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Enhancing Rice Disease Classification Using CLAHE and Transfer Learning on Leaf Image Data

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Abstrak

Penyakit daun padi menjadi ancaman besar bagi ketahanan pangan global karena menurunkan hasil panen dan kualitas beras, sehingga mendorong kebutuhan akan solusi diagnosis yang dapat diterapkan secara luas, objektif, dan otomatis. Penelitian ini menyelidiki dampak Contrast Limited Adaptive Histogram Equalization (CLAHE) dan pembelajaran transfer terhadap klasifikasi tiga penyakit daun padi yang umum—Bacterial Blight, Brown Spot, dan Leaf Smut—dari gambar daun dalam format RGB. Dengan menggunakan dataset yang terdiri dari 2.342 gambar yang dibagi menjadi set pelatihan, validasi, dan pengujian (80:10:10), kami merancang alur eksperimen terkontrol yang mencakup empat skenario: dengan/tanpa CLAHE, serta dengan/tanpa pembelajaran transfer. CLAHE diterapkan sebagai langkah prapemrosesan untuk meningkatkan kontras lokal dan visibilitas lesi di bawah pencahayaan yang heterogen serta latar belakang yang berantakan, sementara pembelajaran transfer memanfaatkan jaringan saraf konvolusional yang telah dilatih sebelumnya pada ImageNet dan disesuaikan untuk pengenalan penyakit padi. Model dilatih dan dievaluasi menggunakan akurasi, skor F1 makro, dan skor F1 tertimbang pada set uji yang disisihkan. Konfigurasi gabungan CLAHE + pembelajaran transfer mencapai kinerja terbaik, dengan akurasi keseluruhan sebesar 0,94 serta skor F1 makro dan tertimbang sebesar 0,94, yang secara signifikan mengungguli model dasar tanpa peningkatan dan tanpa pembelajaran transfer. Analisis kualitatif menunjukkan peningkatan kemampuan pemisahan antara kelas-kelas yang secara visual serupa, terutama Brown Spot dan Leaf Smut, dalam kondisi pencitraan yang menantang. Temuan ini menegaskan keefektifan integrasi peningkatan kontras dengan pembelajaran transfer untuk klasifikasi penyakit padi yang andal dan berorientasi lapangan, serta menyoroti jalur praktis menuju dukungan pengambilan keputusan berbasis gambar yang dapat diandalkan dalam pertanian presisi.

Kata kunci*— Penyakit daun padi; Klasifikasi berbasis gambar; CLAHE; Pembelajaran transfer; Pembelajaran mendalam*

Abstract

Rice foliar diseases pose a major threat to global food security by reducing yield and grain quality, motivating the need for scalable, objective, and automated diagnosis solutions. This study investigates the impact of Contrast Limited Adaptive Histogram Equalization (CLAHE) and transfer learning on the classification of three common rice leaf diseases—Bacterial Blight, Brown Spot, and Leaf Smut—from RGB leaf images. Using a dataset of 2,342 images split into training, validation, and test sets (80:10:10), we design a controlled experimental pipeline comprising four scenarios: with/without CLAHE, and with/without transfer learning. CLAHE is applied as a preprocessing step to enhance local contrast and lesion visibility under heterogeneous illumination and cluttered backgrounds, while transfer learning leverages ImageNet-pretrained convolutional neural networks fine-tuned for rice disease recognition. Models are trained and evaluated using accuracy, macro F1, and weighted

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F1 on a held-out test set. The combined CLAHE + transfer learning configuration achieves the best performance, with an overall accuracy of 0.94 and macro and weighted F1-scores of 0.94, substantially outperforming non-enhanced and non-transferred baselines. Qualitative analysis indicates improved separability between visually similar classes, particularly Brown Spot and Leaf Smut, under challenging imaging conditions. These findings underscore the effectiveness of integrating contrast enhancement with transfer learning for robust, field-oriented rice disease classification and highlight a practical pathway toward reliable image-based decision support in precision agriculture.

Keywords— *Rice leaf diseases; Image-based classification; CLAHE; Transfer learning; Deep learning*

1. INTRODUCTION

Rice is a staple food for more than half of the world's population, and its sustainable production is critically threatened by foliar diseases that can severely reduce yield, compromise grain quality, and undermine food security. Early and accurate diagnosis of rice leaf diseases enables timely intervention, mitigates losses, and supports precision crop management strategies aimed at sustainable intensification [1] [2] [3]. Conventional field scouting by human experts is labor-intensive, time-consuming, and difficult to scale across large and spatially dispersed farms, while also being vulnerable to subjectivity and inconsistent assessments [1] [4] [5]. As a result, there is strong demand for automated, image-based diagnostic systems that can deliver consistent, rapid, and cost-effective support to farmers and agronomists within modern precision agriculture workflows [3] [6] [5].

Designing reliable automated diagnosis for rice diseases is technically challenging because field-acquired leaf images exhibit substantial variability in illumination, background clutter, and image quality, along with overlapping symptoms and fuzzy lesion boundaries [1] [7] [8]. Such variability degrades the visibility of critical disease patterns and complicates feature extraction, particularly when annotated datasets remain limited, class distributions are imbalanced, and disease manifestations differ across growth stages and agroecological zones [9] [10] [11]. These factors jointly increase the risk of overfitting, reduce generalization to new environments, and restrict the practical deployment of deep learning models in real-world farming scenarios [4] [12].

Recent advances in deep convolutional neural networks (CNNs) and transfer learning have significantly improved rice leaf disease classification performance, especially under limited-data regimes where pretrained ImageNet backbones are fine-tuned on domain-specific images [2] [5]. Studies report high accuracy for models such as VGG19, DenseNet121, Xception, InceptionV3, EfficientNet variants, and fusion-based ensembles, demonstrating the effectiveness of feature transfer for rice disease recognition [2] [10] [3]. Nonetheless, the literature also documents cases where carefully designed custom CNNs outperform transfer learning, highlighting that pretrained architectures are not universally superior and that performance remains sensitive to dataset characteristics and optimization strategies [13] [14]. Furthermore, when models are tested on new, expert-validated field images, class-wise performance can degrade and robustness across disease categories becomes uneven, indicating residual gaps in real-world generalization [4] [12].

In parallel with architectural progress, many studies emphasize the importance of image preprocessing, enhancement, segmentation, and augmentation to improve lesion visibility and strengthen robustness against noise, background interference, and illumination changes [2] [15]. Pipelines incorporating background removal, resizing, and generic contrast enhancement have been linked to better classification metrics and improved generalization under challenging conditions [2] [15]. However, despite the clear relevance of lighting variation, blur, fuzzy edges, and complex symptom presentation in field datasets, there is a notable lack of direct, controlled evidence on the specific role of Contrast Limited Adaptive Histogram Equalization (CLAHE) in rice leaf disease classification [1] [11] [16]. Existing works rarely perform ablation studies that compare CLAHE-enhanced inputs against non-enhanced baselines within the same transfer-learning architecture, largely because research has prioritized benchmarking different networks over systematically interrogating preprocessing choices [9] [8] [17].

The present study addresses this gap by investigating whether integrating CLAHE-based local contrast enhancement with state-of-the-art transfer learning backbones can improve the classification of rice leaf diseases, particularly under variable illumination and low-contrast conditions. The central motivation is that CLAHE, by adaptively enhancing local contrast while limiting noise amplification, may increase lesion salience, stabilize feature extraction, and thereby improve both accuracy and robustness compared with standard preprocessing alone [16] [11]. We therefore develop a CLAHE-augmented image preprocessing pipeline coupled with fine-tuned CNN-based transfer learning models for rice disease recognition.

Our contributions are threefold. First, we provide a systematic, CLAHE-focused evaluation within a controlled experimental design, directly comparing CLAHE-enhanced and non-enhanced inputs for identical transfer learning architectures across diverse rice leaf images. Second, we analyze not only overall accuracy but also class-wise performance under variable image quality to assess whether CLAHE preferentially benefits difficult, low-contrast, or illumination-shifted cases, thereby speaking to real-field robustness [9] [10]. Third, we position the empirical findings within the broader scientific foundation of rice disease modeling, clarifying when and how local contrast enhancement substantively contributes beyond architectural tuning and generic preprocessing. Through this analysis, the study seeks to move beyond reporting another high-performing classifier and instead provide mechanistically grounded evidence on the role of CLAHE in enhancing transfer learning-based rice disease diagnosis, thereby supporting more reliable, field-ready decision support tools.

2. METHODS

2.1 Overview of Experimental Design

The proposed methodology follows a structured pipeline for rice leaf disease classification, beginning with dataset preparation and preprocessing, followed by data augmentation, model training under four controlled experimental scenarios, and quantitative evaluation on a held-out test set. The dataset consists of 2,342 rice leaf images belonging to three disease classes (Bacterial Blight, Brown Spot, and Leaf Smut). The images are partitioned into training (1,874 images), validation (234 images), and test (234 images) subsets using an 80:10:10 split to enable unbiased performance assessment and hyperparameter monitoring, consistent with prior rice and plant disease classification studies [5] [26].

Figure 1 illustrates this end-to-end workflow, from data collection through preprocessing, experimental branching, training, and evaluation. The figure emphasizes the separation between data handling (collection, splitting, preprocessing and augmentation) and modeling stages, as well as the factorial manipulation of contrast enhancement (CLAHE) and transfer learning (ConvNeXtBase) to isolate their individual and combined effects on classification performance.

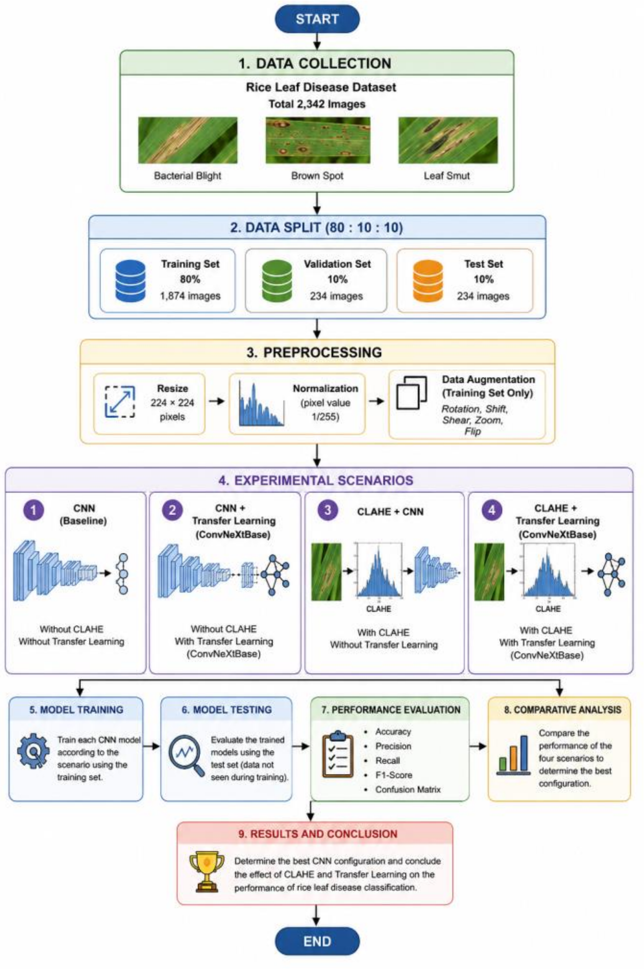

Figure 1. Overall workflow of the proposed rice leaf disease classification methodology

The methodological purpose of this workflow is to support a gap-filling ablation design in which four scenarios are trained and compared under identical data splits, optimizer settings, augmentations, and metrics. This directly addresses the limited evidence on the combined use of CLAHE and ConvNeXt-based transfer learning for rice leaf disease classification while remaining aligned with comparative CNN benchmarking practices in plant disease imaging [27] [28].

2.2 Image Preprocessing

Before model training, all rice leaf images undergo a uniform preprocessing procedure to standardize input size and pixel value distributions. Each image is first resized to 224 × 224 pixels to satisfy the fixed input dimension requirements of both the baseline CNN and the ConvNeXtBase transfer learning model and to align with common practice in ImageNet-pretrained architectures [5] [27]. The resizing operation can be formalized as a mapping from an original image domain to a fixed-size target domain:

$$f(x,y) \rightarrow f'(x',y'), \quad (x',y') \in \{1,\ldots,244\} \times \{1,\ldots,244\}$$

where f(x,y) denotes the original image and f'(x',y') represents the resized image with spatial resolution 224 × 224. This transformation preserves essential lesion structures while reducing computational cost relative to higher resolutions and avoiding excessive loss of fine-grained disease patterns that can occur at lower resolutions [5].

Following resizing, pixel intensities are normalized channel-wise by scaling the original 8-bit range [0, 255] to [0, 1]. For an original pixel value x, the normalized value x' is computed as

$$x' = \frac{x}{255}$$

Here, x is the raw pixel intensity and x' is the scaled value used as CNN input. This normalization improves numerical stability during stochastic gradient-based optimization by constraining input magnitudes, which in turn reduces the risk of exploding or vanishing gradients and facilitates more efficient convergence [28]. Together, resizing and normalization create a consistent and standardized input representation for all subsequent experimental scenarios.

2.3 Data Augmentation

To mitigate overfitting arising from the relatively small dataset size and to enhance robustness to real-world imaging variability, data augmentation is applied exclusively to the training subset using the TensorFlow Keras ImageDataGenerator framework. This generator performs online augmentation, creating a different stochastic transformation of each image at every epoch, thereby increasing the effective diversity of training samples without altering the validation or test distributions [5] [29].

The augmentation strategy includes random rotation, translation, shear, zoom, and flipping operations. Images are rotated by up to 40° around their center, promoting orientation invariance to the varied leaf positions encountered in field conditions. Random width and height shifts of up to 20% of the image dimensions simulate off-centered leaves, encouraging the model to focus on disease patterns rather than absolute spatial location. A shear factor of 0.2 introduces mild affine distortions that approximate changes in camera viewpoint. Zoom augmentation within ±20% allows the CNN to learn lesions at multiple scales, from close-up to more distant views. Horizontal and vertical flips generate mirrored versions of leaves, preserving disease morphology while diversifying orientation. Collectively, these transformations encourage the model to learn more generalizable color, texture, and shape descriptors of rice diseases rather than overfitting to specific acquisition conditions [28] [26].

2.4 CNN Model Training and Hyperparameter Configuration

Four experimental scenarios are defined to disentangle the contributions of CLAHE and transfer learning: (1) baseline CNN trained from scratch without CLAHE, (2) ConvNeXtBase transfer learning without CLAHE, (3) CLAHE-enhanced images with a CNN trained from scratch, and (4) CLAHE combined with ConvNeXtBase transfer learning. In all scenarios, the same resized, normalized inputs and identical augmentation settings are used for the training set, and the same validation and test sets are employed, ensuring a controlled comparative design similar to recent plant disease benchmarking work [27] [23]. CLAHE, when used, is applied as an upstream enhancement to the resized, normalized images in the training and evaluation streams for the corresponding scenarios, in line with evidence that CLAHE is most effective as a contrast enhancer feeding into a downstream CNN feature extractor [23] [28].

Model optimization is performed for 50 epochs, which provides sufficient iterations for convergence while limiting overfitting risk on the modest-sized dataset [5]. A batch size of 64 is used during training to balance hardware efficiency and stable gradient estimates, whereas a smaller batch size of 32 is employed for validation and testing to reduce memory consumption. The Adam optimizer is adopted because of its adaptive moment estimation and empirical success in plant disease image classification [5] [26]. The initial learning rate is set to 1×10^{-4}, a value commonly used in fine-tuning pretrained CNNs as it enables gradual adaptation of high-level filters without destabilizing earlier convolutional layers [27].

Let θ denote the network parameters and $\mathcal{L}(\theta)$ the mini-batch loss. Adam updates θ at iteration t according to

$$\theta_{t+1} = \theta_t - \alpha \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

where α is the learning rate, $\widehat{m}_t$ and $\hat{v}_t$ are bias-corrected first and second moment estimates of the gradient, and ϵ is a small constant for numerical stability. This adaptive update rule facilitates efficient training across layers with heterogeneous gradient statistics.

After training, all four scenarios are evaluated on the unseen test set using accuracy, precision, recall, F1-score, and confusion matrices, enabling both aggregate and class-wise assessment of rice disease classification performance and a rigorous comparison of the marginal and joint benefits of CLAHE and ConvNeXt-based transfer learning [5] [30].

3. RESULTS AND DISCUSSION

3.1 Dataset Visualization and Analysis of Rice Leaf Diseases

Figure 2 presents representative images of the rice leaf disease dataset used in this study. The dataset consists of three major disease categories, namely Bacterial Blight, Brown Spot, and Leaf Smut, each exhibiting distinct visual characteristics, including variations in color, lesion morphology, and leaf tissue damage patterns. Displaying representative images from each category provides an initial understanding of the visual complexity and discriminative features that the Convolutional Neural Network (CNN) is expected to learn during the training process.

Furthermore, the dataset exhibits natural variations in image acquisition conditions, including differences in illumination, camera angle, leaf texture, and background environment. Such variability is essential in deep learning applications, as it enables the model to learn more generalized feature representations rather than memorizing specific image characteristics. Consequently, the visual diversity of the dataset is expected to enhance the robustness and generalization capability of the CNN model when classifying previously unseen rice leaf disease images.

Figure 2. Representative images of the rice leaf disease dataset for the three classes: *Bacterial Blight*, *Brown Spot*, and *Leaf Smut*.

3.1.1 Distribution of Images Across Disease Classes

Figure 3 illustrates the distribution of rice leaf disease images among the three classes, namely Bacterial Blight, Brown Spot, and Leaf Smut, which are divided into training, validation, and testing subsets. The dataset was partitioned using an 80:10:10 ratio, where 80% of the images were allocated for training, 10% for validation, and the remaining 10% for testing.

The stacked horizontal bar chart demonstrates that the number of images is relatively balanced across all classes within each subset, thereby minimizing the risk of model bias toward any particular disease category during training.

Maintaining a balanced dataset is particularly important in deep learning because class imbalance may cause the model to favor classes with a larger number of training samples, resulting in biased predictions. By ensuring a proportional class distribution and adopting a systematic data partitioning strategy, the CNN is expected to learn representative disease patterns from all classes equally, leading to more stable and reliable classification performance during the testing phase.

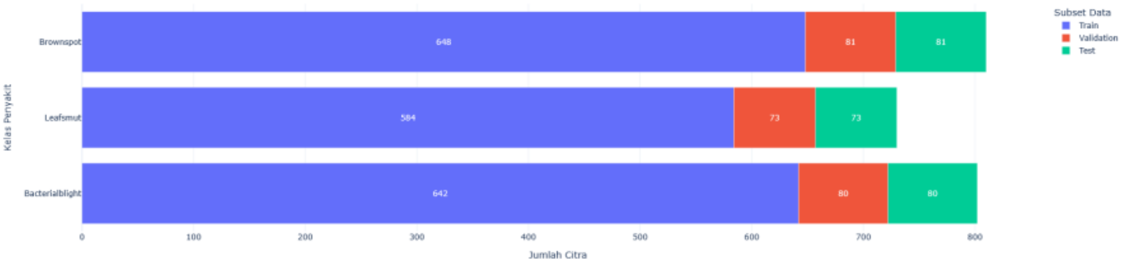

Figure 3. Distribution of rice leaf disease images across the training, validation, and testing subsets for each disease class.

3.1.2 Representative Rice Leaf Disease Images

Figure 4 presents representative samples from each rice leaf disease category used in this study, including Bacterial Blight, Brown Spot, and Leaf Smut. These images provide a visual overview of the morphological characteristics associated with each disease, serving as the primary input for the CNN during the feature learning process. Each disease class exhibits unique visual symptoms, such as differences in leaf discoloration, lesion shape and size, as well as variations in tissue texture caused by disease infection.

In addition, the representative images demonstrate variations in imaging conditions, including differences in lighting, background, and leaf orientation. Such variability is beneficial for improving the model's generalization capability, allowing the classification system to accurately recognize disease symptoms under diverse environmental conditions rather than only under controlled settings. Therefore, the visualization confirms that the dataset contains sufficient visual diversity to support effective CNN training and robust disease classification.

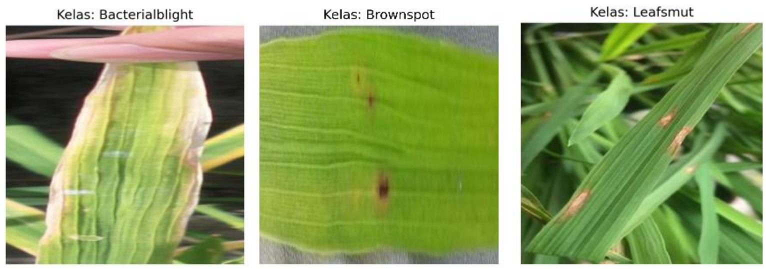

Figure 4. Representative rice leaf disease images for the three disease categories (*Bacterial Blight*, *Brown Spot*, and *Leaf Smut*) used as input data for CNN training and evaluation.

3.2 CNN Model Training Results Under Different Experimental Scenarios

3.2.1 Training and Validation Accuracy and Loss Curves

Figure 5 illustrates the training accuracy and training loss curves of the CNN model trained without applying either CLAHE or transfer learning. The accuracy curve shows a gradual increase during the early training epochs before stabilizing at a relatively low level compared with the other experimental scenarios. This finding indicates that the baseline CNN experienced limitations in extracting discriminative features from rice leaf disease images when relying solely on the conventional CNN architecture without image enhancement or pretrained feature representations.

Meanwhile, the training loss decreased consistently throughout the training process, indicating that the optimization process converged normally. However, the relatively high loss values and suboptimal accuracy suggest that the model failed to achieve satisfactory classification performance. These observations are consistent with the testing results, where this configuration produced the lowest classification accuracy among all experimental scenarios, highlighting the importance of incorporating both CLAHE and transfer learning to improve rice leaf disease classification performance.

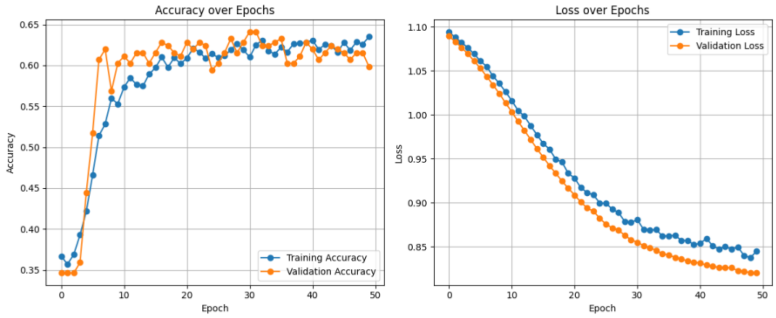

Figure 5. Training accuracy and training loss curves of the CNN model without CLAHE and transfer learning.

Figure 6 presents the training accuracy and training loss curves of the CNN model utilizing transfer learning without applying CLAHE. Compared with the baseline CNN, the accuracy increased more rapidly and converged to a significantly higher value at the end of training. This result indicates that pretrained weights effectively facilitate feature extraction from rice leaf disease images even without image enhancement.

Similarly, the training loss decreased substantially and consistently throughout the training process, demonstrating improved convergence behavior. The simultaneous increase in accuracy and decrease in loss indicate that transfer learning substantially enhances the model's generalization capability. These findings agree with the testing results, which demonstrate a considerable improvement in classification accuracy compared with the baseline CNN, confirming the effectiveness of transfer learning for rice leaf disease classification.

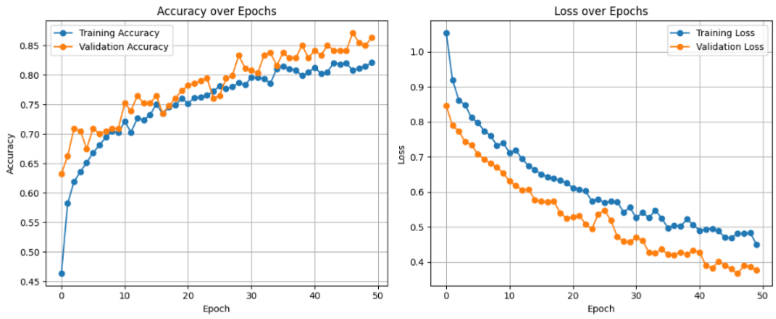

Figure 6. Training accuracy and training loss curves of the CNN model using transfer learning without CLAHE.

Figure 7 shows the training accuracy and training loss curves of the CNN model trained using CLAHE without transfer learning. The accuracy improved compared with the baseline CNN, although the improvement remained limited and did not reach the performance achieved using transfer learning. These findings indicate that CLAHE effectively enhances image contrast, allowing the CNN to better identify disease-related visual characteristics during training.

The loss curve exhibits a stable downward trend throughout the training epochs, indicating satisfactory convergence. Nevertheless, the final accuracy remained lower than that achieved by transfer learning, suggesting that image enhancement alone is insufficient to achieve optimal classification performance. Therefore, while CLAHE contributes positively to model performance, its effectiveness remains inferior to transfer learning for learning complex visual representations.

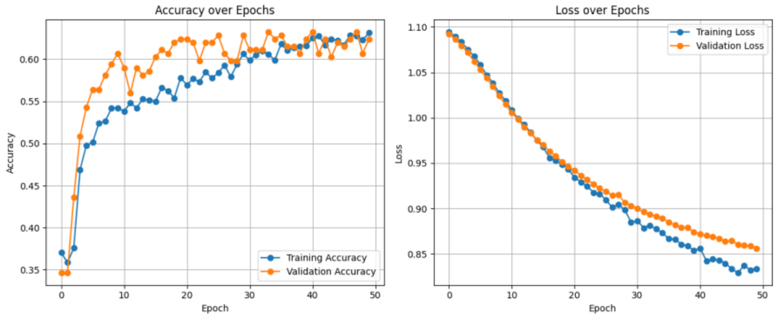

Figure 7. Training accuracy and training loss curves of the CNN model using CLAHE without transfer learning.

Figure 8 presents the training accuracy and training loss curves obtained using the combined CLAHE and transfer learning approach. Among all experimental scenarios, this configuration demonstrated the fastest and most stable improvement in accuracy, achieving the highest final training accuracy. This result suggests that image contrast enhancement through CLAHE and deep feature extraction enabled by transfer learning complement each other effectively in recognizing disease patterns.

Furthermore, the training loss decreased more rapidly and consistently than in the other scenarios, indicating superior convergence characteristics. The simultaneous improvement in accuracy and reduction in loss demonstrate excellent generalization capability. These observations are supported by the testing results, where the combined approach achieved the highest classification accuracy of 0.94, confirming that integrating CLAHE with transfer learning provides the most effective configuration for rice leaf disease classification.

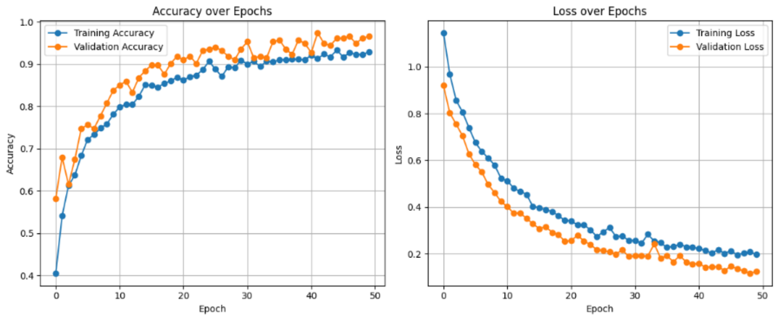

Figure 8. Training accuracy and training loss curves of the CNN model using the combined CLAHE and transfer learning approach.

3.2.2 Model Evaluation Using the Confusion Matrix

Figure 9 presents the confusion matrix of the baseline CNN without CLAHE and transfer learning. For the Bacterial Blight class, the model correctly classified only 37 out of 80 samples, while 14 samples were incorrectly classified as Brown Spot and 29 as Leaf Smut. For the Brown Spot class, 61 of 81 samples were correctly classified, whereas 17 and 3 samples were misclassified as Bacterial Blight and Leaf Smut, respectively. In the Leaf Smut category, only 37 of 73 samples were correctly recognized, with 17 samples misclassified as Bacterial Blight and 19 as Brown Spot.

The substantial number of misclassifications across all disease categories indicates that the baseline CNN was unable to effectively distinguish disease-specific visual characteristics. This observation is consistent with the overall testing accuracy of approximately 58%, demonstrating the limited generalization capability of the conventional CNN without image enhancement or transfer learning.

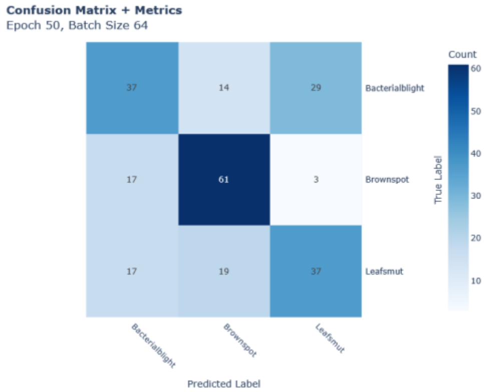

Figure 9. Confusion matrix of the CNN model without CLAHE and transfer learning.

Figure 10 presents the confusion matrix obtained using transfer learning without CLAHE. A significant improvement in correct predictions can be observed across all disease categories. For Bacterial Blight, the number of correctly classified samples increased to 74 of 80, with only 4 and 2 samples misclassified as Brown Spot and Leaf Smut, respectively. For Brown Spot, 77 of 81 samples were correctly identified, while only 2 samples were incorrectly classified into each of the remaining classes. In the Leaf Smut category, 57 of 73 samples were correctly classified, with only 1 sample misclassified as Bacterial Blight and 15 as Brown Spot.

The substantial increase in correct predictions resulted in an overall accuracy of approximately 89%, representing a considerable improvement over the baseline CNN. These findings demonstrate that pretrained feature representations significantly enhance the extraction of discriminative disease features and effectively reduce inter-class misclassification.

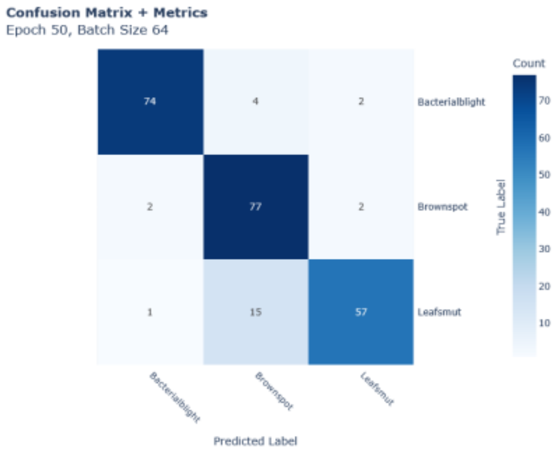

Figure 10. Confusion matrix of the CNN model using transfer learning without CLAHE.

Figure 11 illustrates the confusion matrix of the CNN model trained using CLAHE without transfer learning. The model correctly classified 44 of 80 Bacterial Blight samples, while 18 samples were misclassified as Brown Spot and 18 as Leaf Smut. For the Brown Spot class, 65 of 81 samples were correctly identified, whereas 13 samples were misclassified as Bacterial Blight and 3 as Leaf Smut. In the Leaf Smut class, 41 of 73 samples were correctly classified, while 12 and 20 samples were incorrectly assigned to Bacterial Blight and Brown Spot, respectively.

Compared with the baseline CNN, the application of CLAHE improved the number of correct predictions, particularly for the Brown Spot and Leaf Smut classes. This improvement indicates that CLAHE enhances image contrast, making disease-related features more distinguishable during feature learning. Nevertheless, the overall classification accuracy remained lower than that achieved using transfer learning, indicating that CLAHE alone cannot match the effectiveness of pretrained feature extraction.

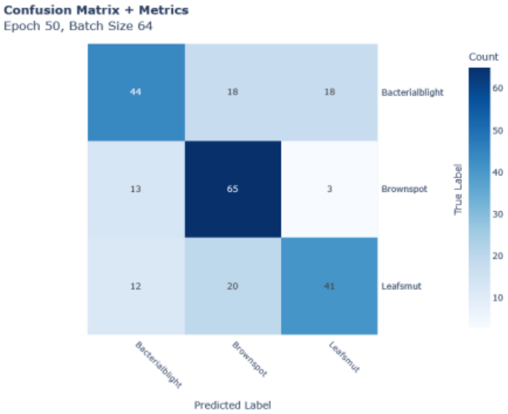

Figure 11**.** Confusion matrix of the CNN model using CLAHE without transfer learning.

Figure 12 presents the confusion matrix obtained using the combined CLAHE and transfer learning approach. The model correctly classified 77 of 80 Bacterial Blight samples, with only 3 samples misclassified as Leaf Smut and no misclassification into the Brown Spot category. For the Brown Spot class, the model achieved excellent performance by correctly classifying 80 of 81 samples, with only one sample misclassified as Leaf Smut and no confusion with Bacterial Blight. Similarly, the Leaf Smut class achieved 64 correct predictions out of 73 samples, with only 9 samples incorrectly classified as Brown Spot and none misclassified as Bacterial Blight.

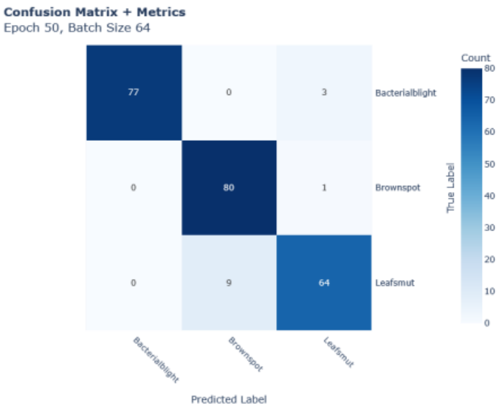

Figure 12**.** Confusion matrix of the CNN model using the combined CLAHE and transfer learning approach.

3.2.3 Classification Report Analysis

The classification report was analyzed to evaluate the performance of the CNN model under four different experimental scenarios. In the baseline scenario, where neither CLAHE nor transfer learning was applied, the model achieved an overall accuracy of 0.58, with a macro average F1-score of 0.57 and a weighted average F1-score of 0.57. The precision, recall, and F1-score values for each disease category remained relatively low. For example, the Bacterial Blight class achieved an F1-score of 0.49, while the Leaf Smut class obtained an F1-score of 0.52. These results indicate that the conventional CNN was unable to extract sufficiently discriminative visual features from the rice leaf disease images.

Applying transfer learning without CLAHE substantially improved the model performance, resulting in an overall accuracy of 0.89, with both macro and weighted average F1-scores reaching 0.89. Performance improvements were consistently observed across all disease classes. In particular, the Bacterial Blight class achieved an F1-score of 0.94, while the Brown Spot class obtained a recall of 0.95. These findings demonstrate that pretrained feature representations significantly enhance the model's capability to recognize disease patterns, even without image enhancement.

When CLAHE was applied without transfer learning, the overall accuracy increased to 0.64, with a macro average F1-score of 0.63. Although this performance exceeded that of the baseline CNN, it remained considerably lower than the transfer learning scenario. This result suggests that enhancing image contrast through CLAHE improves feature extraction; however, image enhancement alone is insufficient to achieve optimal classification performance.

The highest performance was obtained by combining CLAHE with transfer learning. This configuration achieved an overall accuracy of 0.94, with both macro and weighted average F1-scores reaching 0.94. Furthermore, the F1-scores for the individual disease classes were remarkably high, reaching 0.98 for Bacterial Blight, 0.94 for Brown Spot, and 0.91 for Leaf Smut. These findings demonstrate that integrating image enhancement with pretrained feature extraction produces the most accurate and balanced classification performance across all disease categories.

Table 1**.** Classification performance of the CNN model under four experimental scenarios based on precision, recall, F1-score, and support for each rice leaf disease class.

Scenario	Class	Precision	Recall	F1-Score	Support
Without CLAHE and Without Transfer Learning	Bacterialblight	0.52	0.46	0.49	80
	Brownspot	0.65	0.75	0.70	81
	Leafsmut	0.54	0.51	0.52	73
	Accuracy			**0.58**	234
	Macro Avg	0.57	0.57	0.57	234
	Weighted Avg	0.57	0.58	0.57	234
Transfer Learning without CLAHE	Bacterialblight	0.96	0.93	0.94	80
	Brownspot	0.80	0.95	0.87	81
	Leafsmut	0.93	0.78	0.85	73
	Accuracy			**0.89**	234
	Macro Avg	0.90	0.89	0.89	234
	Weighted Avg	0.90	0.89	0.89	234
CLAHE without Transfer Learning	Bacterialblight	0.64	0.55	0.59	80
	Brownspot	0.63	0.80	0.71	81
	Leafsmut	0.66	0.56	0.61	73
	Accuracy			**0.64**	234
	Macro Avg	0.64	0.64	0.63	234
	Weighted Avg	0.64	0.64	0.64	234
CLAHE with Transfer Learning	Bacterialblight	**1.00**	0.96	**0.98**	80
	Brownspot	0.90	**0.99**	0.94	81
	Leafsmut	0.94	0.88	0.91	73
	Accuracy			**0.94**	234
	Macro Avg	**0.95**	**0.94**	**0.94**	234
	Weighted Avg	**0.95**	**0.94**	**0.94**	234

3.2.4 Performance Comparison Across Experimental Scenarios

Table 2 compares the classification accuracy achieved by the CNN model under four experimental configurations: (1) without CLAHE and transfer learning, (2) transfer learning without CLAHE, (3) CLAHE without transfer learning, and (4) the combination of CLAHE and transfer learning. The comparison aims to quantify the contribution of each technique to improving rice leaf disease classification performance.

The baseline CNN without CLAHE or transfer learning achieved an accuracy of 0.58, indicating that the conventional CNN architecture was unable to extract sufficiently representative features from rice leaf disease images. When transfer learning was incorporated without CLAHE, the accuracy increased substantially to 0.89. This considerable improvement demonstrates that pretrained weights provide richer feature representations and facilitate more effective model learning.

Applying CLAHE without transfer learning resulted in an accuracy of 0.64, outperforming the baseline CNN but remaining noticeably lower than the transfer learning configuration. This finding indicates that contrast enhancement through CLAHE improves feature visibility and supports the feature extraction process; however, its contribution is less significant than that of transfer learning.

The highest classification performance was achieved by combining CLAHE with transfer learning, resulting in an accuracy of 0.94. This represents the best performance among all evaluated scenarios and demonstrates that integrating image enhancement with pretrained deep feature extraction produces the most effective classification model.

Table 2**.** Comparison of CNN classification accuracy across four experimental scenarios.

No.	Model Configuration	Accuracy
1	CNN without CLAHE and without Transfer Learning	**0.58**
2	CNN with Transfer Learning without CLAHE	**0.89**
3	CNN with CLAHE without Transfer Learning	**0.64**
4	CNN with CLAHE and Transfer Learning	**0.94**

4. CONCLUSIONS

This study evaluated the individual and combined effects of Contrast Limited Adaptive Histogram Equalization (CLAHE) and transfer learning on rice leaf disease classification using RGB images. Experimental results demonstrate that transfer learning contributed the largest improvement in classification performance, increasing the accuracy from 0.58 in the baseline CNN to 0.89. CLAHE alone also improved classification performance, achieving an accuracy of 0.64, indicating that local contrast enhancement facilitates the extraction of disease-related visual features but is insufficient to provide optimal discrimination without pretrained feature representations.

The integration of CLAHE with transfer learning produced the highest classification performance, achieving an accuracy, macro F1-score, and weighted F1-score of 0.94. The combined approach also reduced misclassification among visually similar disease categories, particularly Brown Spot and Leaf Smut, demonstrating that enhanced lesion visibility and pretrained feature extraction complement each other in learning discriminative representations.

The findings indicate that incorporating CLAHE as a preprocessing stage can improve the effectiveness of transfer learning for rice disease recognition under varying imaging conditions. Future research may extend this approach by evaluating additional rice disease categories, testing larger field-acquired datasets collected under diverse environmental conditions, and investigating lightweight deep learning architectures suitable for real-time deployment on mobile or edge devices to support precision agriculture applications.

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