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Research Article

Analyzing InceptionV3 and InceptionResNetV2 with Data Augmentation for Rice Leaf Disease Classification

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Abstract: This research aims to evaluate and compare the performance of several deep learning architectures, especially InceptionV3 and InceptionResNetV2, with other models, such as EfficientNetB3, ResNet50, and VGG19, in classifying rice leaf diseases. In addition, this research also evaluates the impact of using data augmentation on model performance. Three different datasets were used in this experiment, varying the number of images and class distribution. The results show that InceptionV3 and InceptionResNetV2 consistently perform excellently and accurately on most datasets. Data augmentation has varying effects, providing slight advantages on datasets with lower variation. The findings from this research are that the InceptionV3 model is the best model for classifying rice diseases based on leaf images. The InceptionV3 model produces accuracies of 99.53, 58.94, and 90.00 for datasets 1, 2, and 3, respectively. It is also necessary to be wise in carrying out data augmentation by considering the dataset's characteristics to ensure the resulting model can generalize well.

Keywords: Data augmentation impact; Image classification; Image recognition; Rice leaf disease classification; Transfer learning.

1. Introduction

Rice is the main staple food for Indonesians and is widely consumed by many other countries worldwide. Based on data released by the United States Department of Agriculture (USDA) in July 2023, the level of rice consumption in Indonesia reached 35.2 million metric tons[1]. This makes Indonesia one of the countries with the most considerable rice consumption levels in the world[2], behind Bangladesh, India, and China, apart from being one of the largest rice consumers in the world. Indonesia also occupies a position as one of the largest rice producers in the world. In 2019, Indonesia's rice production was impressive, reaching 34.7 million metric tons. However, in 2022, Indonesia's rice production will decrease to 34 million metric tons. The decline in rice production in Indonesia is caused by several factors, one of which is extreme weather conditions, which trigger the development of disease in rice plants. Each type of disease requires different treatment, and if treatment is late or inappropriate, it can result in greater losses.

The conventional way to identify diseases in rice is usually based on visual observation by experienced experts. This, of course, has some disadvantages, not only can the expert be wrong, but it is also less efficient. Based on these problems, many researchers have studied automatic rice disease diagnosis based on pattern recognition and machine learning[3], [4]. Currently, the development of the application of Machine Learning has brought the emergence of a further science[5], namely Deep Learning. Deep learning is an advanced machine

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learning technique that successfully trains on large amounts of data, automatically learns input features, and provides output based on decision rules[6]–[9]. One of the most popular algorithms in deep learning is the convolutional neural network (CNN). CNNs can be adapted to specific needs by manually arranging appropriate layers [10]–[12]. However, transfer learning techniques are becoming popular and often used in many studies. Transfer learning is the process of pre-initializing a model using weights obtained by training a different model on a larger dataset[13]. This technique is derived from knowledge gained from a training dataset and is used to train a model on a different but relevant task or field, where this concept is generally known as a pre-trained model. Some of the advantages offered by this method include increased model accuracy, higher training time efficiency, and better performance[14].

Conventionally, research on disease identification in rice leaves generally focuses on a limited number of datasets. For example, research conducted by Lu et al. [3] proposed using a manually configured CNN to classify 500 rice leaf disease images and achieved an accuracy of 95%. In another study, Shrivastava et al.[15] proposed using AlexNet for feature extraction and SVM for the classification of 619 rice leaf disease images, which produced an accuracy of 91.37%. Ahad et al.[13] also conducted similar research using several architectures such as DenseNet121, InceptionV3, MobileNetV2, Res-Next101, ResNet152V2, and SeresNext101 to classify 900 rice leaf disease images, which were then augmented to produce a total of 42,876 images. This research shows that DenseNet121 and InceptionV3 can produce the highest accuracy of 97%. Meanwhile, Krishnamoorthy et al. [16] also conducted research by proposing the use of the InceptionResNetV2 architecture to identify diseases in rice plants. In this research, the dataset used consists of 5,200 images divided into four classes. The results of this research show that InceptionResNetV2 succeeded in achieving an accuracy level of 95.67%. Based on the research results in several journals above, InceptionV3 and InceptionResNetV2 can produce promising performance. Apart from that, both architectures also have their respective advantages. InceptionV3, which consists of five convolution layers, one average pooling layer, two max-pooling layers, one Fully Connected (FC) Layer, and 11 inception modules, has the main advantage, namely its unique feature extraction capabilities, which enable it to extract features from images with various size through one level of convolution[10]. Meanwhile, InceptionResNetV2, which is a variant of the inception architecture that integrates the concept of residual connections, has the advantage that the residual connections technique used allows signals in the previous layer to pass directly through the following layers in the network, thereby facilitating the training process on the deep network [17]. Based on the background above, this research aims to:

1. Assess and compare the performance of two main architectures, InceptionV3 and InceptionResNetV2, in classifying rice leaf disease images and comparing several EfficientNet, ResNet, and VGG architectures.
2. Evaluate the impact of using data augmentation on architectural performance in classifying rice leaf disease images.
3. Determine the architecture that provides the best results in classifying rice leaf disease images.

The remainder of this paper is organized into four sections. Section 2 discusses related works; section 3 presents the proposed method and explains the architecture and augmentation techniques used in detail. Section 4 discusses the results and discussions that explain the findings obtained from the experiments. In the last section, a conclusion will be given, which provides a summary of the findings from the experiments that have been carried out.

2. Related Work

This section discusses in more detail some of the related research that inspired it, including some mentioned in the introduction. A number of researchers have conducted research and studies in recent years to diagnose diseases in plants using machine learning and deep learning algorithms. For example, in research conducted by N. Krishnamoorthy et al.[16], the InceptionResNetV2 architecture was proposed to identify diseases in rice plants. In this research, the dataset used consists of 5200 images, which are divided into four classes, namely leaf blast, brown spot, bacterial blight, and healthy. Preprocessing, which includes changing the pixel value scale to a range between 0-1, adjusting the image size to 224x224, and applying data augmentation, was also carried out in this research. The results of this research show that InceptionResNetV2 succeeded in achieving an accuracy level of 95.67%

Ghosal and Sarkar[18] conducted a similar study and proposed using VGG16 architecture. The dataset used is 2,156 images and consists of four classes, namely leaf blast, leaf blight, brown spot, and healthy. The data preprocessing stage is carried out by resizing the image to a size of 224x224 pixels. Augmentation data such as zoom, rotation, and shift are also applied. As a result, the VGG16 architecture achieved 92.4% accuracy in 25 epochs.

Ding Jiang et al. [19] also researched to detect disease in tomato leaf images. This research uses ResNet50 to identify three common diseases that usually occur on tomato leaves: spot blight, late blight, and yellow leaf curl. The dataset used in this research has been resized to a size of 224x224 pixels and has a total of 6794 images after carrying out the data augmentation process. After the training process was carried out for 24 epochs, the results showed that the model created with the ResNet50 architecture achieved an accuracy of 98.0%.

Ümit Atila et al.[20] conducted using several versions of the EfficientNet architecture to classify diseases on plant leaves from several species. The dataset used in this research totaled 61,486 images after data augmentation and consisted of 38 different classes. As a result, the EfficientNetB5 architecture is the best among other EfficientNet architectures with an accuracy of 99.91% on the original dataset, while on the augmented dataset, EfficientNetB4 is the best with an accuracy of 99.97%. Based on some of the literature above, almost all research uses large datasets and data augmentation. Therefore, this research will further test whether these two things can significantly influence architectural performance. Experiments will be carried out using three datasets of different sizes and carried out in two conditions, namely, using data augmentation and without using data augmentation.

3. Proposed Method

This research consists of several stages, as shown in Figure 1. The dataset chosen in this research is public data to facilitate the comparison process. A more detailed discussion will be discussed in section 4. Next, augmentation is carried out specifically for data preprocessing. Furthermore, this section discusses the proposed model design in section 3.1, data augmentation in section 3.2, and model evaluation techniques in section 3.3.

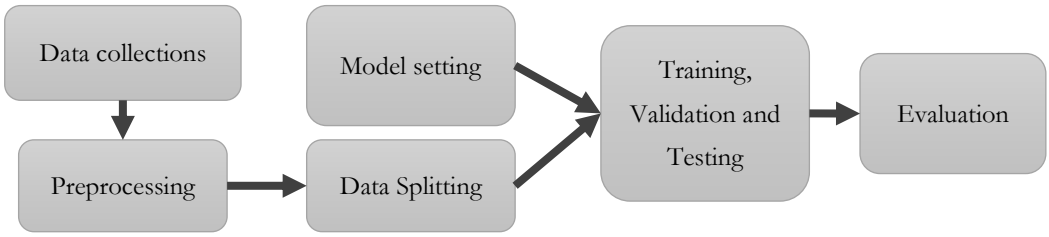


Figure 2. Research stages.

3.1. Model Design

The initial step involves selecting a pre-trained architecture previously trained on a large dataset, such as ImageNet, and creating a base model using that architecture. This basic model is then set as non-trainable so that the learned representation does not change. Next, the input layer is created with image dimensions corresponding to each architecture's optimal size. These images are fed into a base model created from the previously selected architecture. The results from the previous layers are extracted, and global average pooling is carried out to produce global features. Next, these features are input for an output layer consisting of a Dense layer with a softmax activation function, producing predictions for the N desired categories. The final model is then compiled using the categorical cross-entropy loss function, Adam optimizer, and accuracy metrics. The training process is then carried out for ten epochs using the training dataset. Further hyperparameter settings are presented in Table 1.

3.1.1. InceptionV3

Inception V3 is the third release in the Evolutionary Deep Learning Architecture series developed by Google. This architecture consists of 42 layers and uses an input layer to receive images of 299 × 299 pixels. The highlight of this architecture lies in using the Softmax function in its final layer, which allows the model to produce output in the form of class probabilities[21]. Table 2 shows the parameter settings for the InceptionV3 model used in this research.

Table 1. Hyperparameter Model.

Parameter	Values
Optimizer	Adam (Learning rate = 0.001)
Loss function	categorical_crossentropy
Metrics	accuracy
Batch size	32
Epoch	10

Table 2. Parameter Detail of InceptionV3.

Layer(type)	Output Shape	Param#
input_layer (InputLayer)	[(None, 299, 299, 3)]	0
inception_v3 (Functional)	(None, None, None, 2048)	21802784
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
output_layer (Dense)	(None, 4)	8196
Total params: 21810980 (83.20 MB)		
Trainable params: 8196 (32.02 KB)		
Non-trainable params: 21802784 (83.17 MB)		

3.1.2. InceptionResNetV2

InceptionResNet V2 is a variant of the Inception architecture that integrates the concept of residual connections with the Inception architecture[17]. The residual connection technique allows signals in the previous layer to pass directly through the next layers in the network, thereby facilitating the training process in deep networks. In InceptionResNetv2, each Inception block is followed by a filter expansion layer (1x1 convolution), which is used to increase the dimensions of the filter bank before summing with the input. This is necessary to compensate for the dimension reduction that occurs due to the Inception block. Table 3 shows the parameter settings of the InceptionResNetV2 model used in this research.

Table 3. Parameter Detail of InceptionResNetV2.

Layer(type)	Output Shape	Param#
input_layer (InputLayer)	[(None, 299, 299, 3)]	0
inception_resnet_v2 (Functional)	(None, None, None, 1536)	54336736
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1536)	0
output_layer (Dense)	(None, 4)	6148
Total params: 54342884 (207.30 MB)		
Trainable params: 6148 (24.02 KB)		
Non-trainable params: 54336736 (207.28 MB)		

3.2. Data Augmentation

Data augmentation aims to enrich and vary the dataset while increasing the diversity of information that can be learned by the model[22]–[24]. In this research, the data augmentation included width_shift_range and height_shift_range of 10% and zoom_range of 20%. This augmentation was chosen because it tends not to change the input image significantly and does not cause distortion that could change the meaning or appearance of objects in the image. More detailed augmentation settings are presented in Table 4.

Table 4. Data augmentation parameter.

Parameter	Values
width_shift_range	0.1
height_shift_range	0.1
zoom_range	0.2

3.3. Model Evaluation

This research has two evaluation phases: evaluation at the training and validation stages as the first phase and evaluation at the testing stage as the second phase. In the first phase of evaluation, accuracy metrics will be used to measure the level of accuracy in training and validation. A loss function with the categorical_crossentropy parameter will also be applied to measure the difference between model predictions and actual labels in the training data. In the second evaluation phase related to the testing stage, several measurement metrics will be used, such as accuracy, precision, recall, f1-score, and specificity, which are calculated based on the confusion matrix. Then, the evaluation metric used as the main reference in assessing model performance is accuracy. These metrics are selected based on their suitability for situations when the distribution of classes in the data is relatively balanced. Meanwhile, other metrics such as precision, recall, f1-score, and specificity are considered more suitable for evaluating imbalanced data because they calculate model performance by considering values such as false negatives and false positives, so they are more relevant when the data has significant differences between the classes. Equation (1)-(5) are formulas used to calculate accuracy, precision, recall, f1-score, and specificity[25]–[27].

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{precision} = \frac{\text{TP}}{\text{FP} + \text{TP}} * 100\% \tag{2}$$

$$\text{recall} = \frac{\text{TP}}{\text{FN} + \text{TP}} * 100\% \tag{3}$$

$$\text{f1} - \text{Score} = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} \tag{4}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FN} + \text{FP}} \tag{5}$$

True Positive (TP): The number of instances that genuinely belong to the positive class and are correctly classified by the model as positive. True Negative (TN): The number of instances that genuinely belong to the negative class and are correctly classified by the model as negative. False Positive (FP): The number of instances that genuinely belong to the negative class but are incorrectly classified by the model as positive. False Negative (FN): The number of instances that genuinely belong to the positive class but are incorrectly classified by the model as negative.

4. Results and Discussion

This research was conducted using three different datasets obtained from public dataset providers such as Kaggle, UCI Dataset and Mendeley Dataset. The experiments in this research involved two different conditions, namely, using data augmentation and without data augmentation. Detailed information about the dataset used, including name, amount of data, and class name, can be found in Table 5 below. Sample images for each rice disease are presented in Figure 2. The sample images presented in Figure 2 were taken randomly from the three datasets. Furthermore, the distribution of each dataset is also presented in Figure 3.

The datasets used in this study, as described in Table 5, vary widely regarding the number of images and class distribution. Dataset 1 has a fairly balanced distribution, with 5932 images divided into four classes, while Dataset 3 is smaller and unbalanced, with only 120 images divided into three classes. The images in Figure 2 show the different visual characteristics of each disease, while Figure 3 highlights the varying distribution of classes in each dataset. This diversity in dataset size and composition is important for evaluating the robustness of the proposed model, as it ensures the model is tested under various conditions, thereby increasing its generalization and reliability in real-world applications. By using datasets of various scales and class distributions, this study aims to assess the overall performance and robustness of the model in classifying rice leaf diseases.

Table 5. Dataset source and details.

No.	References	Dataset details
1	[28]	Name: Rice Leaf Disease Image Samples Number of images: 5932 Class: Bacterial blight, Blast, Brown Spot, Tungro URL: https://data.mendeley.com/datasets/fwcj7stb8r/1
2	[29]	Name: Rice Disease Image Dataset Number of images: 2092 Class: Brown Spot, Hispa, Leaf Blast, Healthy URL: https://www.kaggle.com/datasets/minhhuy2810/rice-diseases-image-dataset
3	[30]	Name: Rice Leaf Disease Number of Images: 120 Class: Bacterial leaf blight, Brown spot, Leaf smut URL: https://archive.ics.uci.edu/dataset/486/rice+leaf+diseases

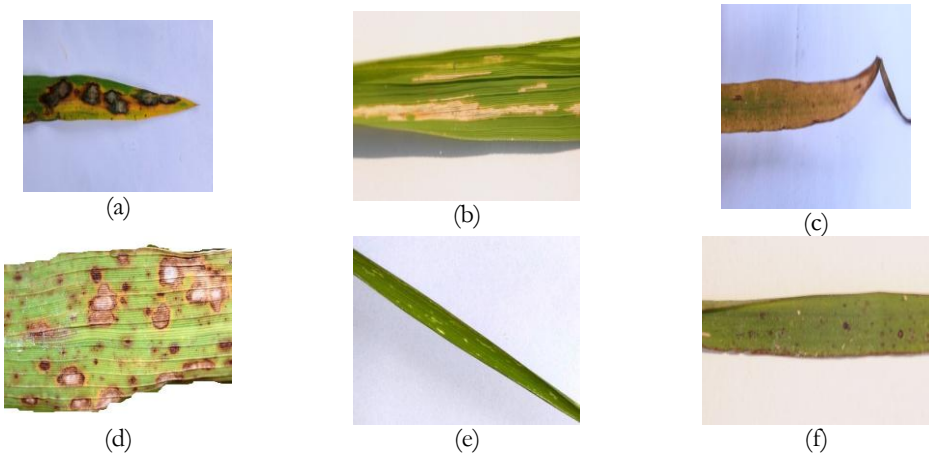


Figure 2. Examples of diseases on rice leaves (**a**)Leaf Blast; (**b**) Bacterial Blight; (**c**) Brown Spot; (**d**) Tungro; (**e**) Hispa; (**f**) Leaf Smut

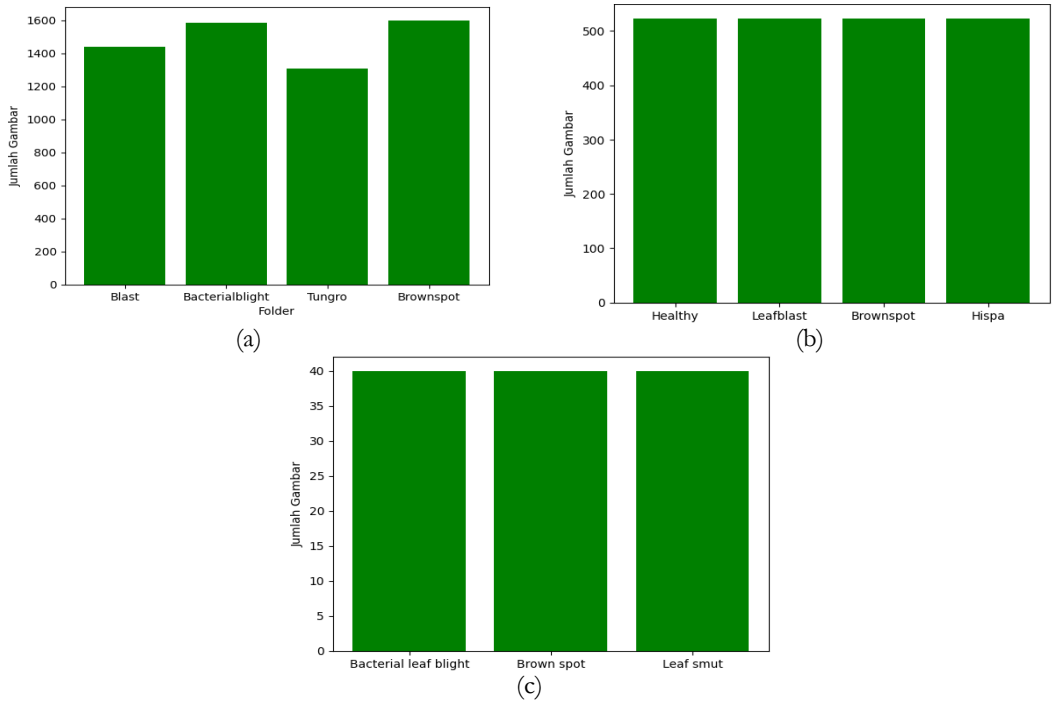


Figure 3. Class distribution of each dataset (**a**) Dataset 1; (**b**) Dataset 2; (**c**) Dataset 3.

In the next stage, the dataset is split into two parts, namely training data and testing data, with a proportion of 75% training and 25% testing. The training dataset is further divided into training and validation datasets, with a proportion of 75% and 25%, respectively. The training data undergoes an augmentation process to improve its performance. A sample application of augmentation is presented in Figure 4.

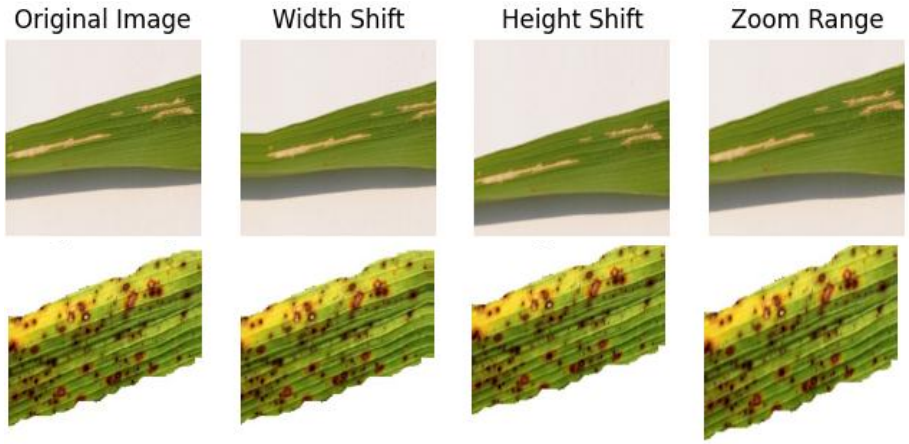


Figure 4. Sample augmentation results

Next, normalization was carried out using rescaling to adjust the dataset scale to a range of 0-1, which aims to speed up the computing process. Additionally, the input image size is also adjusted to match the input_size of the architecture used. Specifically, the InceptionV3 and InceptionResNetV2 models use the same input_size, namely 299 x 299. Next, the model training process is carried out using the training dataset (train_data) and testing dataset (test_data) which have been separated previously. In this training experiment, several hyperparameters were used, which are presented in Table 1. Next, samples of the training and validation process results on dataset 1 are presented in the scatter plot in Figure 5.

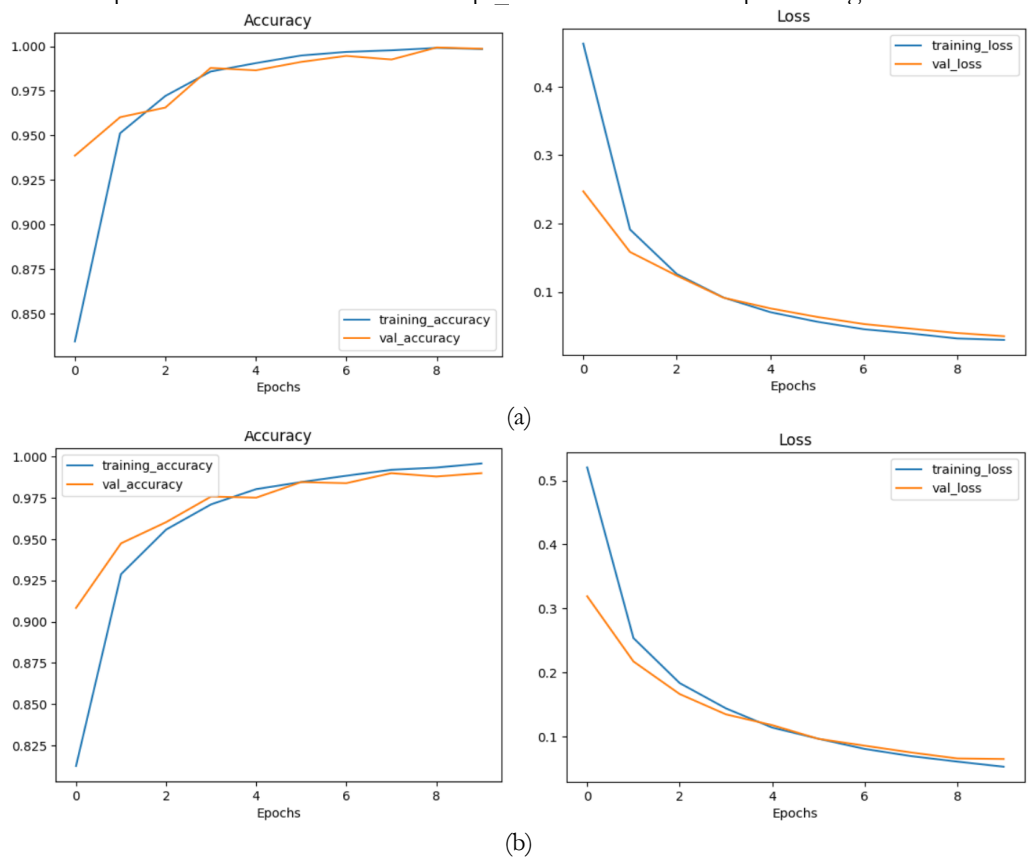
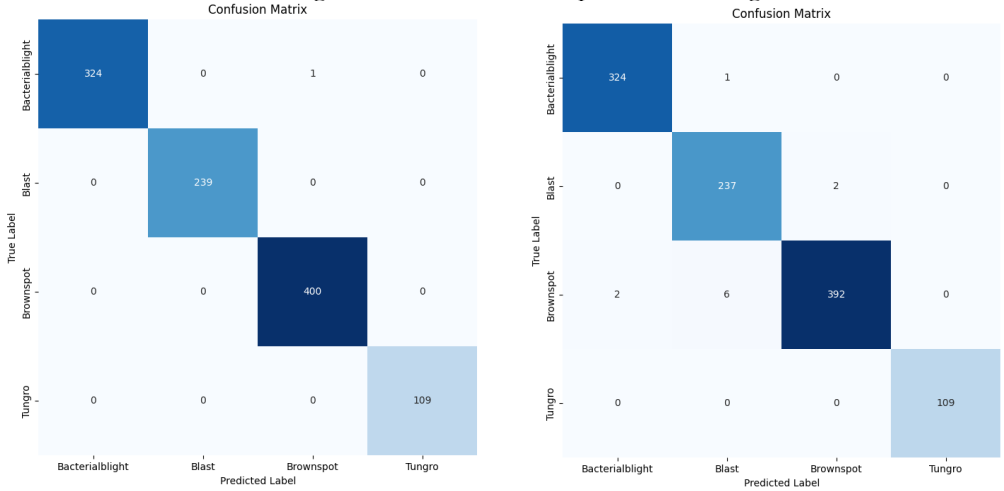


Figure 5. Accuracy and Loss Graph on Dataset 1 (**a**) InceptionV3; (**b**) InceptionResNetV2

Figure 5 displays the accuracy and loss graph during the training and validation process for the InceptionV3 and InceptionResNetV2 models using Dataset 1. In the InceptionV3 accuracy graph (Figure 5a), it can be seen that the training and validation accuracy increases gradually until it approaches 100% at the end of the training, indicating the model's capabilities. to learn and generalize well. The InceptionV3 loss graph shows a steady decline, with shallow training and validation loss values at the end of training. This indicates that the model has no signs of overfitting or underfitting. Likewise, in the InceptionResNetV2 graph (Figure 5b), a similar pattern of increasing accuracy is also visible, with training and validation accuracy almost reaching 100%. The loss graph shows a stable and consistent decrease, with low loss values at the end of training. This shows that the InceptionResNetV2 model can learn important features from the dataset without experiencing overfitting, although the plot is not better than InceptionV3. Overall, both models, InceptionV3 and InceptionResNetV2, show excellent performance in training and validation on Dataset 1. Both models show consistent accuracy improvement and stable loss reduction, indicating that both architectures are suitable for the rice leaf disease classification task with the dataset used in this research. Next, the test results are measured using the confusion matrix presented in Figure 6.



(a) (b)

Figure 6. Confusion matrix results on Dataset 1 (**a**) InceptionV3; (**b**) InceptionResNetV2.

Table 6. Classification of testing data for all datasets without data augmentation in various transfer learning models

Model	Accuracy	Precision	Recall	F1-score	Specificity
Dataset 1					
InceptionV3	**98.04%**	**98.13%**	**98.06%**	**98.08%**	**98.12%**
InceptionResNetV2	97.64%	97.78%	97.62%	97.66%	97.61%
EfficientNetB3	36.14%	38.89%	35.54%	27.94%	35.54%
ResNet50	46.12%	70.13%	43.10%	31.54%	43.10%
VGG19	79.84%	80.23%	80.33%	79.87%	80.37%
Dataset 2					
InceptionV3	**53.86%**	57.85%	53.86%	54.83%	54.83%
InceptionResNetV2	57.52%	59.73%	**57.52%**	**57.10%**	**57.52%**
EfficientNetB3	32.52%	**66.73%**	32.52%	21.98%	32.52%
ResNet50	36.79%	52.46%	36.79%	30.34%	36.78%
VGG19	39.02%	41.56%	39.02%	35.56%	39.02%
Dataset 3					
InceptionV3	**86.67%**	**87.44%**	**85.83%**	**85.38%**	**85.83%**
InceptionResNetV2	76.67%	81.62%	77.78%	75.40%	77.77%
EfficientNetB3	43.33 %	36.32%	37.22%	29.55%	37.22%
ResNet50	43.30%	48.25%	45.56%	41.82%	45.55%
VGG19	50.00%	59.68%	51.67%	49.77%	51.66%

Table 7. Classification of testing data for all datasets with data augmentation in various transfer learning models

Model	Accuracy	Precision	Recall	F1-score	Specificity
Dataset 1					
InceptionV3	**99.53%**	**99.56%**	**99.53%**	**99.54%**	**99.52%**
InceptionResNetV2	98.99%	99.01%	99.12%	99.01%	99.01%
EfficientNetB3	39.51%	50.05%	36.84%	26.84%	36.85%
ResNet50	61.70%	61.76%	61.27%	60.68%	61.27%
VGG19	81.12%	82.33%	81.41%	81.35%	81.41%
Dataset 2					
InceptionV3	57.11%	59.98%	57.11%	56.73%	57.73%
InceptionResNetV2	**58.94%**	63.11%	**58.94%**	**58.88%**	**58.94%**
EfficientNetB3	30.49%	**64.98%**	30.49%	19.88%	30.48%
ResNet50	36.59%	52.59%	36.59%	29.47%	36.58%
VGG19	41.06%	41.58%	41.06%	39.73%	41.05%
Dataset 3					
InceptionV3	**90.00%**	**88.89%**	**89.17%**	**88.85%**	**89.16%**
InceptionResNetV2	83.33%	84.18%	83.61%	82.93%	83.61%
EfficientNetB3	33.33%	77.78%	33.33%	16.67%	33.33%
ResNet50	23.33%	50.00%	25.83%	19.81%	25.83%
VGG19	53.43%	66.35%	55.00%	54.22%	55.00%

The confusion matrix results in Figure 6 also appear satisfactory with minimizing errors. More detailed measurements are presented in Table 6. In Table 6, several measurements are also carried out using other popular transfer planning models such as EfficientNetB3, ResNet50, and VGG19 with standard tuning. Overall, InceptionV3's performance is superior on the first and third datasets, while InceptionResNetV2 is slightly superior on the second dataset based on recall, f1, and specificity, while InceptionV3's accuracy is still the best. Apart from that, an ablation study was also carried out to validate the data augmentation performance and whether it positively or negatively affected classification performance. The results of classification testing on the dataset without augmentation are presented in Table 7.

Based on the results presented in Table 6 and Table 7, it can be seen that the effect of data augmentation varies depending on the size and characteristics of the dataset used. In Dataset 1, data augmentation slightly decreases the accuracy of models such as InceptionV3 and Inception-ResNetV2, but the models still show excellent performance. This shows that data augmentation does not benefit large and diverse datasets significantly. In contrast, on the smaller and less diverse Dataset 2, data augmentation appears to provide a slight advantage to the InceptionResNetV2 and InceptionV3 models, although the increase in accuracy is not very significant. This shows that data augmentation can help improve performance on datasets with lower variation. However, on Dataset 3, which is very small, data augmentation actually reduces accuracy for all models. This may be due to the small size of the dataset, so data augmentation adds excessive variation and makes it difficult for the model to learn relevant features. Overall, it is important to consider the dataset's characteristics before applying data augmentation, as the impact can vary depending on the condition of the dataset used.

5. Conclusions

This study evaluates the performance of several deep learning architectures in rice leaf disease classification and the impact of using data augmentation on model performance. The results show that the InceptionV3 and InceptionResNetV2 architectures excel in accuracy and generalization, especially on large and diverse datasets. The use of data augmentation produces varying results; on smaller, less diverse datasets, data augmentation can improve model performance, whereas, on small datasets, data augmentation can decrease accuracy due to the addition of excessive variation. Therefore, the choice of data augmentation technique must be adjusted to the characteristics of the dataset used. This research makes an essential contribution to understanding the use of deep learning models and data augmentation

techniques in plant disease classification. It offers practical guidance for developing more effective plant disease detection systems.

Author Contributions: Conceptualization: F.M.F. and D.R.I.M.S.; Methodology: F.M.F. and D.R.I.M.S.; software: F.M.F.; validation F.M.F. and D.R.I.M.S; formal analysis: A.R.M.; investigation: A.R.M. and D.R.I.M.S; resources: F.M.F.; data curation: F.M.F. and D.R.I.M.S; writing—original draft preparation: F.M.F. and D.R.I.M.S.; writing—review and editing: A.R.M.; visualization: F.M.F.; supervision: D.R.I.M.S.; project administration: A.R.M.; funding acquisition: All.

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Data Availability Statement: This research uses three public datasets that can be accessed via the URLs described in Table 5.

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

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