

Image Pre-Processing Techniques to Improve DBT Classification Accuracy With CNN ResNet-50

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Abstract: Digital Breast Tomosynthesis (DBT) is a three-dimensional imaging technology that is meant to determine breast cancer more accurately than regular mammograms. But low contrast and noise can make DBT images less clear, which can make deep learning-based classification less accurate. This study seeks to assess the impact of diverse preprocessing techniques on breast cancer classification outcomes utilizing the ResNet-50 Convolutional Neural Network (CNN) model. We looked at four different types of preprocessing: The original image, CLAHE (contrast limited adaptive histogram equalization), color mapping, and Region of Interest (ROI). All DBT images were transformed into 2D format, and oversampling was conducted to rectify the disparity in the quantity of benign and malignant classes. We trained each image variant on the same ResNet-50 architecture and then checked its accuracy, precision, recall, and F1 score. The color mapping technique produced the most accurate results in experiments, with an accuracy of 95% and a consistent and balanced F1 score across all classes. These results show that adequate preprocessing has a big effect on how well CNN models work for DBT image classification and may also make automated breast cancer early detection systems stronger. Supplementary experiments combining ROI segmentation with CLAHE and with color mapping showed that this benefit is combination-dependent: ROI + CLAHE raised accuracy from 86 to 92%, whereas ROI + color mapping matched color mapping alone in overall accuracy (95%) but shifted the balance between classes, improving benign-class metrics at the cost of a small reduction in malignant-class recall indicating that combining techniques helps most when the underlying technique is weaker rather than uniformly improving an already strong one.

Keywords: CNN, Color Mapping, DBT, Image Pre-Processing, ResNet-50

Introduction

Breast cancer remains a major health concern because early and accurate interpretation of breast imaging plays an important role in supporting diagnosis and treatment decisions. It is also the most common cause of cancer death in women, accounting for about 25% of all female cancer cases. This disease happens when cells in breast tissue grow in a way that is not normal. These cells can be either benign or malignant. Breast cancer is still a big health problem all over the world and finding it early is

very important for lowering death rates (Ghalela and Jusman, 2023; Jusman et al., 2024).

Digital Breast Tomosynthesis (DBT) is a 3D imaging technology that tries to determine cancer more accurately than regular mammograms (Harron et al., 2022). However, DBT presents several challenges, including difficulties in processing 3D data that computers struggle to manage, the presence of structural noise, and low tissue contrast. These issues can make classification models less accurate, especially if the images aren't processed correctly before being sent to the deep learning system (Buda et al., 2021).

This study proposes a preprocessing approach based on image enhancement techniques, including color mapping, Contrast Limited Adaptive Histogram Equalisation (CLAHE), and Region of Interest (ROI) cropping. To reduce computational complexity, the volumetric 3D DBT images are first converted into 2D representations prior to analysis. This approach aligns with previous findings suggesting that processing volumetric medical data in 2D form can be a more efficient solution while still maintaining competitive performance in various medical image analysis tasks (Sobirov et al., 2024). Each preprocessed image is then classified using a Convolutional Neural Network (CNN) model with the same architecture and training parameters, allowing for an objective comparison between preprocessing methods (Damarjati et al., 2023).

The objective of this study is to evaluate and compare the classification performance of DBT images based on four preprocessing approaches: Original, CLAHE, ROI, and color mapping. By employing a consistent CNN architecture and number of training epochs, this research aims to identify the most effective preprocessing method for improving the accuracy of breast cancer classification.

Related Work

Previous studies have explored various approaches to improve classification accuracy in medical imaging, particularly Digital Breast Tomosynthesis (DBT), through preprocessing methods, data balancing strategies, and appropriate selection of CNN architectures. The following is a review of relevant studies that support the approaches used in this research.

Beyond DBT-specific studies, the broader application of Machine Learning (ML) and CNN based approaches to disease diagnosis and prediction provides additional context for this research. Shivahare et al. (2024) reviewed the comparative performance of ML algorithms such as SVM, KNN, and Random Forest in diagnosing disease from medical images and patient records, highlighting their consistent contribution to diagnostic accuracy across conditions. Similarly, Chandan et al. (2024) conducted a comprehensive analysis of ML's impact on diagnosis and prognosis across cancer, diabetes, heart, and skin disease, reporting improvements in diagnostic speed, accuracy, and reliability, with effectiveness varying by condition. Singh et al. (2025) proposed a lightweight CNN integrated into an IoT-based healthcare system for real-time disease prediction, emphasising the computational efficiency needed for early diagnosis and remote monitoring, while Swami et al. (2022) compared supervised ML models such as KNN and SVM for predicting diseases including Dengue and COVID-19. Mishra et al. (2025) further demonstrated an edge-enabled cloud IoT architecture combining ML algorithms for multi-disease prediction in elderly care, and Singh et al.

(2026) compiled advances in AI optimisation techniques for data-driven diagnostics and disease prediction. Collectively, these studies underscore the growing role of ML and CNN architectures in improving diagnostic accuracy and efficiency across healthcare domains, reinforcing the relevance of applying CNN-based classification, as pursued in this study, to DBT-based breast cancer detection.

Buda et al. (2021) developed a large-scale dataset consisting of over 22,000 DBT volumes from 5,060 patients and designed a baseline deep learning model to identify architectural deformities and masses in DBT images. In their study, basic preprocessing techniques were applied to reduce computational load, including slice down sampling, skin pixel erosion, and extraction of the main breast region before analysis with CNNs. The experimental results indicated that, although detection using CNNs on DBT is challenging due to visual complexity and noise, effective preprocessing can enhance detection sensitivity. This supports the current study's approach, which also employs segmentation-based and image transformation preprocessing to improve CNN classification accuracy on DBT images.

Faiaz et al. (2024) proposed a color mapping approach to convert NSL-KDD tabular data into colour images, which were then classified using CNNs. By applying various colormaps such as HSV and viridis, they improved the model's ability to recognise complex patterns in non-visual data. Although their research was not focused on medical imaging, the study demonstrates that transforming data into coloured representations can enrich the visual features captured by CNNs. This is relevant to the present study, which applies color mapping to greyscale DBT images to help CNNs better identify tissue patterns.

Wanto et al. (2023) investigated the effect of CLAHE as a preprocessing technique to improve classification accuracy on retinal fundus images. They examined various tileGridSize and clip limit parameters of CLAHE on the performance of several popular CNN models, including MobileNetV1/V2, ResNet50, and VGG19. The results indicated that applying CLAHE significantly enhanced image quality and classification accuracy compared to the original contrast. These findings support the use of CLAHE in this study to enhance image detail in DBT before classification with CNNs.

In the study by Moirangthem et al. (2021), a Region of Interest (ROI) segmentation approach was used to extract tumour areas from brain MRI images prior to classification using CNNs. ROI usage was shown to help the model focus on critical image regions, thereby improving accuracy and training efficiency. A similar approach is adopted in this research to crop and highlight essential areas in DBT images to improve breast cancer tissue classification performance.

Sobirov et al. (2024) proposed converting 3D volumetric medical data into a 2D representation called Super Images (SIs) by arranging 3D slices side-by-side into a 2D grid. This approach aimed to reduce the computational complexity of 3D networks while retaining important spatial information for segmentation tasks. The experiments indicated that 2D models trained on SIs could achieve performance comparable to conventional 3D models, but with significantly fewer parameters and FLOPs. This supports the current study's strategy of converting DBT images from 3D to 2D to enhance computational efficiency without a significant loss in classification performance.

In this study, CNN is employed for breast cancer classification based on DBT images due to its ability to extract spatial features from medical images. Mendes et al. (2023) demonstrated that using a single slice from 2D DBT images can yield high accuracy while maintaining computational efficiency. Moreover, ResNet-50 has proven to be highly effective in classifying 2D medical images such as chest X-rays, achieving 94% accuracy and an F1-score of 89% (Jusman et al., 2024), thus supporting its use for 2D-converted DBT images. To address class imbalance, Rifky et al. (2024) showed that random oversampling can improve CNN sensitivity to minority classes, which is relevant in the context of cancer classification.

Based on these studies, it can be concluded that preprocessing methods such as color mapping, CLAHE, and ROI segmentation, as well as 3D-to-2D conversion and class imbalance handling strategies, are key components that can enhance CNN classification performance on DBT images. These form the foundation for the design and evaluation of the proposed methods in

this study. While each of these preprocessing techniques has been individually validated on other imaging modalities or tasks, a controlled, head-to-head empirical comparison of CLAHE, ROI segmentation, and color mapping under a fixed ResNet-50 architecture and training protocol has not, to our knowledge, been previously reported specifically for DBT classification. The primary contribution of this study is therefore this systematic quantitative comparison, which provides practical, evidence-based guidance for preprocessing choices in future DBT classification pipelines.

Methods

This section describes the methodological stages employed in the study, starting from the processing of the DBT dataset, the application of image enhancement techniques, to the training and evaluation of the CNN model using the ResNet-50 architecture.

Research Flow

This study begins with data collection from the BCS-DBT dataset in DICOM format. The data is then converted into a 2D.png file to facilitate computational processing and CNN- based classification. Three primary preprocessing techniques are applied separately: CLAHE for contrast enhancement, viridis color mapping to transform greyscale images into colour representations, and ROI segmentation based on the largest contour of the tissue structure. Additionally, the original images without any preprocessing are used as a baseline for comparison. All preprocessed images are prepared as input for the ResNet-50 model, with input sizes standardised during training. The research workflow is illustrated in Fig. 1.

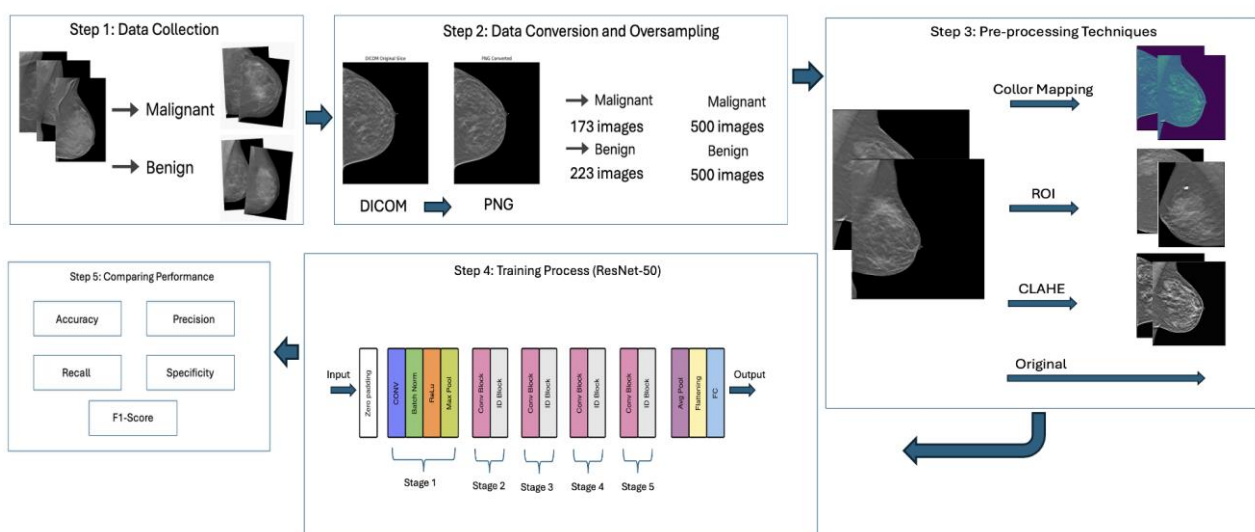


Fig. 1: Research flow

Pre-Processing

- Collection: The Buda et al. (2021) Breast Cancer Screening dataset was used. As shown in Fig. 2, a total of 223 benign and 173 malignant pictures were gathered
- Data Conversion and Oversampling: A data conversion process was performed, starting from the original DICOM format to .PNG. This conversion aimed to reduce computational complexity prior to CNN processing while preserving the structural integrity of the original DICOM images without compromising quality (Sobirov et al., 2024). Subsequently, random oversampling was applied to the dataset to prevent overfitting and underfitting during the CNN training process (Riyadi et al., 2024). Specifically, the ROI segmentation applies a fixed intensity threshold to the grayscale image to separate breast tissue from the black background; contour detection is then performed on the resulting binary mask, and the largest connected contour is selected and used to crop the image to the breast region
- Pre-processing Techniques: Three preprocessing techniques were employed to enhance image quality and included one unprocessed technique for comparison. The three enhancement techniques consisted of CLAHE, ROI segmentation, and Color Mapping

Training Process (ResNet-50)

This study uses ResNet-50 as the architecture for DBT image classification. It is known for being effective at classifying images because it can use residual learning to keep accuracy loss low in deep networks. The ResNet-50 architecture is a deep convolutional neural network with 50 layers. It was based on the idea of residual learning with shortcuts. This method lets the network learn residual functions, which helps with the problem of gradients going away in very deep networks.

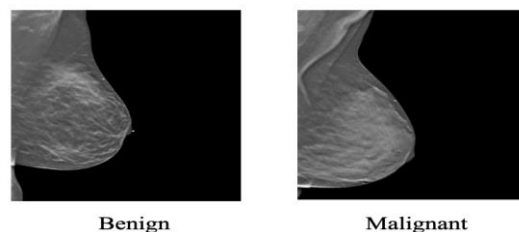


Fig. 2: Data collected DBT

This model has done an impressive job of classifying medical images in the past, such as those of breast and prostate cancer (Jusman et al., 2024). The ResNet-50 architecture is shown in Fig. 3.

During model training, the last layer of the ResNet-50 architecture was fine-tuned to match the number of classes in the DBT dataset. It was done to make the model better.” We used the Adam optimizer with a learning rate of 0.0001 to train for 25 epochs with batch size. The confusion matrix was calculated to determine the accuracy, precision, recall, specificity and F1-score metrics for each class. These were then used to assess the performance of the model.

Comparing Performance

To evaluate the performance of each preprocessing technique, the ResNet-50 model was trained individually on each image variant. The effectiveness of these methods was carefully examined using standard evaluation metrics, specifically accuracy, precision, recall, and F1 score, to determine which approach yields the optimal classification results:

- Accuracy is a way to measure how well the model predicts overall. This metric is often used as a first sign of how well a model works because it takes into account correct predictions for both positive and negative classes. Equation (1) shows how to determine the accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (1)$$

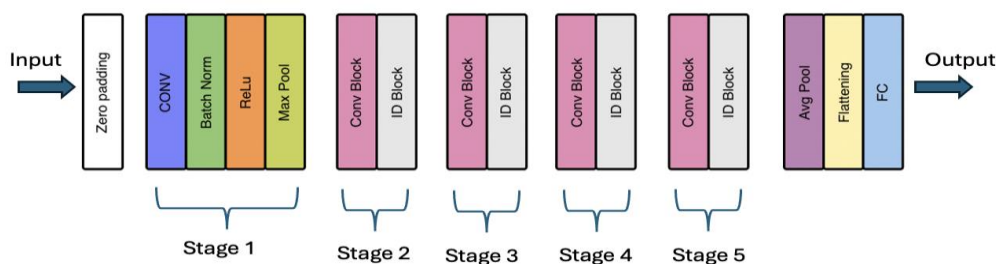


Fig. 3: ResNet-50 architecture

- Recall, or sensitivity, evaluates the model's accuracy in identifying positive cases among all actual positive cases. In situations like fraud detection or illness detection, when missing positive instances might have dire repercussions, this statistic is essential. Equation (2) displays the recall formula:

$$\text{Recall} = \frac{TP}{TP + FN} \times 100\% \quad (2)$$

- Precision tells you how accurate the model's positive predictions are. It is the number of true positive predictions divided by the total number of positive predictions. A high precision value means that the model doesn't often make mistakes. Equation (3) shows the formula for precision:

$$\text{Precision} = \frac{TP}{TP + FP} \times 100 \quad (3)$$

- The F1-score is a measure of evaluation that takes the harmonic mean of precision and recall to provide a single number. This statistic is a trade-off between the model's recall (ability to identify positive examples) and accuracy (ability to give precise positive predictions). Equation (4) is the formula for the F1-score:

$$\text{F1-Score} = 2 \times \frac{\text{sensitivity} \times \text{precision}}{\text{sensitivity} + \text{precision}} \times 100\% \quad (4)$$

Where:

TP = True Positive
 FP = False Positive
 TN = True Negative
 FN = False Negative

This section thoroughly explains all the stages described above, from data preparation and the application of various preprocessing techniques to model training and evaluation. The next chapter will present the classification results of each preprocessing method and conduct a performance analysis using the predefined evaluation metrics.

Results and Discussion

This chapter presents the experimental results of the researcher's classification process on DBT images using the ResNet-50 model under four different preprocessing conditions: Original, CLAHE, color mapping, and ROI. The evaluation results are presented in the form of accuracy, precision, recall, F1-scores, and specificity metrics, which are then analysed to assess the

effectiveness of each technique in improving classification performance.

Visual Results of Pre-Processing Techniques

Before feeding the data into the ResNet-50 model, visual inspection was conducted to observe the effects of each preprocessing technique on the DBT images. Fig. 4, illustrates the visual comparison between the Original, CLAHE, ROI, and Color Mapping techniques.

The detailed visual characteristics resulting from each preprocessing technique are described as follows:

- As shown in Figure 5, the Color Mapping technique transforms the single-channel grayscale DBT images into a three-channel RGB representation (specifically using the viridis colormap). This process links the brightness of pixels to certain colors. For instance, purple is for low intensity (background), and yellow/green is for high intensity (dense tissue). This change is meant to give the CNN more information about the feature space so that the model can identify patterns based on color gradients that show differences in tissue density
- The ROI method focuses on cropping the relevant tissue area. Fig. 4, shows that this process involves cutting out the big black background and separating the breast area. The model can focus its computing power on the breast tissue by getting rid of background pixels that aren't relevant. This cuts down on noise, which could even help with classification
- The CLAHE method, on the other hand, works on improving the texture of the picture instead of changing its size. The local contrast has changed a lot since the first picture. The inside of the breast tissue looks clearer and sharper. This method tries to show small details in benign or malignant masses that show up poorly in DBT images with little contrast
- Original images serve as the baseline, presenting the raw DBT data in grayscale without any enhancement or cropping. These images retain the original noise levels and low contrast typical of raw medical imaging

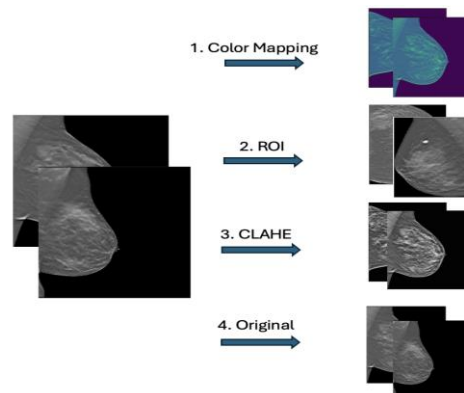


Fig. 4: Visual comparison

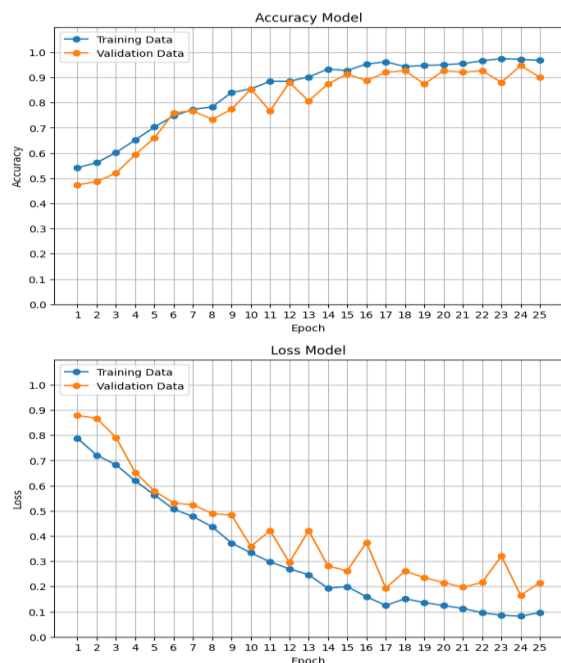


Fig. 5: ResNet-50 pre-processing color mapping technique training results

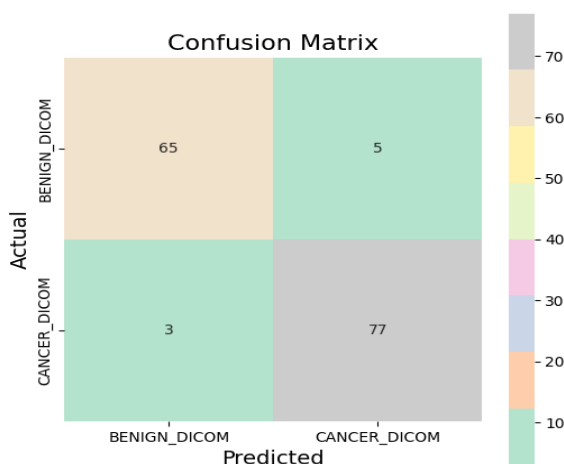


Fig. 6: Confusion matrix color mapping

Results of Pre-Processing Techniques

The researchers presented the training results and confusion matrices of the ResNet-50 model applied to each preprocessing technique, namely original, CLAHE, color mapping, and ROI, for analysis based on evaluation metrics.

Fig. 5, shows the results of training the ResNet-50 model on DBT images that have been processed using color mapping techniques.

The accuracy and loss graphs show a stable training trend, with validation accuracy reaching approximately 95%. Some fluctuations are visible in the validation data, particularly in the loss values, while the training data shows

a consistent decrease in loss. Fig. 6, shows the confusion matrix of the classification results, with 65 benign images and 77 cancer images successfully classified correctly. The color mapping technique yields higher accuracy compared to other preprocessing methods.

Fig. 7, shows the training results using the ROI technique. The accuracy and loss graphs show a stable training trend, with validation accuracy reaching around 90%. The loss on the training data decreases consistently in the loss graph, while the loss on the validation data tends to fluctuate in the middle epoch but still shows a decrease at the end of training.

Fig. 8, displays the confusion matrix, where 79 cancer images and 56 benign images were correctly classified. The ROI technique produces good performance, although slightly below color mapping and the original.

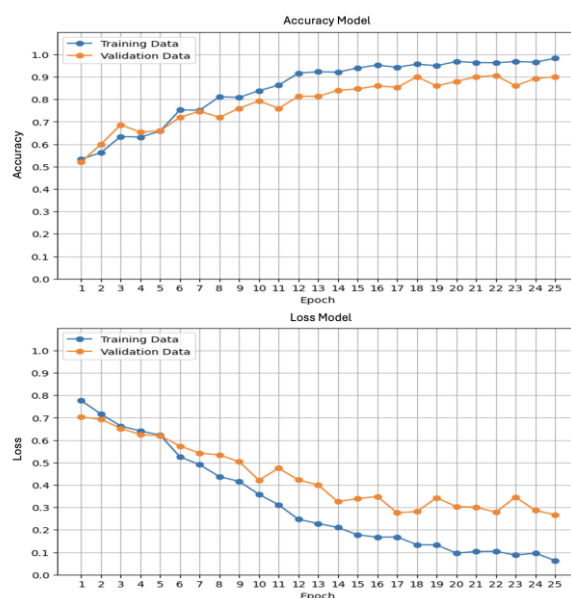


Fig. 7: ResNet-50 pre-processing ROI technique training results

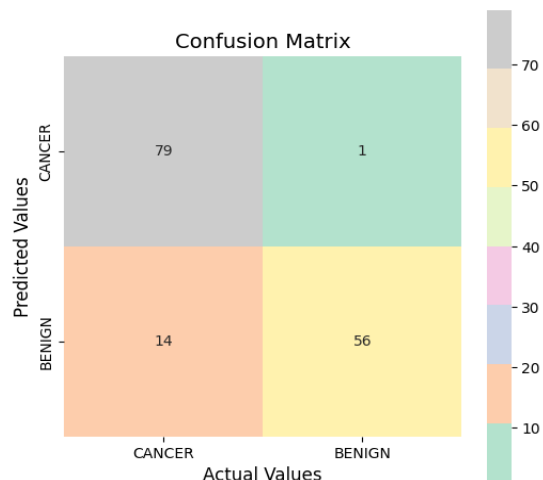


Fig. 8: Confusion matrix ROI

Fig. 9, shows the training results using the CLAHE preprocessing technique. The accuracy and loss graphs show a fairly satisfactory training trend, with validation accuracy reaching around 86%.

Although the loss on the training data decreased consistently, the loss value on the validation data appeared to fluctuate across almost all epochs. Fig. 10, shows a confusion matrix indicating that 65 cancer images and 64 benign images were correctly classified. Compared to other methods, the CLAHE technique produced the lowest accuracy in this experiment.

Fig. 11, shows the training results without preprocessing techniques (original). The accuracy and loss graphs show a stable trend, with validation accuracy reaching approximately 93%. Some fluctuations are visible in the validation accuracy and loss during the middle of the epoch, after which the training data loss consistently decreases. Fig. 12, shows the confusion matrix with 69 cancer images and 70 benign images successfully classified correctly. This original technique shows quite excellent performance even without additional transformations.

Performance Evaluation Tables

The authors summarize the performance of each preprocessing method in a table. The results of the performance evaluation of the ResNet-50 model for each DBT image preprocessing method (color mapping, original, ROI, and CLAHE) are shown in Table 1. The performance of each class was assessed using four major metrics, i.e., accuracy, recall, precision and F1 score. Class 0 is a benign instance, and class 1 is a malignant instance.

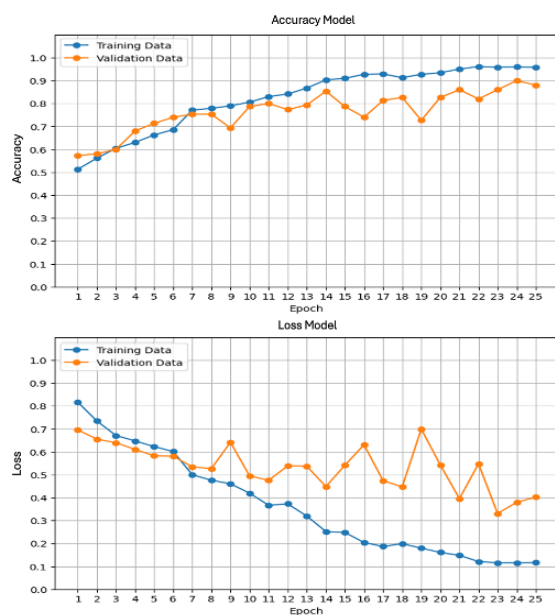


Fig. 9: ResNet-50 pre-processing CLAHE technique training results

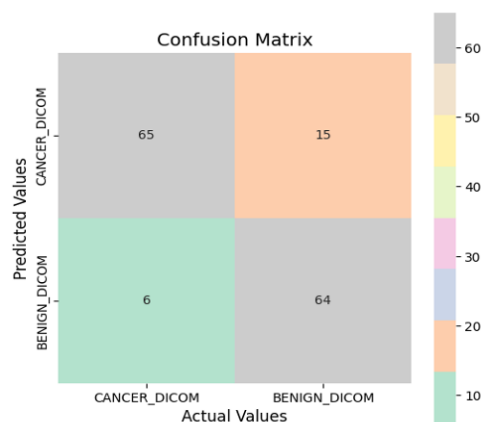


Fig. 10: Confusion matrix CLAHE

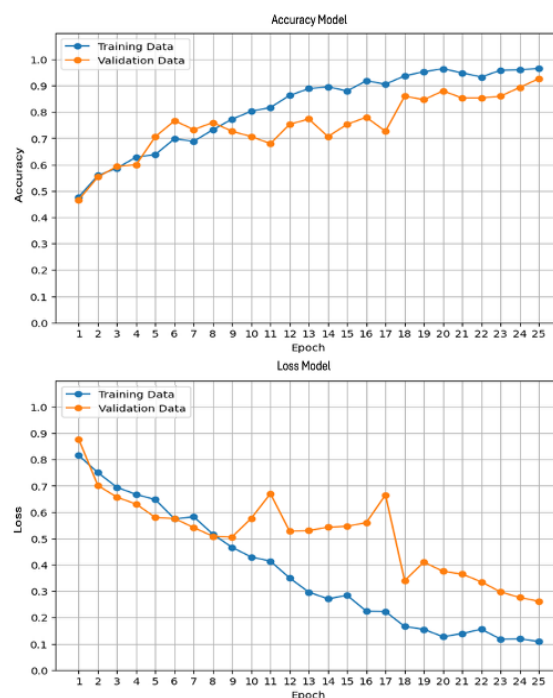


Fig. 11: ResNet-50 pre-processing without preprocessing techniques training results

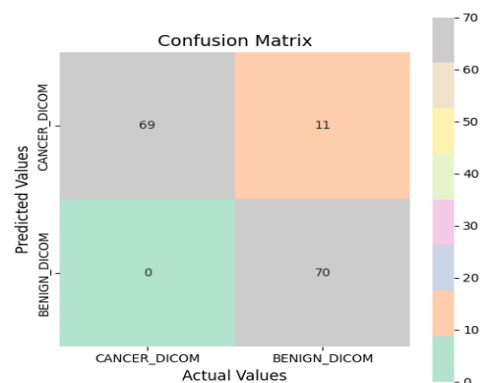


Fig. 12: Confusion matrix without preprocessing techniques

Table 1 shows that the color mapping method had the highest accuracy rate, at 95%. It also had balanced F1 scores of 94 and 95% for the benign and malignant classes, respectively. In terms of precision, this method reached 94% for the malignant class and 96% for the benign class. The original method also worked well, getting 93% of the answers right. However, the model was biased toward the benign class because the recall rate was much higher in that class 100% than in the malignant class 86%. The ROI method was right 90% of the time, but the metrics were less consistent. The CLAHE method, on the other hand, had the worst results, with only 86% accuracy. For instance, the benign class's precision was only 81%, which may suggest that CLAHE might over-amplify background noise in the dense tissue, leading to false positives.

To assess whether combining preprocessing techniques improves upon single-technique performance, two additional experiments were conducted: ROI segmentation combined with color mapping, and ROI segmentation combined with CLAHE. Table 2 summarises the results. The ROI with color mapping combination achieved 95% accuracy, identical to color mapping alone, but with a shifted balance between classes: Benign-class recall and F1 improved from 93% to 96% and 94% to 96%, while malignant-class recall decreased 96% to 94%. Because malignant-class recall the model's sensitivity to true cancer cases is the more clinically critical metric in a screening context, this indicates that ROI cropping does not represent a uniform improvement when combined with color mapping, but rather a trade-off favouring benign-class performance. The ROI with CLAHE combination achieved 92% accuracy, a marked improvement over CLAHE alone 86%; this is consistent with the interpretation that restricting contrast enhancement to the segmented breast region, rather than the full image, reduces the background noise amplification identified as a limitation of standalone CLAHE. These results provide preliminary combinatorial evidence supporting the preprocessing design choices in this study, though a full pairwise ablation across all technique combinations remains a direction for future work.

Figs. 13 and 14 present the training curves and confusion matrix for the ROI + CLAHE combination, respectively, corresponding to the results summarised in Table 2.

Correspondingly, Figs. 15 and 16 present the training curves and confusion matrix for the ROI + color mapping combination.

These findings can also be situated within recent DBT preprocessing literature. Esposito et al. developed a preprocessing tool Digital Breast Imaging Tool (DBIT) that improves image contrast and removes breast skin contour and pectoral muscle prior to CNN-based classification, evaluated on a similarly sized dataset of over 200 DBT volumes divided into benign and malignant cases.

Testing VGG16, ResNet18, and DarkNet19 on preprocessed versus raw images, they reported average classification accuracy improvements of approximately 12%, 26%, and 16%, respectively (Esposito et al., 2024). While the specific techniques differ contrast enhancement and anatomical-structure removal in DBIT versus CLAHE, ROI segmentation, and color mapping in the present study both results converge on the same conclusion: Preprocessing choice substantially affects CNN classification performance on DBT images, reinforcing the practical relevance of the systematic comparison conducted here.

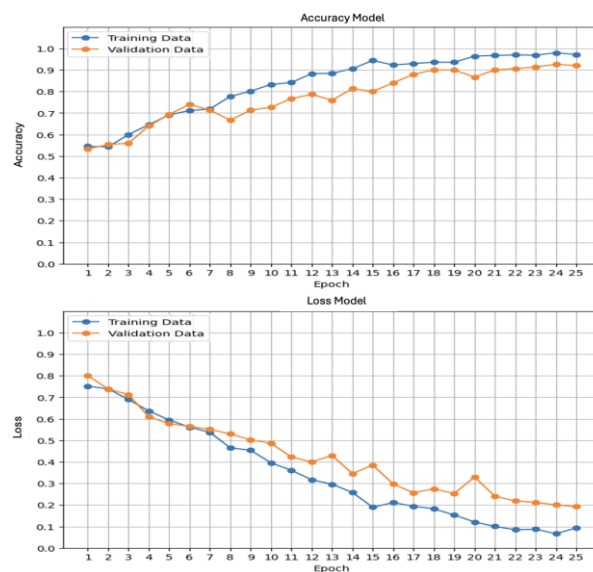


Fig. 13: ResNet-50 pre-processing ROI with CLAHE technique training results

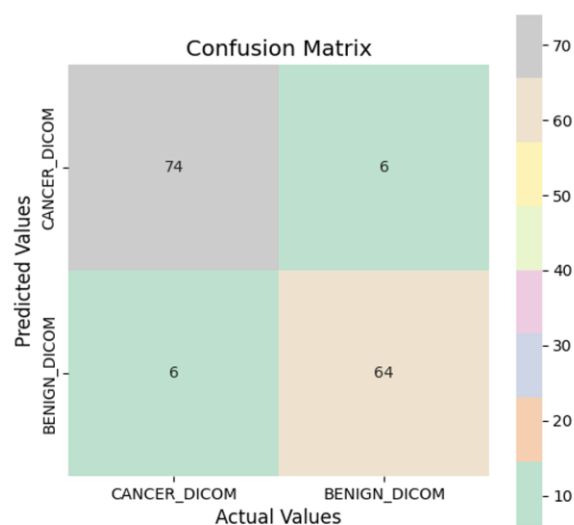


Fig. 14: Confusion matrix ROI with CLAHE

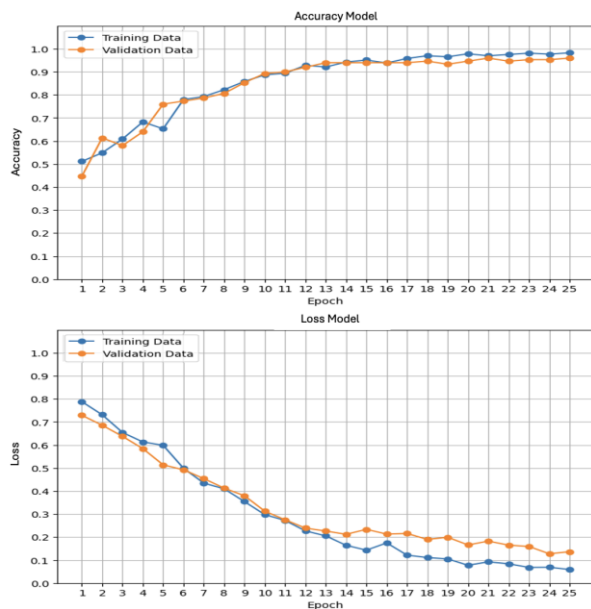


Fig. 15: ResNet-50 pre-processing ROI with color mapping technique training results

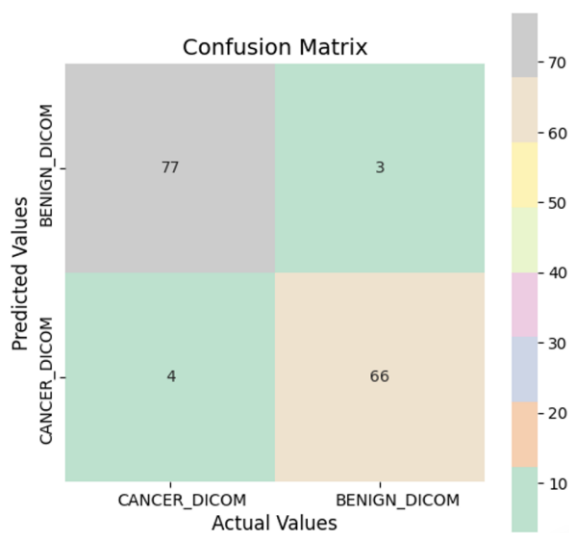


Fig. 16: Confusion matrix ROI with color mapping

Limitations

Several limitations of the preprocessing techniques employed should be acknowledged. First, the resizing and conversion from DICOM to 2D PNG format, together with the ROI cropping step, may discard subtle lesion information located near the cropping boundary or in low-contrast regions, potentially reducing sensitivity to small or diffuse abnormalities. Second, CLAHE's local contrast enhancement can amplify background noise alongside genuine tissue detail, as reflected in its comparatively lower precision for the benign class (Table 1); this trade-

off between contrast enhancement and noise amplification warrants further investigation, for example through adaptive clip-limit tuning. Third, the color mapping transformation is a fixed, non-learned mapping from intensity to color; while it improved classification accuracy in this study, it does not adapt to dataset-specific intensity distributions and its generalizability to other DBT datasets remains to be verified. Fourth, because oversampling in this study duplicated existing minority-class images rather than generating synthetic variations, the model may be more prone to overfitting on duplicated samples compared with augmentation-based balancing strategies; this risk was not directly quantified in the present experiments. Finally, while Table 2 reports supplementary results for two technique combinations between ROI with color mapping and ROI with CLAHE, a full pairwise ablation across all remaining combinations (e.g., CLAHE with color mapping) was beyond the scope of this study and is identified as a direction for future work.

Conclusion

This study evaluated four DBT image preprocessing techniques Color Mapping, Original, ROI, and CLAHE to identify the most effective approach for improving the ResNet-50 model in breast cancer classification. Table 1 shows that the color mapping method was the most accurate overall. The model had a 93% recall rate for the benign class and a 96% recall rate for the malignant class when it came to sensitivity. The accuracy was also very high: 95% for the benign group and 94% for the malignant group. The scores for F1 were 94 and 95%, in that order.

The original technique was 90% accurate, and the ROI technique was 93% accurate. Even though the validation and some of the metrics weren't very good, this still happened. The CLAHE method, on the other hand, was the least accurate 86% and not very stable, especially for the benign class. These results indicate that preprocessing methods are very important for improving the accuracy of DBT image classification. Color mapping is the best way to help CNN models identify patterns in tissue.

Beyond the four single-technique comparisons, supplementary experiments combining ROI segmentation with CLAHE and with color mapping were also conducted (Table 2). The ROI with CLAHE combination raised accuracy from 86 to 92%, indicating that restricting CLAHE's contrast enhancement to the segmented breast region substantially mitigates its tendency to amplify background noise. In contrast, combining ROI with color mapping matched color mapping alone in overall accuracy 95%, but shifted the precision-recall balance between classes: Benign-class recall and F1 improved, while malignant class recall decreased slightly 96 to 94%.

Table 1: Performance evaluation

Pre-processing techniques	Performance evaluation table (%)					
	Accuracy	Recall		Precision		F1-Score
		0	1	0	1	0 1
Color Mapping	95	93	96	96	94	94 95
Original	93	100	86	86	100	93 93
ROI	90	99	80	85	98	91 88
CLAHE	86	91	86	81	92	86 86

Table 2: Combined preprocessing technique evaluation

Pre-processing techniques	Performance evaluation table (%)					
	Accuracy	Recall		Precision		F1-Score
		0	1	0	1	0 1
ROI + Color Mapping	95	96	94	95	96	96 95
ROI + CLAHE	92	93	91	93	91	93 91

Because malignant-class recall is the more clinically critical metric in a screening context, this indicates that ROI cropping does not offer a uniform improvement when applied on top of color mapping. From a computational standpoint, ROI with color mapping also involves an additional processing stage thresholding, contour detection, and cropping prior to the color mapping transformation itself, whereas color mapping alone applies a single transformation directly to the grayscale image; the exact computational overhead of this additional stage was not measured in this study. Given that this added processing is not accompanied by a clear performance benefit, color mapping therefore remains the single most effective and efficient preprocessing technique identified in this study, while ROI with CLAHE represents the most effective combination for improving a weaker baseline technique.

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Author's Contributions

Qodri Aziz: Conducted the major research work, including implementation of image preprocessing, ResNet-50-based CNN classification experiments, data analysis, manuscript drafting, revision, and preparation of supporting documents.

Slamet Riyadi: Was responsible for topic selection, research supervision, research direction, manuscript critical review, and corresponding author.

Suzaimah Binti Ramli: Involved in the research methodology, formulation, and review of the proposed image pre-processing methods.

Nurwahyu Alamsyah: Was involved in testing and evaluation, including model performance analysis, validation of the results, and interpretation of the experimental findings.

Shofwatul 'Uyun: The scientific content of the paper was improved. All authors have read and agreed to the final manuscript.

Ethics

This study utilised publicly available de-identified digital breast tomosynthesis image data from The Cancer Imaging Archive (TCIA). The authors did not intervene, recruit patients, or collect identifiable personal data directly. Therefore, this study did not require any additional ethical approval. The dataset is used for academic and research purposes only.

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