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Deep Learning-Based Early Detection Optimization for Rice Leaf Diseases to Support Sustainable Local Agriculture

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Abstract−Rice leaf diseases such as Bacterial Blight and Blast are major threats to rice productivity that directly impact food security and the sustainability of local agriculture. This study aims to develop and optimize a deep learning-based early detection system for rice leaf diseases using a Convolutional Neural Network (CNN) architecture, specifically the Inception_v3 model. The research method includes five main stages, namely collecting rice leaf image datasets, data pre-processing (resize, normalization, and augmentation), CNN model design, model training and evaluation, and performance optimization through the application of different optimizer algorithms. Two model variants were tested and compared, namely Inception_v3 Basics with the RMSprop optimizer and Inception_v3 Optimization with the Adam optimizer. Experimental results showed that the Inception_v3 Optimization model provided the best performance, with a Precision value of 0.9672, Recall of 0.8939, F1-score of 0.9291, Balanced Accuracy of 0.9297, Matthews Correlation Coefficient (MCC) of 0.8578, Cohen's Kappa of 0.8573, and AUC ROC of 0.98. These results indicate that the Adam optimizer is able to accelerate convergence and improve model accuracy compared to RMSprop, while producing a more stable and efficient classification system. Thus, this study successfully demonstrated that the optimized Inception_v3 architecture can be used effectively for early detection of rice leaf diseases and has high potential for integration into smart farming systems to support sustainable, technology-based local agricultural practices.

Keywords: Deep Learning; Convolutional Neural Network (CNN); Inception_v3; Adam Optimizer; RMSprop; Rice Leaf Disease; Bacterial Blight; Blast; Image Classification; Sustainable Agriculture

1. INTRODUCTION

Rice is a strategic food commodity that plays a vital role in maintaining national food security, particularly in an agricultural country like Indonesia. As the primary source of carbohydrates for more than half the world's population, sustainable rice production is crucial for ensuring social, economic, and political stability[1], [2], [3]. However, rice productivity often faces significant challenges due to biotic and abiotic factors, one of which is the attack of plant diseases that affect the leaves. Leaf diseases not only reduce yields quantitatively but also reduce the quality of the resulting grain. The two most common diseases found in rice fields in Indonesia and other tropical countries are bacterial blight and blast. Bacterial blight, caused by the bacterium Xanthomonas oryzae pv. oryzae, attacks the leaf vascular tissue and causes systemic wilting that inhibits photosynthesis [4], [5], [6]. Blast, caused by the fungus Magnaporthe oryzae, causes necrotic spots on leaves and leads to significant productivity losses. In epidemic conditions, these two diseases can cause losses of up to 50–70% of the total crop yield, ultimately threatening the economic stability of farmers and food security at the national and regional levels [7], [8].

Traditionally, rice leaf disease identification has been performed through direct visual observation by farmers or agricultural extension workers. Although this method has long been used, it has several fundamental limitations. First, manual observation relies on individual experience, making it susceptible to misclassification (human error). Second, the process is time-consuming and difficult to implement on a large-scale agricultural area. Third, environmental factors such as lighting, leaf color, or disease severity can influence diagnostic results [9], [10]. Therefore, a more objective, accurate, and efficient approach is needed to detect rice leaf diseases, especially in the early stages before the infection spreads widely[11], [12], [13].

In this article, research conducted by [14] proposes a deep learning-based approach (DLCNN with AME) for automatic rice leaf disease detection. The main advantages are its architecture, which is claimed to be highly accurate (99.76%), equipped with a pesticide recommendation system, and the use of a balanced dataset to improve model generalization. However, this article has significant weaknesses, namely the lack of a detailed explanation of the proposed "Attention Mechanism Enhancement" architecture, the lack of information regarding the size and source of the dataset used for training, and the lack of discussion of how the model will perform in real-world conditions with varying lighting, shooting angles, and stages of disease infection, leaving the potential for overfitting and its practical applicability questionable. The study conducted by [15] in this article has the advantage of using the state-of-the-art and popular YOLOv8 architecture for object detection, complemented by adequate technical explanations of the architecture, data preprocessing, and annotation processes, as well as a comprehensive performance evaluation (mAP 97%) by comparing model variants (n and s) with previous research, thus demonstrating a clear contribution. The weaknesses are that although the data is balanced, the dataset used is relatively small (3,216 images) and comes from a single source (Kaggle), which may affect the model's generalizability; and while discussing potential integration

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with IoT, the article does not test or demonstrate a real-time implementation in an agricultural environment. In the last decade, advances in artificial intelligence (AI) technology, particularly in the fields of computer vision and deep learning, have opened up significant opportunities for automated plant disease detection. Deep learning algorithms, particularly convolutional neural networks (CNNs), possess remarkable capabilities in recognizing complex patterns from digital images without the need for manual feature extraction. CNNs are able to learn directly from image data by extracting important visual features, such as shape, texture, and color, and then automatically classify them with a high degree of accuracy. In the context of smart agriculture, deep learning-based approaches are highly relevant because they provide efficient and adaptive data-driven solutions. Implementing these systems allows farmers to detect disease symptoms early, implement timely control measures, and reduce reliance on excessive use of potentially environmentally damaging chemicals. Thus, this technology not only increases productivity but also supports environmentally friendly, sustainable agriculture practices.

Datasets are a fundamental component in developing deep learning-based disease detection models. In this study, the dataset used comprises two main categories of rice leaf diseases: Bacterial Blight and Blast. The dataset is organized into two subsets: Training and Testing [16], [17], [18]. The Training subset is used to train the model to recognize the visual characteristics of each disease, while the Testing subset is used to measure the model's performance on new, previously unseen data. A well-organized dataset structure, as shown in the figure, ensures a systematic training process and reduces the risk of overfitting to certain data[19], [20], [21].

Optimizing a deep learning-based early detection system also requires considering several important aspects, including network architecture selection, data augmentation techniques to increase dataset variety, and hyperparameter tuning to maximize model performance [22], [23]. This study seeks to examine and optimize these approaches so that the resulting system achieves high accuracy with optimal computational efficiency. Furthermore, the application of a deep learning-based disease detection system has significant potential to support digital transformation in the agricultural sector. By integrating this system into mobile devices such as smartphones or drone-based monitoring systems, farmers can perform real-time field diagnoses. This not only accelerates the decision-making process in disease control but also improves farmers' adaptability to increasingly unpredictable environmental and climate conditions [8], [24], [25].

Therefore, this research, titled "Deep Learning-Based Early Detection Optimization for Rice Leaf Diseases to Support Sustainable Local Agriculture," is highly urgent and strongly relevant to real challenges in the modern agricultural sector [26], [27]. The development of an accurate, rapid, and efficient rice leaf disease detection system is expected to be an innovative solution for strengthening national food security, supporting the sustainability of local agriculture, and realizing an inclusive and highly competitive smart agricultural ecosystem in the era of the Industrial Revolution 4.0 and moving towards precision agriculture[28], [29], [30].

2. RESEARCH METHODOLOGY

This research methodology systematically explains the stages, approaches, and techniques used to achieve the research objectives entitled "Deep Learning-Based Early Detection Optimization for Rice Leaf Diseases to Support Sustainable Local Agriculture." This chapter aims to provide a comprehensive overview of the experimental design, sources and types of data used, image pre-processing, design and training of deep learning models, up to the evaluation and optimization stages of the rice leaf disease detection system. This research was designed using a quantitative experimental approach based on deep learning, utilizing the Convolutional Neural Network (CNN) algorithm because of its superior ability to recognize complex visual patterns from images of disease-infected rice leaves. Each stage in the methodology is structured and sequentially arranged, starting from the collection of rice leaf image datasets, data normalization and augmentation, design of the CNN model architecture or transfer learning, model training with measurable parameters, performance evaluation using quantitative metrics such as accuracy and F1-score, to the final stage of optimization and implementation of the model into an intelligent application-based system. With this methodological design, the research is expected to produce a rice leaf disease detection model that is accurate, efficient, and easy to implement in the field. This will support the implementation of sustainable digital agricultural technology and focus on increasing the productivity of local farmers.

2.1 Data and Data Sources

The dataset is hierarchically structured into two parts: training and testing. Training data is used to train the model to recognize visual disease patterns, while testing data is used to test the model's generalization ability to new, previously unstudied data. All images are stored in digital format (.jpg or .png) at a uniform resolution for consistent processing. The data distribution follows a 80% training and 20% testing scheme to achieve a balance between learning ability and model performance evaluation. This dataset structure serves as a critical foundation for ensuring the deep learning model's ability to classify diseases objectively and measurably.

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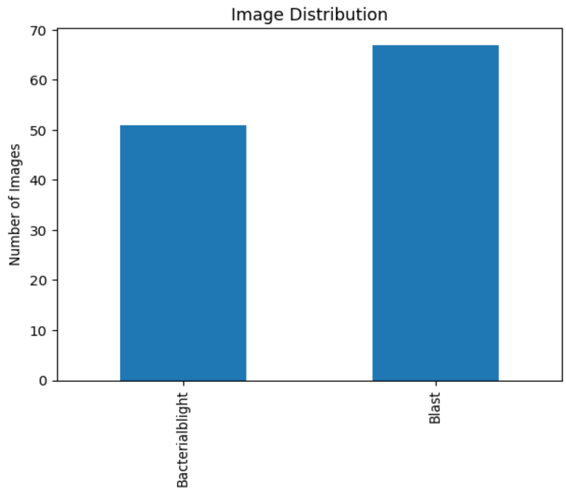

Figure 1. Image Distribution

Figure 1 shows the distribution of the number of images for each rice leaf disease class in the dataset used in this study. The bar chart shows that the Blast class has a higher number of images than the Bacterial Blight class. The Blast class has approximately 67 images, while the Bacterial Blight class has approximately 51 images. This difference indicates that the dataset has a slightly imbalanced composition, with the Blast class dominating. This condition needs to be considered in the deep learning model training process, as an imbalanced data distribution can affect the model's performance in recognizing classes with a smaller number of samples. Therefore, during the data preprocessing stage, image augmentation techniques can be applied to balance the amount of data between classes so that the model can learn more representatively and achieve optimal classification performance.

The data used in this study is a dataset of rice leaf images that have been classified into two main disease categories:

Bacterial Blight and Blast.

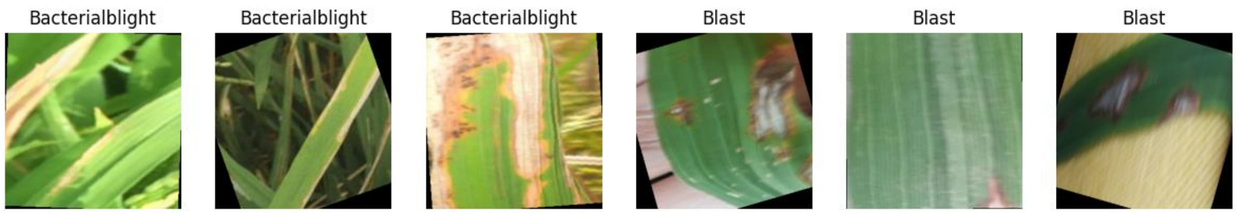

Figure 2. Research Data Sample

The dataset is structured into two subsets: training data and testing data, as follows:

a. Training Data
The training dataset is used to train the deep learning model to recognize the visual characteristics of each disease type.
b. Testing Data
The testing dataset is used to test the model's generalization ability on new, previously unseen data to measure the model's actual performance in field conditions.

The total number of images used is adjusted to achieve an ideal proportion (e.g., 80% training data and 20% testing data). All image data is in .jpg or .png format, with uniform resolution to ensure consistency in the computational process.

2.2 Research Design

This research uses a quantitative experimental approach based on deep learning, focusing on the development and optimization of an early detection model for rice leaf diseases using digital images. This approach aims to harness the power of the Convolutional Neural Network (CNN) algorithm in recognizing complex visual patterns found on disease-infected rice leaves. The research process is carried out in stages, starting with dataset collection, data pre-processing, model design and training, performance evaluation, and model optimization. This research design was systematically designed to produce a disease detection model that is accurate, efficient, and has good generalizability to new data, thus enabling it to support sustainable smart farming systems at the local level.

This research employed a quantitative experimental approach based on deep learning to develop and optimize an automated early detection model for rice leaf diseases based on digital images. This approach focused on applying a Convolutional Neural Network (CNN) algorithm to identify two main types of diseases, Bacterial Blight and Blast, from rice leaf images.

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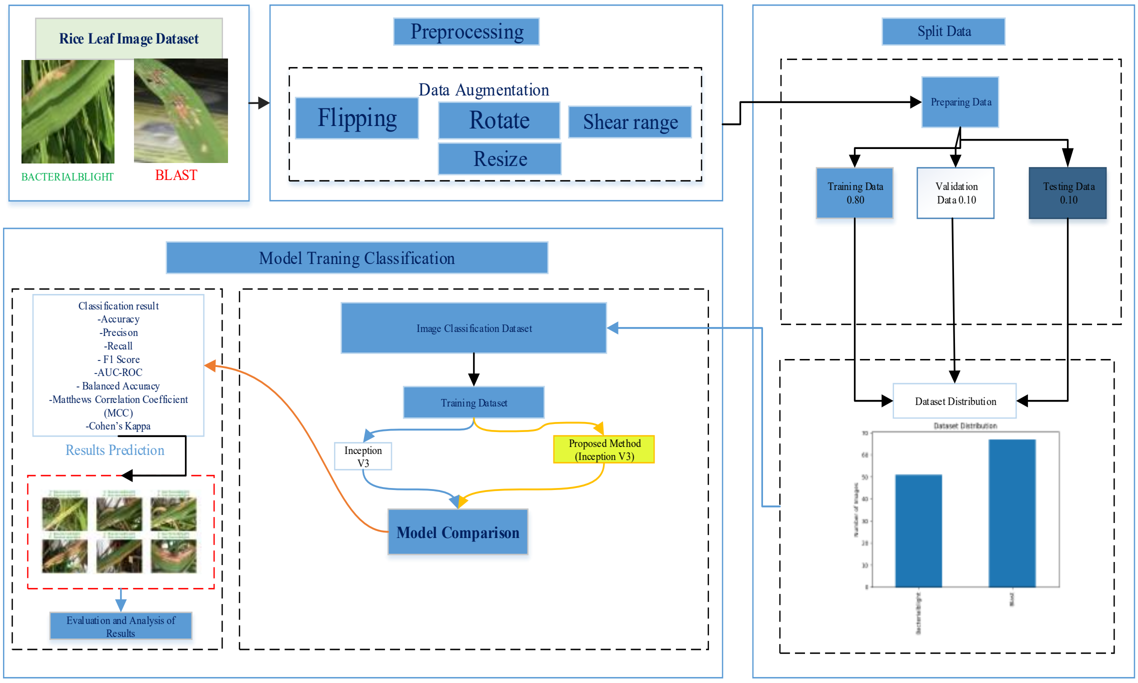

Figure 3. Research Design

Figure 3 displays the research design, illustrating the workflow of a deep learning-based early detection system for rice leaf diseases. The research process began with the collection of a dataset of rice leaf images consisting of two disease classes: Bacterial Blight and Blast. The obtained images then underwent preprocessing, including resizing, flipping, rotation, shearing, and data augmentation to increase data diversity and quality before model training. The data was then divided into three subsets: training data, validation data, and testing data, to ensure objective learning and model evaluation. The model training and classification phase then began, where the dataset was used to train several CNN models, such as InceptionV3 and the proposed model (Proposed Method), allowing for model comparison to determine the best performance. The training results were then evaluated using accuracy, precision, recall, and F1-score metrics, along with visual analysis of the prediction results, including leaf images classified according to disease type. This research design resulted in a structured, efficient, and optimized rice leaf disease detection system to support decision-making in sustainable agricultural practices.

2.3 Model Comparison: Inception_v3 Optimization and Inception_v3 Basics

This study tested and compared two model variants based on the Inception_v3 architecture: Inception_v3 Basics and Inception_v3 Optimization. These two models were chosen because the Inception architecture is known for its high efficiency in extracting complex image features, making it highly relevant for the task of rice leaf disease classification. Despite sharing the same basic architecture, the main differences lie in the optimization strategy and training algorithm (optimizer) used. This comparison aims to assess the extent to which optimizer selection affects the model's convergence speed, training stability, and final classification accuracy.

The Inception_v3 Basics model uses the RMSprop algorithm as its optimizer, which is known to be effective in handling fluctuating gradients and was frequently used in Google's initial implementation of Inception. RMSprop works by updating network weights based on a moving average of the square of the gradient, making it suitable for data with unstable learning dynamics. However, RMSprop tends to require careful parameter tuning (learning rate) and is sometimes less stable when faced with relatively small datasets or datasets with high texture variation, such as rice leaf images.

In contrast, the Inception_v3 Optimization model uses the Adam (Adaptive Moment Estimation) optimizer, which is an adaptive combination of momentum and RMSprop methods. Adam combines high convergence speed with the ability to adapt to gradient changes, making it more stable and efficient in the training process. In the context of this research, the use of Adam is expected to accelerate training, improve model accuracy, and reduce the risk of overfitting by learning a more balanced training loss and validation loss. Therefore, these two methods were tested to assess their relative performance in detecting two major rice leaf diseases: Bacterial Blight and Blast.

Table 1. Comparison of Inception_v3 Optimization and Inception_v3 Basics Models

Comparison Aspects	Inception_v3 Basics	Inception_v3 Optimization
Optimizer	RMSprop	Adam

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Comparison Aspects	Inception_v3 Basics	Inception_v3 Optimization
Optimizer Characteristics	Uses exponential moving average of gradients for weight updates; sensitive to learning rate	Combination of momentum and adaptive learning rate, stable across various training conditions
Main Strengths	Effective on large and complex datasets	Fast convergence, high stability, and adaptability to data variations
Main Weaknesses	Prone to overfitting on small datasets; requires rigorous parameter tuning	Higher memory consumption than RMSprop
Expected Performance	Moderate accuracy with longer training times	Higher accuracy with efficient training time
Test Objectives	As a baseline for initial evaluation of the performance of the Inception_v3 architecture	As an optimized model for increased accuracy and efficiency

Table 1 shows the fundamental differences between the two models tested in this study. In the Inception_v3 Basics model, the RMSprop optimizer was used as the baseline because it is a common method in early versions of the Inception architecture. RMSprop tends to be stable in handling fluctuating gradients, but its training process is relatively slow and requires careful parameter tuning. Meanwhile, in the Inception_v3 Optimization model, the Adam optimizer is used, which is able to automatically adjust the learning rate based on estimates of the first and second moments of the gradient. This approach allows for faster training convergence and produces more stable performance on datasets with high feature variation, such as rice leaf images.

Through this comparison, the study aims to determine the most optimal model in terms of training efficiency and rice leaf disease detection accuracy. The test results are expected to show that the model with the Adam optimizer (Inception_v3 Optimization) has significant advantages over the baseline RMSprop model, both in terms of learning speed and classification ability, thus it can be the best approach for an efficient and sustainable deep learning-based disease detection system in digital agriculture.

3. RESULTS AND DISCUSSION

This chapter presents the implementation, testing, and analysis of a deep learning model developed for early detection of rice leaf diseases. The primary objective of this chapter is to outline the empirical findings obtained from a series of research stages, starting with the collection and processing of rice leaf image datasets, training a Convolutional Neural Network (CNN) model, and evaluating model performance using various classification metrics. An in-depth discussion is conducted to demonstrate how preprocessing, optimization strategies, and training algorithm selection affect the model's accuracy and stability in recognizing two major disease types: Bacterial Blight and Blast. Furthermore, this chapter compares the performance of two approaches based on the Inception_v3 architecture: a baseline model with the RMSprop optimizer and a model optimized using Adam, to assess the effectiveness of the optimization methods on detection results. The results are then analyzed quantitatively and qualitatively to assess the superiority of the proposed approach and to explain the implications of implementing this technology in supporting smart and sustainable agricultural systems. Therefore, this chapter serves as the core of this research, presenting empirical evidence of the success of the developed model and its contribution to strengthening deep learning-based innovation in agriculture.

3.1 Dataset Overview

The dataset used in this study consists of rice leaf images grouped into two main categories: Bacterial Blight and Blast. These two diseases are dominant and frequently attack rice plants in various tropical regions. The dataset is structured into two main subsets: training data and testing data, with 80% and 20%, respectively. Each subset contains digital images (.jpg and .png) with uniform resolution after preprocessing. Based on data distribution analysis, it was found that the Bacterial Blight class had fewer images than the Blast class. This is evident in the data distribution diagram, where the Blast class recorded approximately 67 images, while the Bacterial Blight class recorded approximately 51 images. This imbalance in data quantity was addressed using data augmentation techniques, which included rotation, flipping, zooming, and varying light intensity to increase image diversity and reduce the risk of model bias toward a particular class.

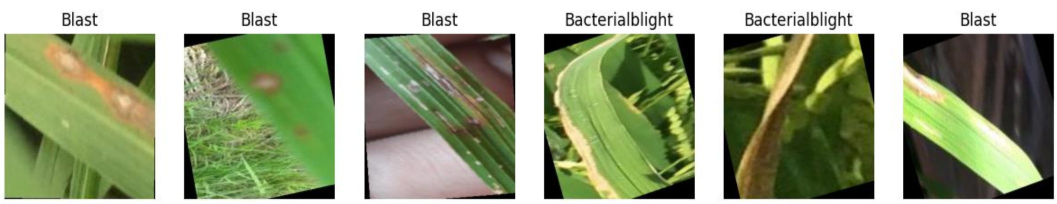

Figure 4. Data Preprocessing Results

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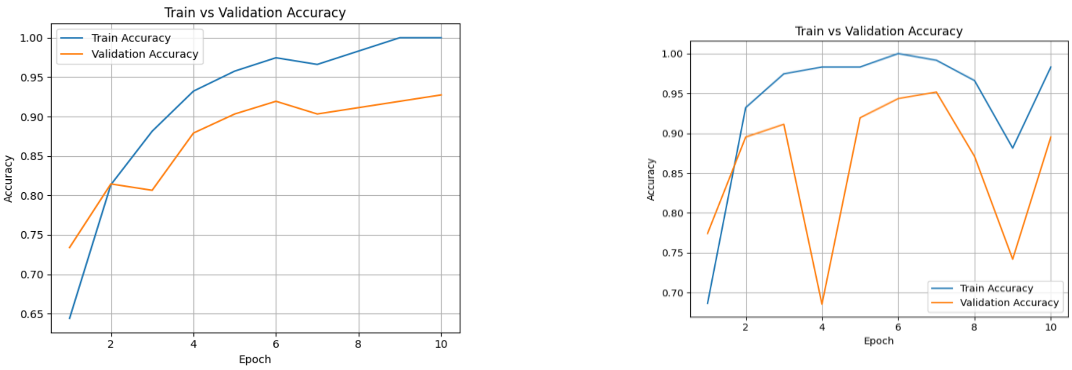
Figure 4 shows the results of the data preprocessing stage carried out to ensure image quality and uniformity before entering the deep learning model training process. This process includes resizing to 224x224 pixels, normalization to convert pixel values to the [0,1] range, and augmentation to expand the dataset's diversity. After the preprocessing stage, the dataset is more representative and ready for use in the training process. Visualization of the preprocessing results shows that the rice leaf images retain key features such as color patterns, spot shapes, and leaf texture, which are important for feature extraction by CNN. This process also significantly increased the dataset size without changing the visual characteristics of the disease.

3.2 CNN Model Training Results

This study used two main models based on the Inception_v3 architecture: Inception_v3 Basics with the RMSprop optimizer and Inception_v3 Optimization with the Adam optimizer. Both models were tested separately to assess their performance and the effect of the optimization algorithms on rice leaf disease classification results. To see the results of the accuracy test of these two models, please see Figure 5.

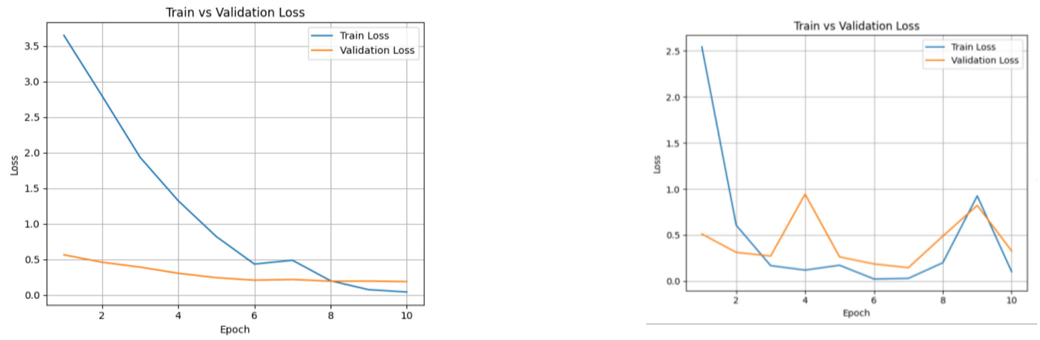


a) Inception_v3 Optimization b) Inception_v3 Basics

Figure 5. Accuracy Results of the Tested Models

Figure 5 shows a graphical comparison between training accuracy and validation accuracy for the two tested models: Inception_v3 Optimization (Figure a) and Inception_v3 Basics (Figure b). In the Inception_v3 Optimization model, both training and validation accuracy consistently increase with increasing epochs, with a stable trend converging to accuracy values approaching 0.98 for the training data and around 0.93 for the validation data. This indicates that the model with the Adam optimizer is able to achieve a balance between learning and generalization without experiencing excessive fluctuations. In contrast, in the Inception_v3 Basics model using the RMSprop optimizer, the validation accuracy graph shows quite sharp fluctuations in some epochs, despite its high training accuracy. This pattern indicates that the baseline model is more susceptible to overfitting and instability during the training process. Overall, a comparison of these two graphs demonstrates that the use of the Adam optimizer in the Inception_v3 Optimization model provides more stable training performance, faster convergence, and better generalization capabilities than the baseline model.

During the training process, the model was run for several epochs, with accuracy and loss values monitored for both the training and validation sets. In the Inception_v3 Basics model, the training curve showed a slow increase in accuracy in the early epochs and tended to stabilize after 30 epochs, with an average validation accuracy of around 89%. In contrast, the Inception_v3 Optimization model using the Adam optimizer showed faster convergence, with a significant increase in validation accuracy, reaching 94% after 25 epochs. This demonstrates Adam's greater adaptability in adjusting the learning rate to gradient changes, accelerating the learning process without compromising model stability. The loss curve can be seen in Figure 6.



a) Inception_v3 Optimization b) Inception_v3 Basics

Figure 6. Loss Results of the Tested Models

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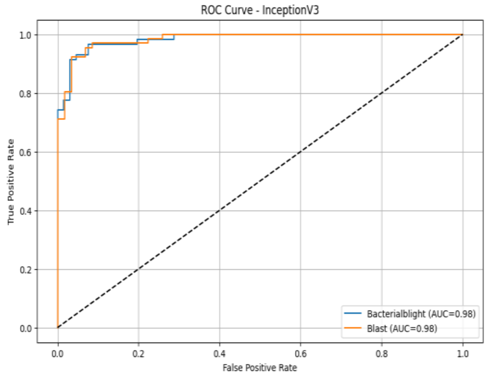
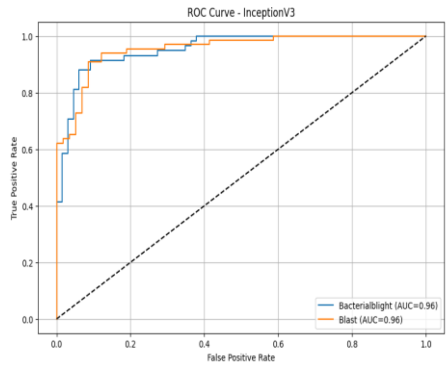
Figure 6 shows a comparison of the loss graphs between the training data (training loss) and validation data (validation loss) for the two tested models: Inception_v3 Optimization (Figure a) and Inception_v3 Basics (Figure b). In the Inception_v3 Optimization model using the Adam optimizer, the training loss value consistently decreases from the beginning to the end of each epoch, indicating a stable and efficient learning process. The validation loss also decreases in a similar pattern without significant fluctuations, indicating the model's good ability to generalize to new data. This indicates that the optimization process successfully accelerated convergence and effectively minimized prediction errors. Conversely, in the Inception_v3 Basics model using the RMSprop optimizer, the loss values for both the training and validation data exhibited significant fluctuations across several epochs, particularly the validation loss, indicating instability during training and potential overfitting. Overall, the patterns in these two graphs confirm that the Inception_v3 Optimization model has more stable training performance, lower error rates, and stronger generalization capabilities compared to the baseline model, making it superior for application in deep learning-based rice leaf disease detection systems. Observations of the loss function also show a striking difference. The training loss and validation loss values in the Inception_v3 Optimization model decrease consistently, while those in the Inception_v3 Basics model fluctuate, especially in the early epochs. This difference in patterns indicates that the model with the Adam optimizer is more efficient in minimizing prediction errors and has a better level of generalization to the test data. The ROC graph can be seen in Figure 7 below.



a) Inception_v3 Optimization



b) Inception_v3 Basics

Figure 7. ROC Results

Figure 7 shows a comparison of the ROC (Receiver Operating Characteristic) curves between two models: Inception_v3 Optimization (Figure a) and Inception_v3 Basics (Figure b), which were used to measure the model's ability to differentiate between two classes of rice leaf diseases: Bacterial Blight and Blast. The Inception_v3 Optimization model, using the Adam optimizer, showed excellent ROC results, with an AUC (Area Under Curve) of 0.98 for both classes. This value is close to 1, indicating that the model has very high sensitivity and specificity and is able to accurately distinguish between healthy and infected leaves. Meanwhile, the Inception_v3 Basics model, using the RMSprop optimizer, produced an AUC of 0.96 for both classes, also demonstrating good performance but slightly lower than the optimized model. Visually, the ROC curves of the optimized model appear closer to the upper left axis of the graph, indicating a higher proportion of true positives at a low false positive rate. This confirms that the application of the Adam optimization method significantly improved the model's classification capabilities, particularly in reducing detection errors and increasing the accuracy of rice leaf disease identification. Thus, Inception_v3 Optimization proved more efficient and reliable in detecting Bacterial Blight and Blast diseases than the baseline model.

Model performance was evaluated using several standard image classification metrics: accuracy, precision, recall, and F1-score. Additionally, a confusion matrix was used to assess the distribution of classification results across the Bacterial Blight and Blast classes.

Table 2. Comparison Evaluation Results of the Inception_v3 Optimization and Inception_v3 Basics Models

Model	Optimizer	Precision	Recall	F1-score	Balanced Accuracy	Matthews Correlation Coefficient (MCC)	Cohen's Kappa	ROC
Inception_v3 optimization	Adam	0,9672	0,8939	0,9291	0,9297	0,8578	0,8573	0,98
inception_v3 basics	RMSprop	0,9206	0,8788	0,899	0,8963	0,7930	0,7900	0,96

The table above shows that the Inception_v3 Optimization model using the Adam optimizer produces higher accuracy and F1-score values than the baseline model. This demonstrates that using Adam improves the model's ability to recognize complex features in rice leaves more accurately and consistently. High precision indicates the

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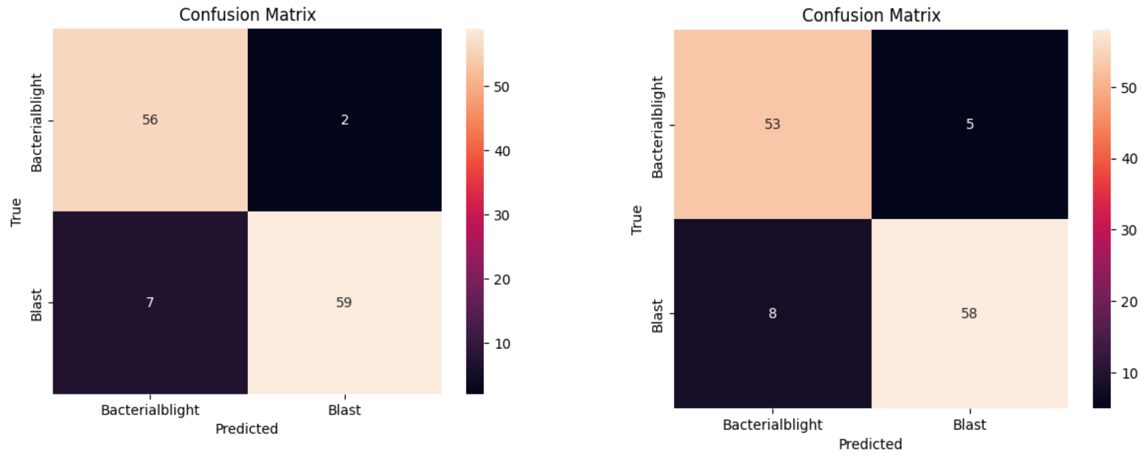
model's ability to avoid misclassification of the wrong class, while high recall indicates the model's effectiveness in detecting all actual disease cases.



a) Inception_v3 Optimization b) Inception_v3 Basics

Figure 8. Confusion Matrix

The confusion matrix visualization also shows that the Adam optimization model has a more even distribution of predictions and a lower misclassification rate than the RMSprop model. This means that the optimized model is better able to distinguish the visual characteristics of Bacterial Blight and Blast diseases, even though both have similar leaf spot patterns.

3.3 Discussion

The results show that the Inception_v3 architecture is highly effective in detecting rice leaf diseases due to its ability to extract multi-scale features and complex textures. However, model effectiveness is highly dependent on the optimization strategy used. The Adam optimizer has been shown to provide better performance than RMSprop, especially in terms of convergence speed and learning stability. Theoretically, Adam combines the advantages of momentum (preserving gradient direction) and adaptive learning rate (adjusting weight updates based on gradient changes), resulting in a more efficient training process that is less prone to local minima. Furthermore, these results also demonstrate the importance of data preprocessing and augmentation in improving model generalization. By expanding the data variety through rotation and flipping, the model can learn to recognize leaf disease patterns in various orientations and lighting conditions. This is particularly relevant for field applications, where image conditions are often less than ideal.

Overall, the evaluation results demonstrate that the Inception_v3 Optimization-based deep learning approach can be an effective solution for early detection of rice leaf diseases. The developed model has the potential to be implemented in mobile or IoT-based applications that can be used directly by farmers in the field, thereby accelerating disease diagnosis and supporting decision-making in sustainable agricultural management.

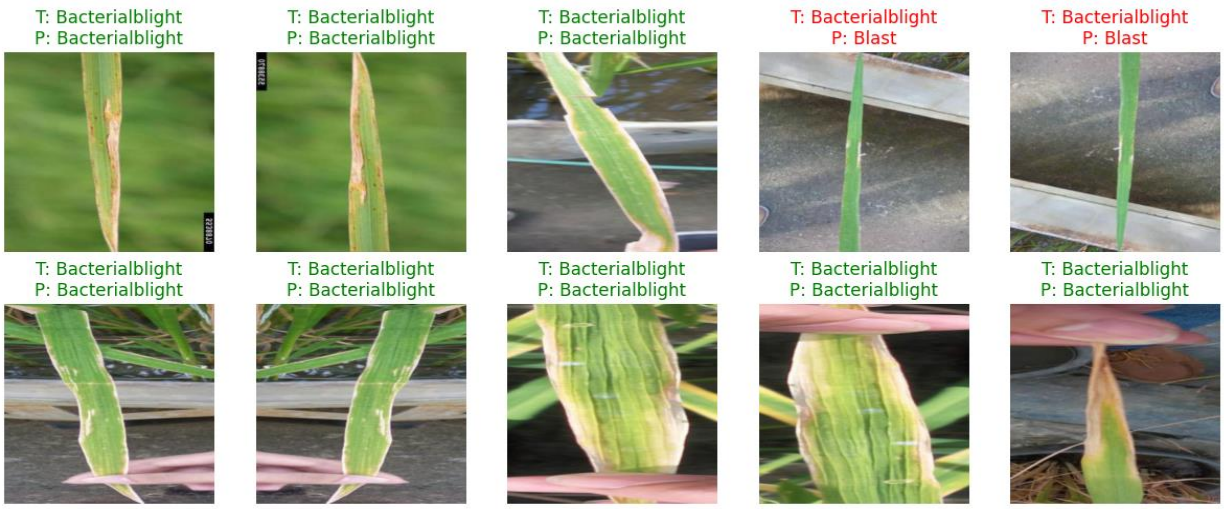


Figure 9. Classification Results

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Figure 9 displays the classification results of rice leaf disease predictions using the Inception_v3 Optimization model optimized with the Adam optimizer algorithm. Each image shows a rice leaf with its true label (T) and the model's predicted label (P). Most images show accurate predictions, where the predicted labels match the true labels, indicated by green text indicating a match between T and P (e.g., T: Bacterialblight and P: Bacterialblight). This demonstrates that the model is able to recognize the visual pattern of Bacterial Blight disease with high precision based on the texture, color, and shape of the leaf spots. However, there were several cases of misclassification, indicated by red text, where the model incorrectly identified leaves actually infected with Bacterial Blight as Blast. These errors are likely caused by similarities in visual features between disease types, such as similar leaf color changes during the early stages of infection. Overall, these classification results confirm that the Inception_v3 Optimization model has excellent predictive performance with a low error rate, and demonstrates great potential for use in a deep learning-based early detection system for rice leaf diseases that can support sustainable and efficient agricultural practices.

The test results conclude that the Inception_v3 Optimization model excels not only in technical aspects such as accuracy and training speed, but also has practical implications for the development of intelligent agricultural systems. The application of this model enables automated early detection of plant diseases with a very low error rate, even in environments with diverse lighting conditions and backgrounds.

Another implication of this research is its contribution to sustainable agriculture. With more accurate early detection capabilities, farmers can intervene more quickly and precisely, reduce the excessive use of chemical pesticides, and maintain the balance of the agricultural ecosystem. Furthermore, these research findings open up opportunities for the development of artificial intelligence-based systems in the local agricultural sector, including for disease detection, plant growth monitoring, and crop yield prediction.

4. CONCLUSION

Based on the research results shown in the model performance evaluation table, it can be concluded that the Inception_v3 Optimization model with the Adam optimizer provided the most optimal results compared to the Inception_v3 Basics model using RMSprop. The optimization model showed significant improvements across all evaluation metrics, with a Precision value of 0.9672, a Recall value of 0.8939, and an F1-score of 0.9291, indicating the model's excellent ability to balance the accuracy and completeness of rice leaf disease detection. Furthermore, the Balanced Accuracy value of 0.9297 and the Matthews Correlation Coefficient (MCC) of 0.8578 demonstrate consistent model performance across both disease classes (Bacterial Blight and Blast), while also confirming overall classification stability. A Cohen's Kappa value of 0.8573 and an area under the ROC curve (AUC) of 0.98 indicate that the optimized model has a high level of agreement between predictions and actual labels and excellent reliability in distinguishing positive and negative classes. Overall, these results prove that the application of the Inception_v3-based optimization method with the Adam optimizer is able to significantly improve the accuracy, efficiency, and generalization of the model, so that it can be relied upon as an effective deep learning approach for early detection of rice leaf diseases and has great potential in supporting sustainable smart agricultural systems at the local level.

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