engineering proceedings

MDPI

Proceeding Paper

Artificial Intelligence-Powered Breast Cancer Prognosis: Optimizing Deep Learning with Image Normalization †

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† Presented at 2025 IEEE International Conference on Computation, Big-Data and Engineering (ICCBE), Penang, Malaysia, 27–29 June 2025.

Abstract

Breast cancer is one of the most fatal cancers for women and requires accurate cancer diagnosis technology. In this research, we incorporated advanced image preprocessing methods, including histogram equalization (HE), stain normalization, intensity normalization, and Richard normalization, along with deep learning, to enhance invasive ductal carcinoma prognosis. Additionally, we evaluated the effectiveness of HE for different image contrast enhancement and model performance optimization methods. The Residual network with 50 layers, the densely connected convolutional network, and the efficient neural network architecture were tested on a publicly available histopathological image dataset. DenseNet showed an accuracy of 0.5523 with Richard normalization and Stain Normalization. ResNet-50 showed an accuracy of 0.5500 when using histogram equalization as a pre-processing step. The results proved that histogram equalization is effective in relieving contrast and feature extraction, which are important in class medical image analysis and dealing with class imbalance problems. The results demonstrate the feasibility of artificial intelligence-based solutions in improving breast cancer prognosis through these inexpensive and efficient prognosis tools.

Keywords: breast cancer; deep learning; image preprocessing; equalization; image normalization; ResNet-50; DenseNet; EfficientNet; histopathological imaging; medical prognosis

1. Introduction

Breast cancer is a leading cause of mortality among women, with approximately 700,000 deaths recorded globally in 2020 [1]. Early detection significantly improves survival rates, yet traditional diagnostic methods, including mammograms, ultrasounds, MRI, and histopathological analysis, face challenges such as high costs, time consumption, and susceptibility to human error [2,3]. These limitations often result in delayed or inaccurate diagnoses. Artificial intelligence (AI), particularly deep learning, offers a transformative approach to breast cancer detection by automating image analysis, enhancing diagnostic accuracy, and reducing false-positive and false-negative rates [4,5].

AI systems efficiently process large datasets, identify critical patterns, and support medical professionals in decision-making, with the added potential to improve accessibility in resource-limited regions [6,7]. Despite its promise, AI-based breast cancer detection is still in its infancy, requiring further research to enhance model reliability and clinical applicability [8,9].

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Academic Editors: Teen-Hang Meen, Wei Chien and Cheng-Fu Yang

Published: 16 April 2026

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This study aims to advance breast cancer prognosis by enhancing the predictive accuracy of deep learning models in identifying invasive ductal carcinoma (IDC) using histopathological images. We systematically evaluated the impact of advanced preprocessing techniques, histogram equalization, stain normalization, intensity normalization, and Richard normalization on the performance of the residual network with 50 layers (ResNet-50), the densely connected convolutional network (DenseNet), and the efficient neural network architecture (EfficientNet) architectures [10–12]. By identifying the optimal combination of preprocessing methods and model configurations, classification outcomes were enhanced to ensure the scalability and robustness of these models across diverse datasets and imaging conditions [7,13]. By developing precise, cost-effective, and scalable AI-driven tools, medical professionals can improve patient prognostic outcomes [4,8].

2. Literature Review

The development of AI-based tools for breast cancer detection, particularly for IDC, offers significant potential for both societal and commercial impact. IDC, a highly aggressive subtype comprising nearly 80% of breast cancer cases, requires early detection to improve patient outcomes [4,9]. Current diagnostic methods, reliant on manual analysis, are time-intensive, error-prone, and heavily dependent on specialized expertise, often unavailable in resource-limited settings [5,14]. Deep learning-based solutions automate and streamline this process, enabling faster, more accurate, and cost-effective cancer detection [3,5]. Such AI-driven technologies revolutionize healthcare by reducing labor costs, supporting scalability, and introducing revenue models such as AI-as-a-Service (AIaaS) for broader accessibility [1,8]. Socially, they enable general access to quality diagnostic tools, bridge healthcare disparities, and support healthcare professionals by alleviating workload and enhancing focus on complex cases [6,7]. The promise of improved patient care and reduced global health inequities underscores the transformative potential of AI in advancing breast cancer detection and prognosis.

In this research, deep learning was used to detect IDC in histopathological images. Deep learning models are well-suited for image classification tasks, especially in medical imaging, due to their ability to automatically extract hierarchical features from complex image data. Three state-of-the-art deep learning models were utilized: ResNet-50, DenseNet, and EfficientNet. Each model was selected due to its strengths and suitability. Figure 1 shows the detection ontology of breast cancer.

2.1. ResNet-50

ResNet-50 is a deep convolutional neural network known for its skip connections, which allow the effective training of deep networks. The skip connections help mitigate the vanishing gradient problem by passing information across layers, making ResNet-50 ideal for tasks like medical image classification, where deep architectures are necessary to capture intricate details [13,15].

- Feature extraction: Its 50-layer deep architecture allows for the extraction of detailed features from histopathological images, which is crucial for detecting subtle differences between healthy and cancerous tissues [16,17].
- High accuracy: ResNet-50 consistently achieves high accuracy in image classification tasks, making it a reliable benchmark in this project [15,18].
- Robustness in learning: ResNet-50's skip connections help it learn more effectively from medical images, which require attention to fine details that may signal disease [3,14].

The architecture of ResNet-50 is presented in Figure 2.

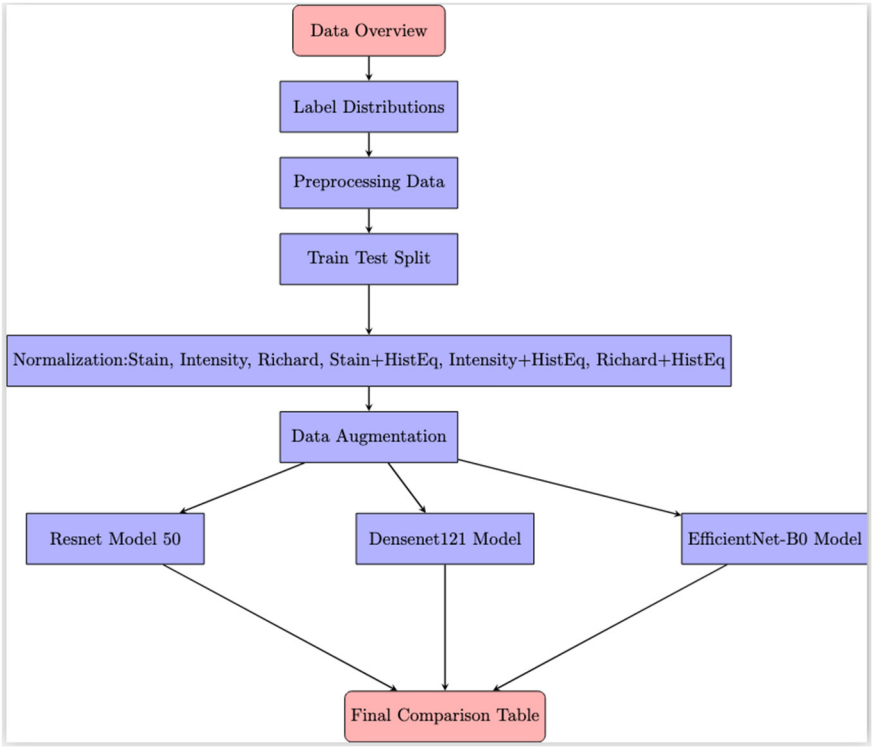

Figure 1. Breast cancer detection ontology.

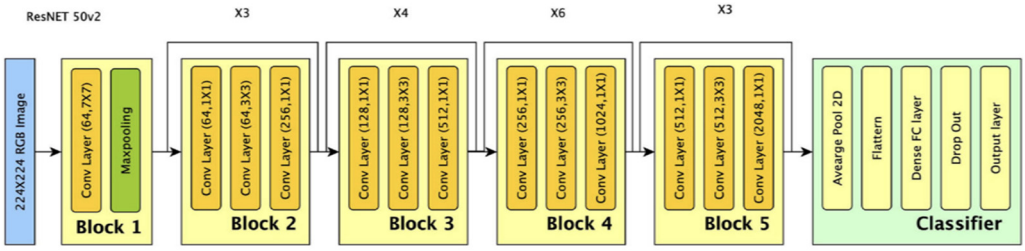

Figure 2. ResNet-50 architecture.

2.2. DenseNet

DenseNet was selected for its unique architecture, where each layer is connected to every other layer, ensuring efficient feature reuse [18]. This architecture allows DenseNet to achieve high performance with fewer parameters, making it an efficient model for deep learning tasks in medical imaging [7].

- Efficient feature reuse: The dense connections ensure that features learned earlier in the network are reused throughout the model, making it highly efficient at extracting important patterns in histopathological images [19].
- Gradient flow: DenseNet's architecture enhances the flow of gradients, improving the training process, especially when working with complex medical images, where differentiating between IDC-positive and IDC-negative patches is difficult [2,5].
- Fewer parameters: Despite its deep architecture, DenseNet uses fewer parameters than ResNet-50, making it memory-efficient and better suited for balancing accuracy and resource constraints [15].

The architecture of DenseNet is presented in Figure 3.

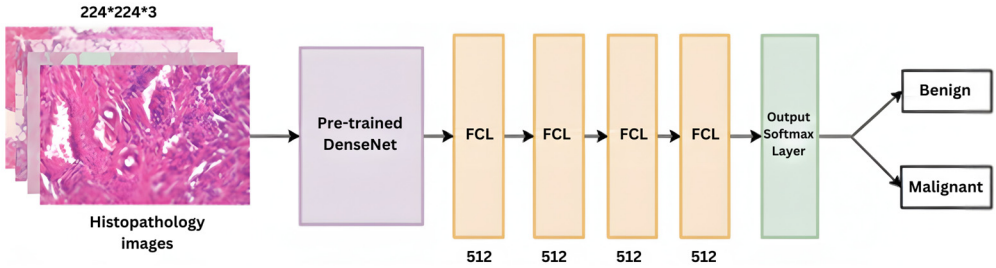

Figure 3. DenseNet architecture.

2.3. EfficientNet

EfficientNet was chosen as the primary model for its balance between accuracy and computational efficiency. EfficientNet uses compound scaling to scale the network's depth, width, and resolution in a balanced manner, ensuring optimal performance with fewer parameters [13,20].

- Balanced performance and efficiency: EfficientNet is designed to deliver high accuracy while keeping computational requirements low, making it ideal for processing large histopathological datasets [16].
- Compound scaling: EfficientNet's ability to scale its parameters uniformly ensures a high level of feature extraction across different levels of granularity, which is essential for medical images where both high-level and low-level features indicate disease [7,9].
- Fewer parameters, high accuracy: Compared with ResNet-50 and DenseNet, EfficientNet achieves comparable or better accuracy with fewer parameters, making it highly efficient and effective for medical applications [15,18].
- Scalability: EfficientNet offers scalable models such as EfficientNet-B0 for quick development and EfficientNet-B7 for higher accuracy, providing flexibility in handling different computational resources during the project [21].

The architecture of EfficientNet is presented in Figure 4.

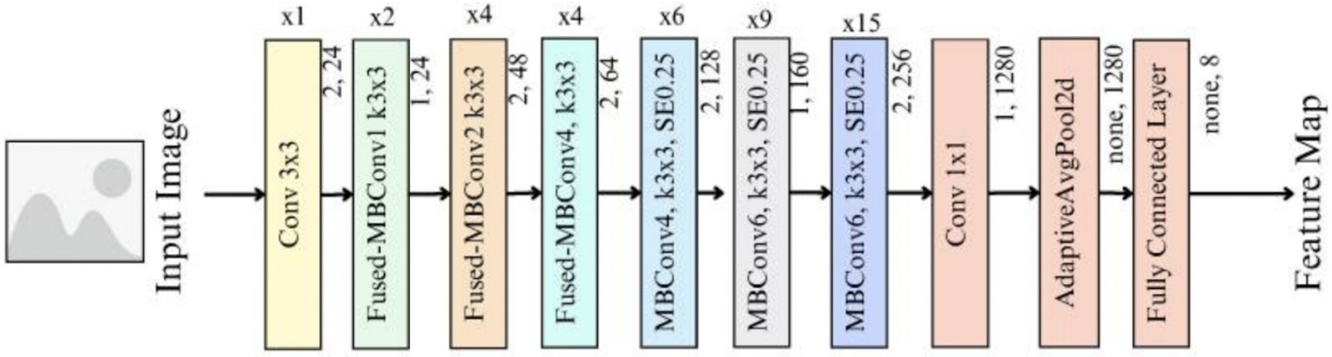

Figure 4. EfficientNet architecture.

3. Methodology

Figure 5 outlines the method used in this study for detecting IDC in histopathological images. It involved data collection and preprocessing (including normalization and augmentation) and training multiple deep learning models. Each model was evaluated for their performance to select the best model for IDC detection.

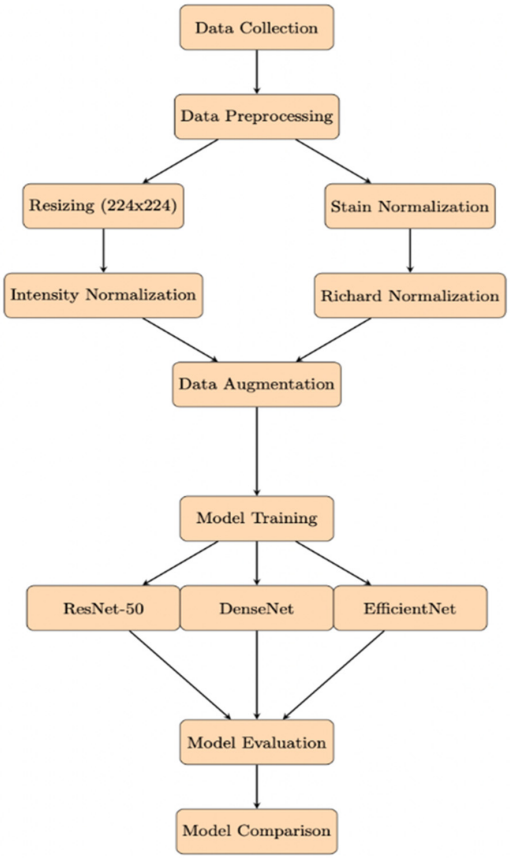

Figure 5. Methodology used in this study.

3.1. Dataset

The dataset used in this study comprises histopathological whole-slide images of breast tissue specimens, aimed at detecting invasive ductal carcinoma (IDC)—a prevalent and aggressive form of breast cancer. From these slides, 277,524 image patches (50 × 50 pixels each) were extracted and categorized based on pathologists' analysis: IDC Positive (Class 1, 78,786 patches), indicating cancerous tissue, and IDC Negative (Class 0, 198,738 patches), representing healthy or other non-IDC subtypes (Figure 6). The images, stored in .png format, were resized to 224 × 224 pixels to meet the input requirements of deep learning models such as ResNet, DenseNet, and EfficientNet (Table 1). A total of 113 patient samples were used for training and 49 for validation.

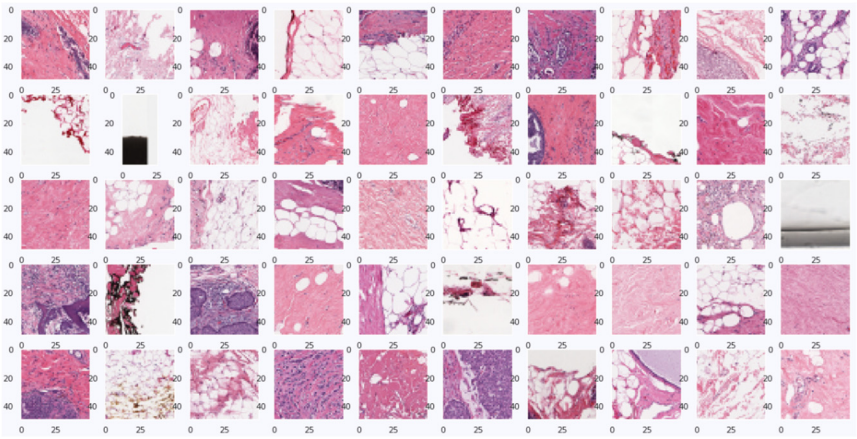

Figure 6. Sample images from dataset [1].

Table 1. Comparison of deep learning models used for breast cancer prognosis, highlighting their purposes, implementations, and advantages in medical imaging.

Model	Purpose	Implementation	Advantages
ResNet-50	Chosen for its ability to handle deep neural networks with skip connections that mitigate the vanishing gradient problem, enabling it to learn complex patterns.	Pre-trained on ImageNet and fine-tuned on the IDC dataset, with images resized to 224 × 224 pixels and normalized.	Effectively extracts features from complex medical images, allowing detection of subtle patterns in cancerous tissues.
DenseNet	Selected for its dense connections that enhance gradient flow and feature reuse, making it efficient in learning from medical images with subtle variations.	Pre-trained on ImageNet and fine-tuned on the IDC dataset.	Leverages all learned features effectively, improving its ability to detect cancerous tissue.
EfficientNet	Chosen for its computational efficiency through compound scaling, balancing the network's depth, width, and resolution, making it suitable for large-scale datasets.	Trained on the pre-processed dataset, with images resized and normalized.	Balances accuracy and computational efficiency, ideal for resource-constrained environments like medical prognostics.

3.2. Data Preprocessing

Data resizing was necessary to standardize image dimensions, which vary due to differences in medical imaging sources. Deep learning architectures such as ResNet-50, DenseNet, and EfficientNet require a fixed input size. Therefore, all images were resized to 224 × 224 pixels in this research. This standardization facilitates uniform data representation, preserves essential image features, and enhances computational efficiency. Python 3 libraries, including OpenCV 4.10.0 and TensorFlow 2.16.1, were employed. Specifically, OpenCV's cv2.resize(image, (224, 224)) function and TensorFlow's ImageDataGenerator enabled real-time resizing during data loading, streamlining the workflow and optimizing model training.

Data normalization was also important in classifying histopathological images in the detection of invasive ductal carcinoma (IDC). Feeding unscaled pixel values into neural networks results in unstable training dynamics and slower convergence. Normalization mitigates these issues by reducing pixel intensity variance, promoting smoother gradient flow during backpropagation, and facilitating the extraction of meaningful features. In this study, pixel values were normalized by dividing them by 255, effectively transforming them into fractional values between 0 (black) and 1 (white). This process involves scaling pixel values, originally ranging from 0 to 255, to a normalized range, typically between 0 and 1. This operation was conducted using Python libraries such as NumPy (image = image/255.0) and integrated into TensorFlow's preprocessing pipeline via ImageDataGenerator, thereby enhancing model performance and training efficiency. Additional normalization techniques were applied to address domain-specific challenges in histopathological imaging.

- Stain normalization: Variability in staining protocols and equipment introduces color inconsistencies that obscure tissue morphology. The Macenko algorithm is used to standardize the color space by aligning images to a reference stain profile, ensuring consistent input and improving model generalization.
- Intensity normalization: Pixel values are normalized to a uniform range (e.g., [0, 1] or [−1, 1]) to compensate for differences in brightness and contrast caused by imaging conditions. By dividing raw pixel values by 255, intensity normalization stabilizes training, reduces the risk of gradient instability, and improves data manageability for deep learning models.
- Richard normalization: Contrast enhancement methods such as histogram equalization and contrast-limited adaptive histogram equalization (CLAHE) are employed to amplify critical features in histopathological images. These techniques redis-

tribute pixel intensities to highlight malignant regions while preserving structural integrity, thereby facilitating more accurate differentiation between healthy and cancerous tissues.

3.3. HE

Histogram equalization was applied to enhance the contrast of the histopathological images before feeding them into the models. Histogram equalization is used to adjust the contrast of an image by redistributing the intensity values, making features in the image more distinguishable for the models.

Pixel values in 8-bit images were divided by 255 to scale them into the range of [0, 1], making the data easier for the model to process. This was conducted using NumPy ('image = image/255.0') or integrated into TensorFlow's preprocessing pipeline with 'ImageDataGenerator'. By converting pixel intensities to a range between 0 (black) and 1 (white), consistent input is ensured, improving the efficiency of model training and enabling the network to learn patterns more effectively.

- Enhance image contrast: In medical imaging, such as histopathological images of breast tissue, the contrast between cancerous and non-cancerous is not always sharp. Applying histogram equalization helps enhance these contrasts, making cancerous regions more detectable.
- Improve feature extraction: By improving the contrast, the models better detect patterns and structures, which are critical for distinguishing between IDC-positive (+) and IDC-negative (−) regions in tissue samples.

3.4. Data Augmentation

The main objective of data augmentation is to increase the variability of the training data, enabling the model to learn from a wider range of possible image scenarios [22]. Medical images, such as histopathological images used in this project, look similar to one another. Without augmentation, the model might memorise the training data and fail to generalise to new, unseen images, leading to overfitting.

- Random sampling (IDC(−) = 1000, IDC(+) = 1200)
- Random brightness (0.5 px~2.0 px)
- Random shear (x: 0.0~0.2, y: 0.0~0.2)
- Class weights in the loss function
- Oversampling of the minority class
- Undersampling the majority class
- Combination of oversampling and undersampling

4. Result and Discussion

We evaluated the performance of ResNet-50, DenseNet, and EfficientNet using HE, stain normalization, intensity normalization, and Richard normalization.

4.1. Effectiveness of HE

ResNet-50 demonstrated robustness with or without HE, achieving an accuracy of 0.5500 with HE and 0.5477 without it, indicating a modest enhancement through contrast improvement. DenseNet showed a similar trend, achieving 0.5455 with HE and 0.5409 without it. Notably, DenseNet peaks at 0.5523 under stain normalization (without HE) and Richard normalization (with HE), surpassing ResNet-50. EfficientNet, however, performed worse than the other models, with an accuracy of 0.5023 with HE and 0.5136 without it, showing limited sensitivity to HE.

https://doi.org/10.3390/engproc2026128049

4.2. Stain Normalization

DenseNet achieves its highest accuracy of 0.5523 under stain normalization without HE, demonstrating significant benefits. ResNet-50 also performed well, achieving an accuracy of 0.5318 without HE and 0.5136 with HE, although the improvement was less pronounced than DenseNet. EfficientNet remains stable, with an accuracy of 0.5318 in both cases, indicating that the addition of HE has minimal impact, while stain normalization maintained its performance.

4.3. Intensity Normalization

ResNet-50 demonstrated notable improvement when intensity normalization was combined with HE, reaching an accuracy of 0.5432 compared with 0.4932 without HE. This underscores the importance of contrast enhancement for ResNet-50 in histopathological image classification. DenseNet exhibited stable performance, with accuracies of 0.5250 with HE and 0.5182 without HE, indicating limited sensitivity to HE. EfficientNet showed marginal gains, showing accuracies of 0.5364 with HE and 0.5250 without HE, suggesting modest benefits from this preprocessing strategy.

4.4. Richard Normalization

Richard Normalization, particularly when combined with HE, was effective for ResNet-50 and DenseNet. ResNet-50 showed an accuracy of 0.5409 with HE, while DenseNet showed 0.5523 under this combination, demonstrating its effectiveness. EfficientNet, however, showed less improvement, achieving an accuracy of 0.5091 with HE, reaffirming its relatively low performance across all techniques.

The overall performance of the models is presented in Table 2.

Table 2. Overall performance of models (The crown icon denotes that the method has been formally recognized as appropriate and valid for addressing the objectives of this study).

	ResNet-50	**DenseNet**	**EfficientNet**
Histogram Equalization (HE)	0.5500	0.5455	0.5023
Without Histogram Equalization (HE)	0.5477	0.5409	0.5136
Stain Normalisation Without Histogram Equalization (HE)	0.5318	0.5523 	0.5318
Stain Normalisation With Histogram Equalization (HE)	0.5136	0.5273	0.5159
Intensity Normalisation Without Histogram Equalization (HE)	0.4932	0.5023	0.5250
Intensity Normalisation With Histogram Equalization (HE)	0.5432	0.5182	0.5364
Richard Normalisation Without Histogram Equalization (HE)	0.5250	0.5250	0.5023
Richard Normalisation With Histogram Equalization (HE)	0.5409	0.5523 	0.5091

5. Conclusions

DenseNet emerged as the most effective model, achieving the highest accuracy of 0.5523 under both stain normalization (without histogram equalization) and Richard nor-

malization (with histogram equalization). ResNet-50 demonstrated competitive performance, reaching an accuracy of 0.5500 with histogram equalization and maintaining consistent results across various preprocessing techniques. In contrast, EfficientNet consistently underperformed, suggesting the need for further optimization or alternative preprocessing strategies to improve its classification efficacy.

Author Contributions: Conceptualization, C.Y.Y., D.J.W.P. and S.M.L.; methodology, C.Y.Y., D.J.W.P. and S.M.L.; validation, C.Y.Y., D.J.W.P. and S.M.L.; formal analysis, C.Y.Y., D.J.W.P. and S.M.L.; investigation, C.Y.Y., D.J.W.P. and S.M.L.; resources, C.Y.Y., D.J.W.P. and S.M.L.; data curation, C.Y.Y., D.J.W.P. and S.M.L.; writing—original draft preparation, C.Y.Y., D.J.W.P. and S.M.L.; writing—review and editing, C.Y.Y., D.J.W.P. and S.M.L.; visualization, C.Y.Y., D.J.W.P. and S.M.L.; supervision, C.W.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the paper.

Acknowledgments: The authors would like to express their heartfelt gratitude to Tunku Abdul Rahman University of Management and Technology (TAR UMT) for providing the resources throughout this research.

Conflicts of Interest: The authors declare no conflicts of interest.

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