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Optimizing rice leaf disease classification through convolutional neural network architectural modification and augmentation techniques

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ABSTRACT

This research focuses on advancing the accuracy of rice leaf disease classification by integrating convolutional neural networks (CNN) and deep learning models. With Indonesia ranking third in global rice production, effective crop management is crucial for sustaining agricultural output. This study employs innovative data augmentation techniques, including random zoom and others, to enhance model training robustness. The experimentation involves eight scenarios with varied architectural configurations applied to a residual network (ResNet)50 layer model to optimize disease classification performance. Featuring Random zoom without the multilayer perceptron (MLP) component, it emerges as the most effective, demonstrating superior accuracy and performance metrics. A grid search is conducted to optimize MLP layers, revealing a three-layer configuration as the most effective. We found that data augmentation and the MLP layer can increase the accuracy of the disease classification task. The method proposed in this study will likely have a much higher proportion of correct disease classification by combining MLP and zoom augmentation. Specifically, the model with three MLP layers and zoom augmentation demonstrated significantly higher accuracy, achieving test accuracy, precision, recall, and F1-score of 0.92, 0.94, 0.92, and 0.92, respectively.

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1. INTRODUCTION

Rice cultivation [1] is pivotal in global agriculture, serving as a primary food source for diverse populations worldwide. Indonesia, ranking third in global rice production behind China and India, plays a significant role in sustaining this crucial agricultural output [2]. A key focus is effective crop management, particularly disease and pest control, to ensure continued high production levels. Unchecked diseases pose a substantial threat to both food security and economic stability. Addressing these challenges has prompted researchers to explore innovative solutions, particularly leveraging advancements in digital image analysis. Studies have investigated the application of sophisticated algorithms, including deep learning techniques like convolutional neural networks (CNN) [3]–[6]. These algorithms have been applied to accurately identify and classify various rice leaf diseases that hinder optimal crop growth and yield.

A notable area of exploration involves utilizing these advanced technologies to categorize distinct rice leaf diseases, such as brown spot, leaf blast, leaf blight, and leaf smut, distinguishing them from a healthy leaf [7]–[9]. Researchers have conducted extensive analyses using datasets from reputable sources like Kaggle or the University of California Irvine (UCI) Machine Learning Repository, containing diverse images of diseased rice plants for model training. In addition to dataset selection, augmentation techniques have emerged as critical factors in refining the accuracy and reliability of disease classification models. Data augmentation [3], [6], [10], [11] aims to enhance the diversity of training data, enabling the development of more robust and versatile models. Moreover, they also explored variations in model architectures by experimenting with different layers, activation functions, and network structures, including alterations in CNN and multilayer perceptron (MLP) configurations to optimize performance and achieve higher accuracy rates in disease classification.

In Lu *et al.* [12]'s investigation, CNNs are trained on a dataset of 500 images from a rice experimental field, achieving 95.48% accuracy in identifying ten common rice diseases. Zhang *et al.* [13] used 2-D spectral images and 1-D spectra, employing CNNs, support vector machine (SVM), random forest (RF), and partial least squares-discriminant analysis (PLS-DA), achieving high accuracy. Ritharson *et al.* [14] proposed tailored CNN models, outperforming transfer learning approaches with 99.94% accuracy. In Jesie *et al.* [15]'s experiment result, a hybrid CNN model identifies five paddy leaf diseases, surpassing previous methods. Cui and Tan [16] compared YOLOv3 with traditional CNN models, achieving improved recall, precision, F1-score, and accuracy for rice disease classification. Lu *et al.* [5] combined CNN and bidirectional gated recurrent unit (BiGRU) modules, reaching 98.21% accuracy in identifying four rice diseases, offering a reliable recognition method.

In Gupta *et al.* [17]'s research, hyperparameters of EfficientNetV2 are fine-tuned for higher accuracy in detecting plant diseases. The Plant Diseases Dataset with 38 classes is used, intentionally exposing neural networks to a noisy training dataset. Petchiammal *et al.* [18] introduced PaddyNet, a 17-layer model achieving 98.99% accuracy in paddy leaf disease detection using a dataset of 16,225 samples. Zhang *et al.* [19] resolved the problem of significant CNN model parameters by proposing a multi-scale convolution module with visual geometry group (VGG), achieving 97.1% test accuracy and 26.1 M memory requirement. Prathima *et al.* [4] favored residual network-50 (ResNet50) over AlexNet for mobile applications due to a smaller model size with comparable accuracy. Dogra *et al.* [20] proposed a VGG19 model with transfer learning, achieving 93.0% accuracy in rice leaf disease identification. Ahad *et al.* [3] compared six CNN architectures, highlighting an ensemble model with 98% accuracy using transfer learning. Simhadri *et al.* [21] employed transfer learning on 15 CNN models, with InceptionV3 outperforming others with 99.64% accuracy. Khan *et al.* [22] proposed a model achieving 100% accuracy in testing samples, demonstrating high confidence in diagnosing rice leaf diseases for agricultural support.

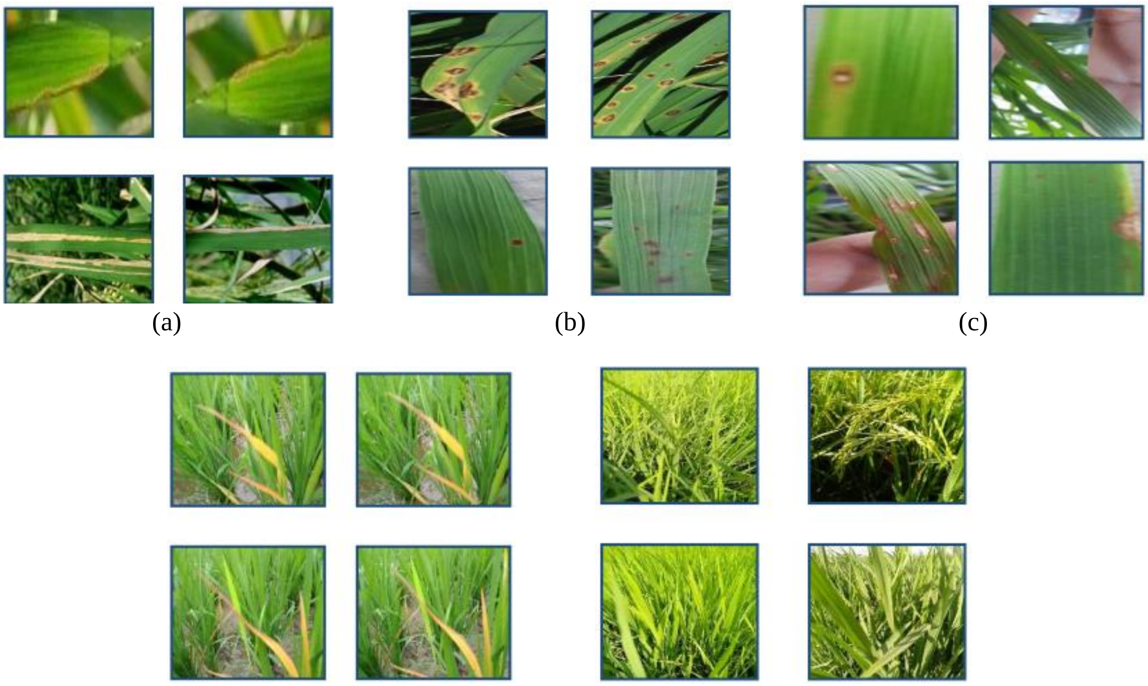
Liu *et al.* [23] investigated rice blast, false smut, and bacterial wilt, expanding the dataset and optimizing a new deep-learning model. Initial model accuracy is insufficient, leading to a comprehensive analysis of parameters (*e.g.*, iteration times, batch size, learning rate, and optimization algorithm). Using the confusion matrix for evaluation, the optimized model achieves 98.64% accuracy, effectively identifying diseases. Dixit *et al.* [24] proposed a hybrid model, disturbance storm time (DST), combining dilated convolutional neural network (DCNN), SVM, and transfer learning to detect rice plant disease. The DST model attains 95% training and 85% validation accuracy, offering consistent results across multiple datasets. Pandi *et al.* [25] studied plant leaf disease detection using deep learning and developed a DCNN with global average pooling (GAP) to address computational challenges. Hasan *et al.* [26] developed a DCNN with GAP that outperforms classic CNN with a 5.49% improvement in training accuracy, showcasing effectiveness in classifying bacterial blight, blast, brown spot, and Tungro.

Our study investigates the influence of data augmentation, employing zoom, contrast adjustment, rotation, and flip techniques, on augmenting the accuracy of disease classification models in rice plants. While previous research has examined the broad effects of data augmentation on aspects like overall accuracy and model robustness, it has not explicitly analyzed the performance of individual augmentation methods. Consequently, there is a research gap concerning the distinct contributions of each data augmentation technique toward enhancing accuracy. Bridging this gap could yield valuable insights into refining augmentation strategies for more efficient disease management in rice cultivation.

This paper is divided into several sections, each serving a distinct purpose. The introduction provides an overview of the topic and outlines the motivation for the study. Furthermore, Section 2 describes the methodology or approach used in our research. The following section presents the results, discussion, and comprehensive analysis and interpretation. The section incorporates tables, graphs, or figures that facilitate comparisons with previous studies or theoretical frameworks to enhance the discussion. Lastly, the conclusion summarizes the key results and discusses their implications.

2. METHOD
2.1. Dataset

The rice leaf disease dataset [27] was sourced from the Kaggle repository. The dataset comprised 6,034 images meticulously partitioned into three subsets (training, validation, and testing data). It encompasses five distinct categories: Bacterial leaf blight, brown spot, blast, tungro, and normal, as shown in Figure 1. Based on a study [28], bacterial leaf blight, as in Figure 1(a) causes water-soaked lesions on leaves that turn yellowish and brown. Moreover, the brown spot, shown in Figure 1(b) appears as small, dark-brown lesions with a yellowish halo on the leaves. Therefore, blast like in Figure 1(c) features are spindle-shaped or diamond-shaped leaf lesions. Tungro disease in Figure 1(d) [28] leads to stunted growth, yellowing of leaves, and reduced tillering. “Normal” in Figure 1(e) refers to healthy, disease-free rice plants exhibiting vigorous growth and producing a good yield of grains.



(a) (b) (c)

(d) (e)

Figure 1. The rice plant disease in (a) bacterial leaf blight, (b) brown spot, (c) blast, (d) tungro, and (e) normal

According to Caasi *et al.* [29], extensive field assessments conducted in Indonesia have highlighted the four most prevalent rice diseases that significantly impact crop yields. The first blast is caused by the fungus *Pyricularia oryzae,* which is notorious for inflicting severe damage and leading to substantial yield losses. The second is brown spot, a disease attributed to the fungus *Cochliobolus miyabeanus*, distinguished by the appearance of brown lesions on the rice leaves, ultimately weakening the plant and reducing productivity. The third major threat is tungro, a viral disease transmitted by green leafhoppers in rice. This disease is particularly detrimental as it results in leaf yellowing, stunted growth, abnormal pod development, and a marked reduction in yield. Lastly, bacterial leaf blight, caused by the pathogen *Xanthomonas oryzae*, manifests through water-soaked spots that spread along the leaf veins, compromising the plant’s structural integrity and vitality. These diseases pose significant challenges to rice cultivation and necessitate vigilant monitoring and management to mitigate their impact on agricultural output. The importance of managing these diseases is underscored by Azzam *et al.* [28], who highlighted the recent advancements in breeding rice varieties resistant to tungro, addressing a critical need for control measures in tropical Asia, where such viral diseases are particularly destructive. In brief, Table 1 depicts five target classification classes with their respective dataset quantities. The dataset includes 479 image data for bacterial leaf blight, 1,088 for tungro, 1,764 for normal, 965 for brown spot, and 1,738 for blast. The selection of the number and types of rice leaf diseases is based on recent studies that assess the prevalence and impact of these diseases in Indonesia and Southeast Asia.

Table 1. Detail of dataset

Class Name	Total Number of Images
Bacterial leaf blight	479
Tungro	1,088
Normal	1,764
Brown spot	965
Blast	1,738
Total	**6,034**

2.2. Data augmentation

A pivotal stage involved experimentation with diverse data augmentation techniques. The study explored methodologies such as random zoom, random brightness, horizontal flip, vertical flip, and their various combinations to augment the dataset. The specific augmentation parameters play a pivotal role in enhancing the diversity of the training dataset. These parameters are carefully selected to introduce variations that enable the model to generalize effectively across different conditions. The first parameter, zoom range=[1.5, 2.0], is integral for controlling the level of zoom applied to images during training. This parameter allows the model to learn from images at varying scales, with values between 1.5 and 2.0, indicating that the images may be magnified to different extents. The second parameter, brightness range=[1.2, 2.0], is crucial for adjusting the brightness of images within a specified range. The parameter introduces variability in brightness levels during the training process. The third set of parameters, vertical flip=true and horizontal flip=true, contributes to the augmentation methodology by allowing the model to learn from vertically and horizontally flipped versions of the images. The augmented data can aid in improving the model’s robustness to different orientations.

By integrating these augmentation techniques into the training process, the methodology artificially diversifies the dataset, exposing the model to a broader range of scenarios. This approach enhances the model’s ability to handle real-world variations, including changes in scale, lighting conditions, and image orientations. The methodology, rooted in the judicious application of augmentation parameters, aims to foster a more resilient and adaptable machine learning model for practical applications, particularly in computer vision tasks.

Figure 2 illustrates the sample images produced by the augmentation techniques employed in this study. Figure 2(a) indicates an original image from the dataset. Figure 2(b) results from augmentation using the random zoom technique. Figure 2(c) results from augmentation using the random brightness technique. Figure 2(d) is generated from the vertical flip augmentation technique. Finally, Figure 3(e) is generated using the horizontal flip augmentation technique.

(a) (b) (c) (d) (e)

Figure 2. The sample of (a) original image and augmented images which are (b) random zoom, (c) random brightness, (d) vertical flip, and (e) horizontal flip

2.3. Experiment scenario

The researchers employed two convolutional neural network (CNN) architectures in the experiment to study rice leaf disease classification. The first architecture is called “vanilla ResNet50,” and the second is labeled “ResNet50-MLP.” The term “vanilla” implies that it is the standard or original version of the ResNet50 architecture without additional modifications or components. Figure 3 depicts the visual representation or diagram of the vanilla ResNet50 architecture, showcasing the CNN model’s layers, connections, and overall structure. ResNet50 is a specific variant of the ResNet architecture that consists of 50 layers and is known for its effectiveness in image classification tasks.

On the other hand, Figure 4 illustrates the ResNet50-MLP architecture. “MLP” in the name indicates that this architecture incorporates an MLP component along with the standard ResNet50 structure. MLP is an artificial neural network with multiple layers, often used to enhance the model’s ability to capture complex patterns and relationships in data. By utilizing both vanilla ResNet50 and ResNet50-MLP architectures, the researchers aim to compare and evaluate the performance of these models in the context of classifying rice leaf diseases. It allows them to analyze the impact of adding an MLP component to the standard ResNet50 architecture on the accuracy and effectiveness of disease classification.

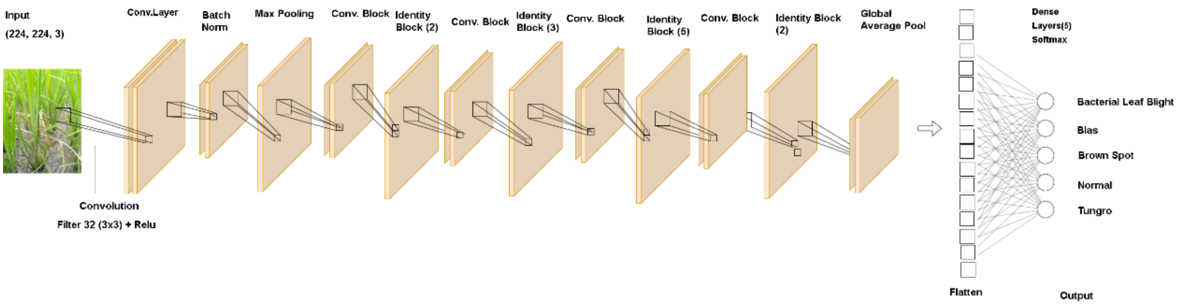


Figure 3. Architecture of ResNet50

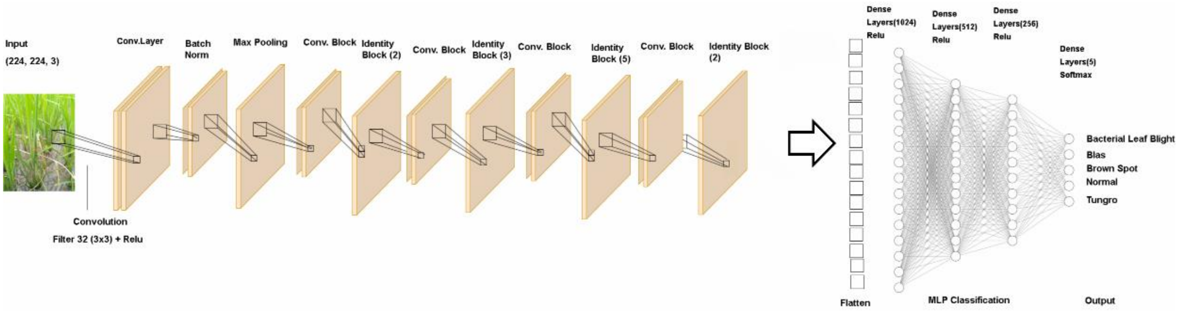


Figure 4. Architecture of ResNet50-MLP

The provided table unveils a comprehensive series of experimental scenarios; each intricately entwined with distinctive architectural configurations and augmentation techniques applied to a ResNet50 layer model. These scenarios, denoted by labels S1 to S8, encompass a rigorous exploration seeking to optimize the classification of rice plant diseases, as shown in Table 2. Each experimental scenario tests various combinations of architecture configurations and augmentation techniques on the ResNet50 layer model. The numbering of scenarios from S1 to S8 reflects a meticulous exploration to optimize the classification of rice plant diseases. Analyzing the results of each scenario will provide valuable insights for developing more effective models for addressing rice plant health issues.

Table 2. The experiment scenarios

Architecture	Scenario
ResNet50 layers	S1
ResNet50 layers + random zoom	S2
ResNet50 layers – MLP	S3
ResNet50 layers – MLP + random zoom	S4
ResNet50 layers – MLP + random brightness	S5
ResNet50 layers – MLP + horizontal flip	S6
ResNet50 layers – MLP + vertical flip	S7
ResNet50 layers – MLP + data augmentation (random zoom, random brightness, vertical flip, horizontal flip)	S8

In Scenario 1 (S1), the study initiates by employing the ResNet50 layer architecture, establishing a fundamental benchmark to comprehend the model's baseline performance in disease classification. The ResNet50 has proven to be robust and widely used convolutional neural network architecture in various computer vision tasks, including image classification. Its deep structure, featuring skip or residual connections, enables practical training of deep networks while mitigating the vanishing gradient problem.

The ResNet50 architecture also balances model complexity and computational efficiency, making it suitable for applications with limited computational resources.

Scenario 2 (S2) extends the ResNet50 layer architecture by integrating random zoom augmentation, aiming to assess the impact of this technique on the model's disease classification accuracy. Conversely, Scenario 3 (S3) experiments by excluding the MLP component from the architecture, probing the effects of this alteration on disease classification performance. Further nuanced investigations unfold in Scenarios 4 (S4) through 7 (S7). Each scenario examines the isolated effects of specific augmentation techniques: random zoom, random brightness, horizontal flip, and vertical flip. These techniques are applied alongside the ResNet50 layer architecture with the MLP component. The aim of these scenarios is to discern the individual influences of these augmentation methods on the model's classification accuracy and efficacy. This analysis facilitates understanding the optimal combination of augmentations for improved performance.

Scenario 8 (S8) explores comprehensively by amalgamating multiple augmentation techniques: random zoom, random brightness, vertical flip, and horizontal flip with the ResNet50 layer architecture, excluding the MLP component. This comprehensive scenario aims to evaluate the collective impact of diverse augmentation strategies on the model's disease classification capabilities.

This comprehensive breakdown correlates specific architectural setups and augmentation approaches with their respective experimental scenarios. It facilitates a detailed examination of their separate and combined impacts on the model's performance measures and computational effectiveness. Each scenario represents a distinctive combination of architectural adjustments and augmentation methods, enriching our comprehension of how these changes influence the model's ability to classify diseases in rice plant images. Such nuanced insights are essential for progressing agricultural technology and enhancing crop management methodologies.

2.4. Evaluation

The model's efficacy was tested in this phase by presenting new, unseen rice plant image data comprising 25 test samples. The evaluation stage involved the model generating output from the testing phase. This assessment utilized the confusion matrix method, analyzing the model's performance metrics as accuracy, precision, recall, and F1-score, based on the 25 test images.

3. RESULTS AND DISCUSSION

3.1. Grid search for optimizing the MLP layers

In the conducted grid search to optimize the MLP model, different configurations of MLP layers were explored, and the results are presented in the Table 3. The objective was to identify the best architecture for the given task, as indicated by various evaluation metrics, including test accuracy, F1-score, precision, and recall. We selected the one with the number of layers 3 as it achieved the highest accuracy, as shown in Table 3.

Table 3. The grid search result

Number of layers	Test accuracy	F1-Score	Precision	Recall
1	0.72	0.71	0.78	0.72
3	0.92	0.92	0.94	0.92
5	0.88	0.88	0.89	0.88

3.2. Scenarios performances comparison

As shown in Table 4, the results from the experimental scenarios (S1 to S8) reveal a diverse spectrum of performance metrics concerning the classification of rice plant diseases using the ResNet50 layers model with varying architectural configurations and augmentation techniques. Scenario 4 (S4) emerges as the most notable performer in this exploration, show-covering the highest accuracy rate of 0.92 alongside robust precision, recall, and F1-score, all at 0.94, 0.92, and 0.92, respectively. This scenario, featuring the ResNet50 layer architecture without the MLP component but incorporating random zoom augmentation, demonstrates superior capabilities in accurately identifying and classifying rice plant diseases.

Conversely, scenarios employing singular augmentation techniques, such as random zoom (S2), random brightness (S5), horizontal flip (S6), and vertical flip (S7), exhibit moderate performance with consistent accuracy rates around 0.84 and corresponding precision, recall, and F1-score within a similar range. While effective to a degree, these scenarios demonstrate relatively comparable but moderate success in disease classification compared to the standout performer. Scenario 3 (S3), excluding the MLP component from the ResNet50 layer architecture, displays a noteworthy improvement in performance compared to the baseline scenario (S1), with an accuracy rate of 0.88. This alteration highlights the potential influence of architectural components on the model's disease classification capabilities. Scenario 8 (S8) involves a comprehensive amalgamation of multiple augmentation techniques with the ResNet50 layer architecture, devoid of the MLP component, with a balanced accuracy rate of 0.76. While not the highest performer, it demonstrates competitive precision, recall, and F1-score around 0.82, 0.76, and 0.78, respectively, indicating a relatively effective albeit not the most superior performance.

Table 4. The experiment scenario's result

Scenario	Time per step	Acc	Precision	Recall	F1-score
S1	457 ms	0.8	0.86	0.8	0.8
S2 Random zoom	778 ms	0.84	0.87	0.84	0.84
S3 MLP	477 ms	0.88	0.9	0.88	0.88
S4 MLP + zoom	787 ms	0.92	0.94	0.92	0.92
S5	589 ms	0.84	0.88	0.84	0.82
S6	457 ms	0.76	0.8	0.76	0.75
S7	975 ms	0.84	0.88	0.84	0.85
S8	1,000 ms	0.76	0.82	0.76	0.78

The enhanced performance achieved by applying random zoom data augmentation stands out compared to alternative techniques. This superiority can be ascribed to the increased detail introduced into the image data. By allowing for random variations in zoom levels, the model gains access to a more diverse and intricate set of features, making the data more informative and conducive to improved learning. A noteworthy aspect contributing to the success of random zooming is the potential for advantageous precision. When the augmentation process happens to align with the inherent characteristics of the data, the model is exposed to particularly beneficial instances. This accidental alignment can lead to a more refined learning experience, aiding the model in honing its accuracy levels.

However, it is crucial to acknowledge that the advantages associated with random zoom may not universally apply to all cases or scenarios. The effectiveness of this augmentation technique depends on the nature of the data and the specific learning task at hand. As such, considerations should be made regarding the appropriateness of employing random zoom based on the dataset's characteristics and the model's objectives. Overall, the outcomes underscore the significance of architectural configurations and augmentation techniques in shaping the ResNet50 layer model's proficiency in classifying rice plant diseases. Scenario 4 (S4) notably stands out as the most effective configuration, emphasizing the potential impact of random zoom augmentation on enhancing the model's accuracy and overall disease classification capabilities.

Table 5 shows the comparison of performance metrics for different methods in rice leaf disease classification. Dogra *et al.* [20] with their VGG19 model with transfer learning achieved an accuracy of 93.0%, while Dixit and Verma [24] reported a slightly lower accuracy of 85% for DST. On the other hand, DCNN with GAP by Pandi *et al.* [25] achieved the highest accuracy among the referenced studies, with 96.5%. In contrast, our proposed method, introduced in 2024, attained an accuracy of 92%. While DCNN with GAP [25] achieved the highest accuracy, our method demonstrates competitive performance, falling slightly behind but still maintaining a high level of accuracy in rice leaf disease classification.

Table 5. The performance comparison with existing research

Method	Year	Accuracy
VGG19 model with transfer learning [20]	2023	93.0%
DST [24]	2023	85.0%
DCNN with GAP [25]	2023	96.5%
Proposed method	2024	92.0%

This study explored a comprehensive analysis of disease classification in rice plants using the ResNet50 layer model with various architectural configurations and augmentation techniques. However, further and in-depth studies may be needed to confirm its efficacy across different datasets and environmental conditions, especially regarding its generalizability and robustness in real-world agricultural settings.

4. CONCLUSION

In summary, this research addresses the critical role of rice cultivation in global agriculture, particularly in Indonesia, the third-largest global rice producer. Recent experiments suggest that innovative digital image analysis solutions can achieve effective crop management for sustained production levels. By harnessing advanced algorithms such as CNNs, researchers endeavor to precisely identify and classify rice leaf diseases, which pose significant threats to crop growth and yield. Utilizing a comprehensive dataset from reputable repositories like Kaggle, the study conducts training and testing of machine learning models. Central to this process are data augmentation techniques, including random zoom and others, which play a crucial role in diversifying the training dataset and bolstering model robustness across varied conditions.

The paper introduces eight experimental scenarios, each combining distinctive architectural configurations and augmentation methodologies applied to a ResNet50 layer model. Notably, Scenario 4, which incorporates random zoom augmentation without the MLP component, emerges as the most effective, achieving the highest accuracy and robust performance metrics. The study also includes a grid search to optimize the MLP layers, revealing the effectiveness of a three-layer configuration. Overall, these findings underscore the significance of architectural configurations and augmentation techniques in developing accurate models for classifying rice plant diseases, contributing valuable insights to improve food security through timely disease detection and intervention strategies.

Our study shows that zoom augmentation and MLP layers affect disease classification accuracy. Future research could explore integrating explainable AI (XAI) techniques for model interpretability and testing the model’s transferability to different regions and rice varieties. Real-time monitoring systems in the field could enable adaptive responses to changing disease patterns. Collaboration between experts could lead to user-friendly applications for early disease detection. Finally, applying the model alongside precision agriculture and sustainable farming practices could enhance long-term crop health and food security.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Kaggle repository at: *https://kaggle.com/competitions/paddy-disease-classification*.

REFERENCES

[1] P. Seelwal and T. R. Rohilla, "Optimized light-weight deep learning model for rice disease identification," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 2s, pp. 657–664, 2024.

[2] O. Wallach, "This is how much rice is produced around the world - and the countries that grow the most," *Visual Capitalist*. 2024. Accessed: Jan. 11, 2024. [Online]. Available: https://www.weforum.org/agenda/2022/03/visualizing-the-world-s-biggest-rice-producers/

[3] M. T. Ahad, Y. Li, B. Song, and T. Bhuiyan, "Comparison of CNN-based deep learning architectures for rice diseases classification," *Artificial Intelligence in Agriculture*, vol. 9, pp. 22–35, 2023, doi: 10.1016/j.aiia.2023.07.001.

[4] S. Prathima, N. G. Praveena, K. Sivachandar, S. S. Nath, and B. Sarala, "Generic paddy plant disease detector (GP2D2): an application of the deep-CNN model," *International Journal of Electrical and Computer Engineering Systems*, vol. 14, no. 6, pp. 647–656, 2023, doi: 10.32985/IJECES.14.6.4.

[5] Y. Lu, X. Wu, P. Liu, H. Li, and W. Liu, "Rice disease identification method based on improved CNN-BiGRU," *Artificial Intelligence in Agriculture*, vol. 9, pp. 100–109, 2023, doi: 10.1016/j.aiia.2023.08.005.

[6] C. R. Rahman *et al.*, "Identification and recognition of rice diseases and pests using convolutional neural networks," *Biosystems Engineering*, vol. 194, pp. 112–120, Jun. 2020, doi: 10.1016/j.biosystemseng.2020.03.020.

[7] J. P. Shah, H. B. Prajapati, and V. K. Dabhi, "A survey on detection and classification of rice plant diseases," in *2016 IEEE International Conference on Current Trends in Advanced Computing (ICCTAC)*, Mar. 2016, pp. 1–8, doi: 10.1109/ICCTAC.2016.7567333.

[8] F. Jiang, Y. Lu, Y. Chen, D. Cai, and G. Li, "Image recognition of four rice leaf diseases based on deep learning and support vector machine," *Computers and Electronics in Agriculture*, vol. 179, Dec. 2020, doi: 10.1016/j.compag.2020.105824.

[9] N. V. R. R. Goluguri, K. Suganya Devi, and N. Vadaparthi, *Image classifiers and image deep learning classifiers evolved in detection of Oryza sativa diseases: survey*, vol. 54, no. 1. Springer Netherlands, 2021, doi: 10.1007/s10462-020-09849-y.

[10] B. S. Bari *et al.*, "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework," *PeerJ Computer Science*, vol. 7, Apr. 2021, doi: 10.7717/peerj-cs.432.

[11] P. K. Sethy, N. K. Barpanda, A. K. Rath, and S. K. Behera, "Deep feature based rice leaf disease identification using support vector machine," *Computers and Electronics in Agriculture*, vol. 175, Aug. 2020, doi: 10.1016/j.compag.2020.105527.

[12] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of rice diseases using deep convolutional neural networks," *Neurocomputing*, vol. 267, pp. 378–384, 2017, doi: 10.1016/j.neucom.2017.06.023.

[13] J. Zhang, Y. Yang, X. Feng, H. Xu, J. Chen, and Y. He, "Identification of bacterial blight resistant rice seeds using terahertz imaging and hyperspectral imaging combined with convolutional neural network," *Frontiers in Plant Science*, vol. 11, no. June, pp. 1–15, 2020, doi: 10.3389/fpls.2020.00821.

[14] P. I. Ritharson, K. Raimond, X. A. Mary, J. E. Robert, and A. J, "DeepRice: A deep learning and deep feature based classification of rice leaf disease subtypes," *Artificial Intelligence in Agriculture*, vol. 11, pp. 34–49, Mar. 2024, doi: 10.1016/j.aiia.2023.11.001.

[15] R. S. Jesie, M. S. G. Premi, and T. Jarin, "Comparative analysis of paddy leaf diseases sensing with a hybrid convolutional neural network model," *Measurement: Sensors*, vol. 31, no. November 2023, p. 100966, 2024, doi: 10.1016/j.measen.2023.100966.

[16] J. Cui and F. Tan, "Rice plaque detection and identification based on an improved convolutional neural network," *Agriculture (Switzerland)*, vol. 13, no. 1, pp. 1–15, 2023, doi: 10.3390/agriculture13010170.

[17] T. Gupta, Titunath, and V. Jain, "Plant disease detection using deep learning," *International Conference on Sustainable Computing and Smart Systems, ICSCSS 2023 - Proceedings*, vol. 15, no. 6, pp. 202–206, 2023, doi: 10.1109/ICSCSS57650.2023.10169268.

[18] A. Petchiammal, D. Murugan, and K. S. Briskline, "PaddyNet: an improved deep convolutional neural network for automated disease identification on visual paddy leaf images," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 6, pp. 1141–1149, 2023, doi: 10.14569/IJACSA.2023.01406122.

[19] C. Zhang, R. Ni, Y. Mu, Y. Sun, and T. L. Tyasi, "Lightweight Multi-scale convolutional neural network for rice leaf disease recognition," *Computers, Materials and Continua*, vol. 74, no. 1, pp. 983–994, 2023, doi: 10.32604/cmc.2023.027269.

[20] R. Dogra, S. Rani, A. Singh, M. A. Albahar, A. E. Barrera, and A. Alkhayyat, "Deep learning model for detection of brown spot rice leaf disease with smart agriculture," *Computers and Electrical Engineering*, vol. 109, no. PA, p. 108659, 2023, doi: 10.1016/j.compeleceng.2023.108659.

[21] C. G. Simhadri and H. K. Kondaveeti, "Automatic recognition of rice leaf diseases using transfer learning," *Agronomy*, vol. 13, no. 4, 2023, doi: 10.3390/agronomy13040961.

[22] A. R. Khan, I. Abunadi, B. Alghofaily, H. Ali, and T. Saba, "Automatic diagnosis of rice leaves diseases using hybrid deep learning model," *Journal of Advances in Information Technology*, vol. 14, no. 3, pp. 418–425, 2023, doi: 10.12720/jait.14.3.418-425.

[23] H. Liu, Y. Cui, J. Wang, and H. Yu, "Analysis and research on rice disease identification method based on deep learning," *Sustainability (Switzerland)*, vol. 15, no. 12, pp. 1–13, 2023, doi: 10.3390/su15129321.

[24] A. K. Dixit and R. Verma, "Advanced hybrid model for multi paddy diseases detection using deep learning," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 9, no. 1, pp. 1–8, 2023, doi: 10.4108/eetpht.9.4481.

[25] S. S. Pandi, A. Senthilselvi, J. Gitanjali, K. ArivuSelvan, J. Gopal, and J. Vellingiri, "Rice plant disease classification using dilated convolutional neural network with global average pooling," *Ecological Modelling*, vol. 474, no. July, p. 110166, 2022, doi: 10.1016/j.ecolmodel.2022.110166.

[26] M. M. Hasan, A. F. M. S. Uddin, M. R. Akhond, M. J. Uddin, M. A. Hossain, and M. A. Hossain, "Machine learning and image processing techniques for rice disease detection: A critical analysis," *International Journal of Plant Biology*, vol. 14, no. 4, pp. 1190–1207, Dec. 2023, doi: 10.3390/ijpb14040087.

[27] P. Doctor, "Paddy doctor: paddy disease classification," *Kaggle*. Kaggle, 2022. Accessed: Jun. 01, 2023. [Online]. Available: https://kaggle.com/competitions/paddy-disease-classification

[28] O. Azzam and T. C. B. Chancellor, "The biology, epidemiology, and management of rice tungro disease in Asia," *Plant Disease*, vol. 86, no. 2, pp. 88–100, Feb. 2002, doi: 10.1094/PDIS.2002.86.2.88.

[29] O. Caasi, C. Hongo, A. Suryaningsih, S. Wiyono, K. Homma, and M. Shishido, "Relationships between bacterial leaf blight and other diseases based on field assessment in Indonesia," *Tropical Agriculture and Development*, vol. 63, no. 3, pp. 113–121, 2019, doi: 10.11248/jsta.63.113.

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