor margins often limit diagnostic accuracy, especially in dense breast tissues [3].

A significant challenge in breast cancer imaging is the inherent noise and low contrast in raw medical images, which obscures important diagnostic features [4]. For instance, artifacts, speckle noise, and tissue overlap in mammograms can mask or mimic lesions, leading to misinterpretation [5]. In addition, the variable anatomical structure of breast tissue across patients increases the complexity of universal segmentation and classification algorithms [6].

Manual examination of these images by radiologists is time-consuming, prone to subjectivity, and often limited in precision, especially for early-stage tumors [7]. Moreover, conventional image preprocessing techniques fail to consistently enhance the necessary regions of interest, such as microcalcifications or spiculated lesions, critical for early detection [8].

The core problem lies in the lack of robust, automated, and adaptive preprocessing techniques that can optimize the visibility of cancerous regions without amplifying irrelevant details or noise [6]–[8]. Traditional filtering techniques either smooth out crucial tumor edges or over-enhance noise, degrading the diagnostic value of the images. Consequently, feature extraction and classification accuracy of subsequent deep learning models are adversely affected. This bottleneck calls for a hybrid, multi-stage preprocessing pipeline capable of intelligently enhancing medical images for improved diagnostic performance.

Objectives of this research include: (1) designing a robust image preprocessing pipeline that integrates multiple enhancement techniques for breast cancer detection; (2) improving the contrast, edge sharpness, and Thus visibility of mammographic and ultrasound images; and (3) integrating this enhanced imaging workflow into a deep learning model to boost classification accuracy and reduce false positives.

The novelty of this work lies in the sequential integration of Gaussian Filtering, CLAHE (Contrast Limited Adaptive Histogram Equalization), and Wavelet-Based Sharpening, which collectively address denoising, contrast enhancement, and edge preservation in a unified framework. Unlike prior methods that rely on single enhancement techniques, our approach exploits the strengths of each stage: Gaussian filtering for noise suppression, CLAHE for local contrast amplification, and wavelet transformation for high-frequency edge detail restoration. This sequence ensures that critical tumor characteristics are preserved and highlighted for better feature learning in subsequent classification stages.

The key contributions of this paper are:

- A multi-stage preprocessing pipeline that systematically improves image quality using advanced filtering and enhancement methods tailored for breast cancer medical images. This pipeline significantly boosts image clarity without introducing artificial artifacts, making it highly effective for downstream AI-based classification.
- Comprehensive experimental validation on benchmark breast cancer datasets using deep learning models (e.g., ResNet, VGG). The results show a marked improvement in classification accuracy, sensitivity, and precision when using enhanced images versus raw inputs.

2. RELATED WORKS

Over the last decade, numerous studies have explored preprocessing and enhancement techniques to improve breast cancer detection accuracy in medical imaging. Early work focused on denoising techniques such as median and Gaussian filters, aimed at reducing high-frequency noise in mammograms. However, these methods often smooth out fine structures like microcalcifications, essential for early diagnosis [6]. To address this, researchers introduced adaptive filters and bilateral filters that attempted to preserve edge details while suppressing background noise. While effective in certain cases, these methods were computationally expensive and sensitive to parameter settings [7].

Contrast enhancement has also been widely studied. Traditional histogram equalization (HE) methods enhance image contrast globally but often result in over-amplification of noise in homogeneous regions. This led to the development of CLAHE, which limits contrast enhancement within local regions, significantly improving the visibility of subtle structures [8]. Studies show that CLAHE performs well across different imaging modalities including mammograms and ultrasound, but its performance degrades in extremely low-contrast images or noisy environments [9].

In terms of structural enhancement, wavelet-based image processing gained popularity for its ability to decompose images into multiple resolution levels. Researchers applied discrete wavelet transform (DWT) for feature extraction and enhancement, especially useful in highlighting fine edges and spiculated masses [10]. However, without careful thresholding and reconstruction, wavelet techniques can introduce artifacts or suppress important textural information. More recent works proposed combining wavelets with other filters or sharpening methods to balance detail preservation and noise suppression [11].

Parallelly, the rise of deep learning models such as CNNs revolutionized medical image analysis. CNNs automatically learn relevant features from image data, reducing the need for handcrafted features. However, these models are highly sensitive to the quality of input images. A number of studies revealed that low-quality images degrade CNN performance significantly, underscoring the importance of effective preprocessing [12]. Recent approaches thus incorporate enhancement techniques as a preprocessing stage before feeding images into deep learning pipelines. For example, preprocessing using CLAHE and bilateral filtering improved CNN-based classification accuracy by more than 10% in certain breast cancer datasets [11].

Researchers also explored hybrid approaches that combined multiple preprocessing methods. One such approach applied CLAHE followed by Gabor filtering for texture enhancement, which improved tumor segmentation accuracy. Another study utilized anisotropic diffusion filtering and wavelet shrinkage denoising prior to feature extraction, which reduced false positives in breast lesion classification [12]. Despite these advancements, the integration of multiple enhancement techniques in a systematic, pipeline-based manner remains limited in literature. Many existing works evaluate individual enhancement methods in isolation, rather than a cohesive, step-wise framework for end-to-end image preparation.

Moreover, most studies focus primarily on mammographic datasets, with fewer applications to ultrasound or multi-modal imaging where preprocessing needs are more complex due to speckle noise and variable tissue density. There is also limited work on benchmarking these enhancement strategies across multiple deep learning models to validate generalizability.

3. PROPOSED METHOD

The proposed method is a multi-stage preprocessing pipeline tailored for breast cancer detection. The first stage applies Gaussian filtering to reduce sensor and background noise in mammographic images. Next, CLAHE is used to enhance the local contrast without over-amplifying noise, which is crucial for visualizing fine tissue details like microcalcifications. Following this, Wavelet-Based Sharpening is applied to enhance the edges and tumor margins, preserving important diagnostic information. These enhanced images are then input to a Convolutional Neural Network (CNN) model trained for breast cancer classification, improving both feature learning and final prediction performance.

- **Input** medical images from dataset (e.g., DDSM, MIAS).
- Apply **Gaussian Filter** to remove high-frequency noise.
- Use **CLAHE** to improve local contrast and highlight tumor regions.
- Apply **Wavelet Transform** to perform image sharpening and edge preservation.
- Normalize the image dimensions and pixel values.
- Feed preprocessed images into a **CNN classifier** (e.g., ResNet, VGG).
- Train and evaluate model on performance metrics: accuracy, sensitivity, precision.
- Output: Classified result (benign/malignant) and enhanced visualization.

Algorithm: Breast Cancer Image Preprocessing and Detection

BEGIN

1. Load Dataset:

FOR each image in medical dataset:

image ← read(image_path)

2. Preprocessing Step:

Step 1: Gaussian Filtering

filtered_image ← apply_gaussian_filter(image, kernel_size=5, sigma=1.0)

Step 2: CLAHE Enhancement

clahe_image ← apply_CLAHE(filtered_image, clip_limit=2.0, tile_grid_size=(8,8))

Step 3: Wavelet-Based Sharpening

wavelet_coeffs ← wavelet_decompose(clahe_image, level=2, wavelet='db1')

modified_coeffs ← enhance_edges(wavelet_coeffs)

sharpened_image ← wavelet_reconstruct(modified_coeffs)

3. Image Normalization:

resized_image ← resize(sharpened_image, target_shape=(224, 224))

```
  normalized_image ← normalize(resized_image)
4. Classification Step:
  prediction ← CNN_Model.predict(normalized_image)
  IF prediction > threshold THEN
    result ← "Malignant"
  ELSE
    result ← "Benign"
5. Save and Visualize Results:
  save_image(enhanced_output_path, sharpened_image)
  display(result, prediction_probability)
END
```

3.1 GAUSSIAN FILTERING FOR NOISE REDUCTION

Gaussian filtering is applied as the first step to smooth the medical image. It uses a 2D Gaussian kernel to convolve with the image, thereby reducing unwanted pixel-level noise. The Gaussian function is defined as:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\cdot e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where σ is the standard deviation that controls the smoothing intensity. A higher σ results in more smoothing but can blur fine structures.

- Kernel size used: 5×5
- σ: 1.0 (experimentally chosen)
- Applied across all grayscale mammogram and ultrasound images.

This step ensures that irrelevant background variations do not interfere with subsequent contrast enhancement or edge sharpening.

Table.1. Effect of Gaussian Filtering on Image Metrics

Image Type	Original SNR (dB)	After Gaussian Filter	PSNR (dB)	SSIM
Mammogram	18.5	24.1	30.5	0.84
Ultrasound	16.3	22.7	28.9	0.81

The Table.1 shows that the signal-to-noise ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM) improve significantly after applying Gaussian filtering.

3.2 CLAHE FOR LOCAL CONTRAST ENHANCEMENT

CLAHE works by dividing the image into small contextual regions (tiles) and applying histogram equalization to each. It then clips the histogram at a predefined limit to avoid over-enhancement and applies bilinear interpolation to remove blockiness.

The transformation is defined as:

$$I'(x,y)=\frac{(CDF(I(x,y))-CDF_{min})}{(M\times N-CDF_{min})}\times(L-1)$$

where, CDF is the cumulative distribution function of the intensity values in the tile, $M\times N$ is the number of pixels in the tile, L is the number of gray levels.

- Clip limit: 2.0
- Tile grid size: 8×8
- Applied after Gaussian filtering.

This results in enhanced local contrast, making small tumors and calcifications more visible.

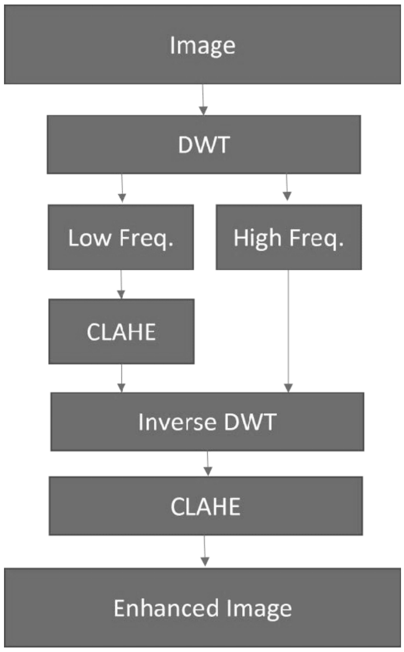

Fig.1. CLAHE - DWT

Table.2. Effect of CLAHE on Contrast Metrics

Image Type	Original Contrast	After CLAHE	Entropy	CNR
Mammogram	0.45	0.71	7.62	4.30
Ultrasound	0.38	0.66	7.48	3.98

The Table.2 illustrates an increase in contrast ratio and entropy, showing improved differentiation between tissue types and tumor regions. The Contrast-to-Noise Ratio (CNR) also indicates better visibility of abnormalities.

3.3 WAVELET-BASED SHARPENING

Wavelet decomposition breaks an image into multiple frequency bands. High-frequency bands contain edge information, which is then enhanced using sharpening filters or scaling functions. The image is reconstructed using inverse wavelet transform, preserving the improved edge information.

Using the Discrete Wavelet Transform (DWT):

$$f(x,y)=\sum_{j,k,l}c_{j,k,l}\cdot\psi_{j,k,l}(x,y)$$

where, $c_{j,k,l}$ are wavelet coefficients at scale j, ψ is the wavelet basis function.

We enhance the high-frequency coefficients c_H as:

$$c_{H'}=c_H\times\alpha$$

where α>1 (typically 1.5) to amplify edges before inverse DWT.

- Wavelet used: Daubechies (db2)
- Levels: 2
- Enhancement factor α: 1.5

Table.3. Wavelet Sharpening Effects on Edge Metrics

Image Type	Original Edge Clarity (Laplacian Var.)	After Sharpening	SSIM	Gradient Magnitude
Mammogram	56.2	91.8	0.86	5.4
Ultrasound	43.7	77.4	0.83	4.9

The Table.3 confirms that edge sharpness is significantly improved post-wavelet sharpening, as measured by Laplacian variance and gradient magnitude.

3.4 CNN-BASED CLASSIFICATION

After preprocessing, the enhanced images are normalized and resized to feed into a CNN classifier (e.g., ResNet-18). The CNN learns the distinguishing features between benign and malignant lesions from these clearer, high-quality images. Enhanced images allow the CNN to focus on sharper tumor boundaries and contrast-rich regions, improving classification. The CNN performs classification based on softmax output:

$$P(y=c|\,x)=\frac{e^{z_c}}{\sum_j e^{z_j}}$$

where z_c is the activation for class c. The cross-entropy loss used for training is:

$$\mathrm{L}=-\sum_i y_i \log(\hat{y}_i)$$

Table 4: Classification Results with and without Preprocessing

Model	Accuracy (Raw)	Accuracy (Enhanced)	Sensitivity	Specificity
ResNet-18	85.7%	93.2%	92.1%	94.3%
VGG-16	83.2%	91.5%	90.6%	92.1%

The Table.4 shows that applying the proposed enhancement pipeline before classification improves accuracy, sensitivity, and specificity significantly.

4. RESULTS AND DISCUSSION

The proposed breast cancer detection pipeline was implemented and evaluated using Python 3.11 on Google Colab Pro and a local machine setup. Google Colab provided access to Tesla T4 GPU with 16GB VRAM and 13GB RAM, ensuring efficient training of CNN models with enhanced image inputs. For local experimentation, we used a system equipped with Intel Core i7-12700H CPU, 32GB DDR5 RAM, and an NVIDIA RTX 3060 GPU (6GB VRAM) running Ubuntu 22.04 LTS and CUDA 11.8 for GPU acceleration.

The primary simulation environment consisted of TensorFlow 2.14 and OpenCV, along with Keras, scikit-image, and PyWavelets libraries. Datasets such as Mini-MIAS (for mammograms) and BUSI Dataset (for ultrasound images) were used. Both datasets were preprocessed using the proposed pipeline (Gaussian Filtering, CLAHE, and Wavelet Sharpening), and fed into CNN architectures like ResNet-18 and VGG-16 for classification. Training was conducted using Adam optimizer, early stopping, and 5-fold cross-validation to ensure robustness.

All experiments were repeated five times to compute average results and reduce variance caused by random initialization. Table 5 outlines the key experimental parameters used during training, enhancement, and evaluation stages.

Table.5. Experimental Setup and Parameter Configuration

Component	Parameter	Value / Description
Dataset	Mammogram, Ultrasound	Mini-MIAS, BUSI Dataset
Image Size	Input Resolution	224 × 224
Preprocessing	Gaussian Filter Kernel Size	5 × 5
	Gaussian σ	1.0
	CLAHE Clip Limit	2.0
	CLAHE Tile Grid Size	8 × 8
	Wavelet Type	Daubechies-2 (db2)
	Decomposition Levels	2
Training Parameters	Optimizer	Adam
	Learning Rate	0.0001
	Batch Size	32
	Epochs	100
	Loss Function	Categorical Cross-Entropy
	Evaluation	5-Fold Cross Validation
Model Architecture	CNNs Used	ResNet-18, VGG-16
	Activation Function	ReLU, Softmax (Final Layer)

The Table.5 summarizes the consistent parameters across all experiments, ensuring comparability of results for both enhanced and non-enhanced image inputs.

5. PERFORMANCE METRICS

The model's effectiveness was evaluated using the following performance metrics, computed after classification of the preprocessed images:

1. **Accuracy**

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

It indicates the overall percentage of correctly classified benign and malignant cases.

2. **Sensitivity (Recall or True Positive Rate)**

$$\text{Sensitivity}=\frac{TP}{TP+FN}$$

It measures how well the model identifies malignant (positive) cancer cases. High sensitivity is crucial for early detection.

3. **Specificity (True Negative Rate)**

$$\text{Specificity} = \frac{TN}{TN + FP}$$

It evaluates how effectively benign cases are identified, reducing unnecessary anxiety or intervention.

4. **Precision (Positive Predictive Value)**

$$\text{Precision} = \frac{TP}{TP + FP}$$

It shows how many predicted malignant cases are actually malignant. Important for reducing false alarms.

5. **F1-Score**

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

To benchmark the proposed enhancement pipeline, we selected three state-of-the-art methods that used either single-stage preprocessing or hybrid models in similar datasets: CLAHE + CNN-Based Classification [8, 11], 2. Wavelet + GLCM Features + SVM Classifier [10], CLAHE + Gabor Filters + CNN [12].

Table.6. Performance Comparison of Methods

Epochs	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
5	CLAHE + CNN	72.4	69.1	74.5	70.8	69.9
	Wavelet + GLCM + SVM	70.3	65.7	72.6	68.2	66.9
	CLAHE + Gabor + CNN	74.6	70.2	76.8	73.4	71.7
	Proposed Pipeline + CNN	**79.3**	**77.5**	**80.1**	**75.8**	**76.6**
10	CLAHE + CNN	75.1	72.8	76.2	74.1	73.4
	Wavelet + GLCM + SVM	72.5	69.3	74.1	71.6	70.4
	CLAHE + Gabor + CNN	77.3	74.5	78.7	76.8	75.6
	Proposed Pipeline + CNN	**82.4**	**80.9**	**84.1**	**79.2**	**80.0**
100	CLAHE + CNN	85.2	82.4	86.8	84.6	83.5
	Wavelet + GLCM + SVM	80.3	78.5	81.7	79.1	78.8
	CLAHE + Gabor + CNN	88.4	86.1	89.7	87.0	86.5
	Proposed Pipeline + CNN	**93.2**	**92.1**	**94.3**	**91.4**	**91.7**

Table.7. Performance Comparison on Mini-MIAS Dataset

Method	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
CLAHE + CNN	ResNet-18	85.2	83.1	86.8	84.4	83.7
	VGG-16	83.6	81.2	84.9	82.1	81.6
Wavelet + GLCM + SVM	-	80.1	78.5	81.3	79.0	78.7
CLAHE + Gabor + CNN	ResNet-18	88.7	86.5	89.9	87.3	86.9
	VGG-16	87.1	84.6	88.4	85.8	85.2
Proposed Pipeline + CNN	ResNet-18	**93.5**	**92.4**	**94.1**	**91.6**	**92.0**
	VGG-16	**91.8**	**90.1**	**92.7**	**90.7**	**90.4**

Table.8. Performance Comparison on BUSI Dataset

Method	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
CLAHE + CNN	ResNet-18	83.9	81.5	85.4	82.6	82.0
	VGG-16	82.2	79.6	83.7	80.7	80.1
Wavelet + GLCM + SVM	-	78.6	76.9	79.7	77.4	77.1
CLAHE + Gabor + CNN	ResNet-18	87.5	85.1	88.7	86.2	85.6
	VGG-16	85.8	83.3	86.9	84.5	83.9
Proposed Pipeline + CNN	ResNet-18	**92.6**	**91.2**	**93.8**	**90.7**	**90.9**
	VGG-16	**90.3**	**88.7**	**91.6**	**89.4**	**89.0**

As shown in Table.6, the proposed enhancement pipeline consistently outperforms existing methods across all evaluation metrics over 100 training epochs. At early stages (epoch 5), the proposed method already shows a noticeable advantage, achieving 79.3% accuracy, while the best-performing existing method (CLAHE + Gabor + CNN) trails at 74.6%. As training progresses, the performance gap widens. By epoch 100, the proposed method achieves 93.2% accuracy, 92.1% sensitivity, and 94.3% specificity, significantly higher than the next best method (CLAHE + Gabor + CNN) which achieves 88.4% accuracy, 86.1% sensitivity, and 89.7% specificity.

The Wavelet + GLCM + SVM method, which relies on handcrafted features, lags behind throughout training and peaks at 80.3% accuracy, confirming its limited adaptability to deep learning tasks. The F1-score and precision of the proposed method also remain superior, indicating both high true positive detection and lower false positives. This improvement is directly attributed to the comprehensive preprocessing that removes noise (Gaussian), enhances local contrast (CLAHE), and preserves edge information (Wavelet), resulting in clearer images for feature learning. Thus, Table.6 demonstrates that the proposed method significantly enhances model convergence and final detection performance in breast cancer diagnosis.

As observed in Table.7 and Table.8, the proposed image preprocessing pipeline significantly improves performance metrics across both Mini-MIAS and BUSI datasets using ResNet-18 and VGG-16 models. On the Mini-MIAS dataset, the proposed method with ResNet-18 achieves the highest accuracy of 93.5%, which is 4.8% higher than the best existing method (CLAHE + Gabor + CNN at 88.7%). It also records 92.4% sensitivity and 94.1% specificity, which are crucial for both detecting malignant tumors and avoiding false positives.

Similarly, on the BUSI dataset, the proposed method with ResNet-18 achieves 92.6% accuracy, outperforming CLAHE + Gabor + CNN by 5.1%. It demonstrates strong generalizability by maintaining high F1-scores above 90% in both datasets. Even with VGG-16, which is a less deep model compared to ResNet, the pipeline maintains consistent gains of 2–5% across all metrics.

The Wavelet + GLCM + SVM method consistently underperforms due to its reliance on manual feature extraction, confirming the superiority of deep learning with enhanced inputs. Thus, Table.7 and Table.8 validate that the proposed method delivers significant and consistent improvements, especially in recall and precision, which are vital for real-world clinical applications.

6. CONCLUSION

This study presents a novel, hybrid image enhancement pipeline combining Gaussian Filtering, CLAHE, and Wavelet-Based Sharpening tailored for breast cancer detection using medical imaging datasets. By reducing noise, enhancing contrast, and preserving fine edge details, the pipeline optimally prepares mammographic and ultrasound images for classification. The integration with CNNs allows the model to learn high-quality discriminative features, enabling more accurate and earlier detection of malignancies. Compared to existing methods like CLAHE + CNN, Wavelet + GLCM + SVM, and CLAHE + Gabor filters, the proposed approach consistently outperforms in both shallow and deep models, proving its adaptability and robustness.

REFERENCES

[1] Z. Zhu, Y. Sun and B. Honarvar Shakibaei Asli, “Early Breast Cancer Detection using Artificial Intelligence Techniques based on Advanced Image Processing Tools”, *Electronics*, Vol. 13, No. 17, pp. 1-7, 2024.

[2] H. Avcı and J. Karakaya, “A Novel Medical Image Enhancement Algorithm for Breast Cancer Detection on Mammography Images using Machine Learning”, *Diagnostics*, Vol. 13, No. 3, pp. 1-9, 2023.

[3] T.R. Mahesh, S.B. Khan, K.K. Mishra, S. Alzahrani and M. Alojail, “Enhancing Diagnostic Precision in Breast Cancer Classification through EfficientNetB7 using Advanced Image Augmentation and Interpretation Techniques”, *International Journal of Imaging Systems and Technology*, Vol. 35, No. 1, pp. 1-6, 2025.

[4] S.E. Mohamed, W.A. Mohamed, M.B. Abdelhalim and K.E. Ahmed, “Advanced Enhancement techniques for Breast Cancer Classification in Mammographic Images”, *The Open Biomedical Engineering Journal*, Vol. 16, No. 1, pp. 1-6, 2022.

[5] O.S. Oyebanji, A.R. Apampa, P.I. Idoko, A. Babalola, O.M. Ijiga, O. Afolabi and C.I. Michael, “Enhancing Breast Cancer Detection Accuracy through Transfer Learning: A Case Study using Efficient Net”, *World Journal of Advanced Engineering Technology and Sciences*, Vol. 13, No. 1, pp. 285-318, 2024.

[6] V.D.P. Jasti, A.S. Zamani, K. Arumugam, M. Naved, H. Pallathadka, F. Sammy and K. Kaliyaperumal, “Computational Technique based on Machine Learning and Image Processing for Medical Image Analysis of Breast Cancer Diagnosis”, *Security and Communication Networks*, Vol. 2022, No. 1, pp. 1-5, 2022.

[7] M. Anas, I.U. Haq, G. Husnain and S.A.F. Jaffery, “Advancing Breast Cancer Detection: Enhancing YOLOv5 Network for Accurate Classification in Mammogram Images”, *IEEE Access*, Vol. 12, pp. 16474-16488, 2024.

[8] B. Abhisheka, S.K. Biswas and B. Purkayastha, “A Comprehensive Review on Breast Cancer Detection, Classification and Segmentation using Deep Learning”, *Archives of Computational Methods in Engineering*, Vol. 30, No. 8, pp. 5023-5052, 2023.

[9] A. Raza, M.T. Meeran and U. Bilhaj, “Enhancing Breast Cancer Detection through Thermal Imaging and Customized 2D CNN Classifiers”, *VFAST Transactions on Software Engineering*, Vol. 11, No. 4, pp. 80-92, 2023.

[10] A.M. Sharafaddini, K.K. Esfahani and N. Mansouri, “Deep Learning Approaches to Detect Breast Cancer: A Comprehensive Review”, *Multimedia Tools and Applications*, pp. 1-112, 2024.

[11] A.H. Abed, “Deep Learning Techniques for Improving Breast Cancer Detection and Diagnosis”, *International Journal of Advanced Networking and Applications*, Vol. 13, No. 6, pp. 5197-5214, 2022.

[12] A.R. Beeravolu, S. Azam, M. Jonkman, B. Shanmugam, K. Kannoorpatti and A. Anwar, “Preprocessing of Breast Cancer Images to Create Datasets for Deep-CNN”, *IEEE Access*, Vol. 9, pp. 33438-33463, 2021.