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Rice Plant Disease Detection with Data Augmentation Using Transfer Learning

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A B S T R A C T

Rice is a staple food source for most people around the world, including Indonesia, which is an agrarian country where most of its population grows and consumes rice. However, rice plants also suffer from various diseases, especially on the leaves, such as bacterial leaf blight, rice blast, dan rice tungro. If the infection or disease in rice plants is not identified early on, it will decrease production and harm farmers. To address this problem, information technology can be utilized in identifying diseases using image processing and image classification. The dataset was taken from public repositories, and data augmentation was also used in this research to increase the dataset's training accuracy. With this background, a disease detection system approach is proposed using Deep Learning method using Convolutional Neural Network (CNN) and several transfer learning architectures, namely VGG16, NASNetMobile, and Xception, for rice leaf disease detection. The best experimental results were obtained using the Xception architecture, where the training accuracy value is 99.13%, validation accuracy is 97.22%, and the testing accuracy is 97.22%.

Keywords: Rice Plant Disease, Data Augmentation, Transfer Learning, Deep Learning, CNN

1. Introduction

In this highly advanced world, humans have experienced many developments in fulfilling their daily needs, such as in politics, economics, social, health, agriculture, technology, and others. The agricultural field still faces many problems, especially the damage to crops caused by diseases that attack plant leaves. The function of leaves is vital for plants to carry out photosynthesis, and disease in plant leaves attacks almost all types of plants, including major food commodity crops such as rice.

Rice is an important crop as it serves as the staple food source for most countries worldwide, including Indonesia, which is an agrarian country where most of the population grows rice. The problem of rice diseases is quite crucial and commonly faced by farmers, especially since most farmers cannot detect early attacks by pests or diseases on rice crops. If left untreated, plant diseases can reduce crop yields, so early detection is necessary to prevent and effectively control plant diseases (Chen, Chen, Zhang, Sun, &Nanehkaran, 2020). In addressing this issue, information technology can be utilized to identify diseases by using digital image processing. The use of image processing in plant disease detection can assist agricultural managers in taking effective and efficient steps (Rozaqi, Sunyoto, &Arief, 2021).

Deep learning has become a hot topic in the world of machine learning due to its significant capability in modeling various complex data, such as images and sounds. Convolutional Neural Network (CNN) is currently the most effective deep learning method for image recognition due to its brain-like functionality, where a computer is given image data to learn, recognize each visual element in the image, and understand the patterns, allowing the computer to identify the image. The study entitled "Automatic Diagnosis of Rice Diseases Using Deep Learning" conducted by Ruoling Deng et al. (2021) aimed to develop an automatic diagnosis method for rice diseases using ensemble models and implemented it in a smartphone application. The overall accuracy achieved was 91%, which is considered good given the similarity between some types of rice diseases. Therefore, further research can still be conducted to improve the method. In another research titled "Rice Leaf Disease Classification Using CNN" conducted by PallapothalaTejaswini et al. (2022), the researchers found that a 5-layer convolution model had the highest accuracy of 78.2%, while others like VGG-16 had lower accuracy of 58.4% with 1600 image datasets. Different research results with varying levels of accuracy can occur due to differences in the quantity and quality of datasets or the type of CNN architecture used.

Based on the above background, there is still an opportunity for research related to rice plant disease detection and the use of CNN deep learning methods, such as comparing different architectures and experimenting with different dataset sizes. Therefore, researchers conducted an analysis and research on “Rice Plant Disease Detection with Data Augmentation using Transfer Learning”. With this research, it is expected to determine the accuracy level of the obtained model and how well the CNN model can classify rice leaf disease images more effectively and accurately.

2. Related Works

Before conducting research on the identification of diseases on rice plant leaves, the researcher first conducted a literature review related to previous studies conducted by other researchers as a reference in developing the research to be conducted. From the literature review conducted by the researcher, several previous research studies related and relevant to the study were obtained.

Hasan Matin et al. (2020) conducted a study titled "An Efficient Disease Detection Technique of Rice Leaf Using AlexNet" in which they applied the AlexNet technique to detect three prevalent rice leaf diseases: bacterial blight, brown spot, and leaf smut. They claimed to have achieved an accuracy of over 99% through efficient technique adjustment and image augmentation. However, the dataset used in the study consisted of only 120 images that were augmented to become 900 images. Research was conducted by HeriAndrianto et al. (2020) by developing a deep learning-based rice disease detection system, which consists of a machine learning application on a cloud server and an application on a smartphone that showed that the rice plant disease detection application based on a smartphone works well, which is capable of detecting diseases in rice plants with a detection system performance having a training accuracy of 100% and a testing accuracy of 60%. However, this research still has a weakness, which is only using one CNN architecture, namely VGG16, which happened to be suitable for 1600 dataset images. Another study was conducted by Hossain et al. (2020) where the researchers proposed a new CNN-based model to recognize rice leaf diseases by reducing network parameters with a dataset of 4199 rice leaf disease images resulting in the highest training accuracy of 99.78% and validation accuracy of 97.35%. Although the accuracy results are quite high, the dataset used is a private data source from only one region in Bangladesh.

Purbasari et al. (2021) also conducted research on rice plant disease detection with CNN using a dataset of 2239 rice leaf disease images from a public source, successfully detecting diseases in leaf images automatically with the best training accuracy obtained being 91%. This experiment's results can be improved by experimenting with more variations of CNN architectures and the number of hidden layers and nodes in each layer. In 2021, A A JE VeggyPriyangka et al. conducted a study to design an application for classifying rice diseases based on leaf color and texture using Convolutional Neural Network method with data augmentation on a dataset. The researchers tested the parameter variations of epoch and data augmentation and obtained a test accuracy of 95.24%. However, the study used a dataset that was too small, consisting of only 108 images, resulting in poor performance of the three image criteria used in the testing process. The researchers suspected that the training data size was incompatible with the testing dataset because the convolutional neural network requires a large amount of manually labeled data for training. Later in 2021, Ulfah Nur Oktaviana et al. conducted research titled "Classification of Rice Diseases Based on Leaf Images Using Trained Resnet101 Model". The researchers developed a model that could classify three types of rice plant diseases using 120 Rice Leaf Disease images. The model was developed using transfer learning with pre-trained Resnet101 model and additional architecture layers, showing a classification performance of 100% on validation data with a loss value of 5.61%. However, further review and validation are needed as the study only used three types of rice leaf diseases, and the total dataset only consisted of 120 images.

Another study was conducted by SunuJatmika et al. in 2022, which discussed the application of deep learning CNN method for classifying or identifying rice leaf diseases using an 800-image dataset, resulting in good accuracy of 90%. Other models achieved an accuracy of only 62%. However, the study had limitations as the dataset consisted of only 800 images and other models had lower accuracy. In the same year, PallapothalaTejaswini et al. aimed to help farmers detect rice leaf diseases for a healthy harvest. The researchers found that the 5-layer convolution model had the best accuracy of 78.2%, while others such as VGG16 had a lower accuracy of 58.4%. In the future, there is still potential for research to include more diseases and algorithms, making disease detection wider, easier, and faster.

3. Research Methodology

A. Research Flow

This study consists of several stages in the process of classifying rice plant diseases, starting from problem identification, literature review, algorithm and method determination, data collection, data preprocessing including data augmentation, CNN scenario, data training, result evaluation, and conclusion drawing. All of these stages are illustrated in Figure 1.

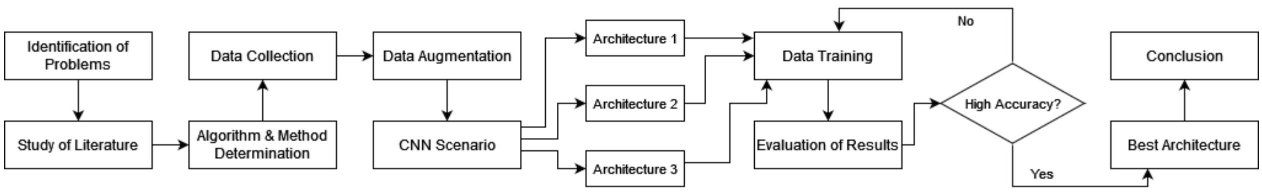


Figure 1 - Research Flow

B. Data Collection

Data collection is the stage of collecting the dataset that will be used in the study. The dataset used is secondary data on rice leaf diseases taken from the public Kaggle dataset called Leaf Rice Disease with the URL *www.kaggle.com/datasets/tedisetiady/leaf-rice-disease-indonesia*. The dataset consists of 3 classes of images, namely bacterial leaf blight, rice blast, and rice tungro virus, which have a total of 240 images with 80 rice leaf images in each class in the .jpg file extension. Examples of each image data for each class used are shown in Figure 2.

(a) (b) (c)

Figure 2 - (a) Bacterial Leaf Blight; (b) Rice Blast; (c) Rice Tungro Virus

C. Data Augmentation

This stage is part of preprocessing with the process of image augmentation or creating new images by rotating anticlockwise, rotating clockwise, horizontal flip, vertical flip, warp shift, adding noise, and blurring image. Thus, the augmented data plus the original data results in 480 images per class, with a total dataset of 1440 images. Next, the dataset is split or divided, with the dataset consisting of 1440 images of rice leaves, which are then divided into 80% for training data, 10% for validation data, and 10% for testing data. The details can be seen in Table 1.

Table 1 – Dataset Split

	Bacterial Leaf Blight	**Rice Blast**	**Rice Tungro Virus**
Training Data	384	384	384
Validation Data	48	48	48
Testing Data	48	48	48
Total	480	480	480

D. Model Design

CNN, which stands for Convolutional Neural Network, is a type of deep neural network that is commonly used for image recognition and processing. CNNs are often used to recognize objects or detect certain features in an image (Arrofiqoh et al, 2018). The development of the CNN architecture will adopt transfer learning from three popular architectures, namely VGG16, NASNetMobile, and Xception. Then, from the transfer learning model, 1 convolutional layer, max pooling, dropout, flatten, and finally dense layer are added to each model. The model summary is shown in Figure 3.

(a)

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 8, 8, 512)         14714688

 conv2d (Conv2D)             (None, 8, 8, 32)          147488

 max_pooling2d (MaxPooling2  (None, 4, 4, 32)          0
 D)

 dropout (Dropout)           (None, 4, 4, 32)          0

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 3)                 1539

=================================================================
Total params: 14863715 (56.70 MB)
Trainable params: 149027 (582.14 KB)
Non-trainable params: 14714688 (56.13 MB)
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 NASNet (Functional)         (None, 8, 8, 1056)        4269716

 conv2d (Conv2D)             (None, 8, 8, 32)          304160

 max_pooling2d (MaxPooling2  (None, 4, 4, 32)          0
 D)

 dropout (Dropout)           (None, 4, 4, 32)          0

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 3)                 1539

=================================================================
Total params: 4575415 (17.45 MB)
Trainable params: 305699 (1.17 MB)
Non-trainable params: 4269716 (16.29 MB)
```

(c)

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 xception (Functional)       (None, 8, 8, 2048)        20861480

 conv2d_4 (Conv2D)           (None, 8, 8, 32)          589856

 max_pooling2d (MaxPooling2  (None, 4, 4, 32)          0
 D)

 dropout (Dropout)           (None, 4, 4, 32)          0

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 3)                 1539

=================================================================
Total params: 21452875 (81.84 MB)
Trainable params: 591395 (2.26 MB)
Non-trainable params: 20861480 (79.58 MB)
```

Figure 3 - (a) Model Summary VGG16; (b) Model Summary NASNetMobile; (c) Model Summary Xception

4. Results and Discussion

Epoch is a process of training in NN (Neural Network) in one round when the entire dataset goes back to the initial stage of this process. If only using 1 epoch in training data with a neural network model, it will be too large and burden the training process because the data used is quite a lot, so data rate per batch division or commonly called batch size is needed (Rozaqi, Sunyoto, &Arief, 2021).

In this study, the classification process was carried out using 1440 images that had been divided into training data, validation data, and testing data. The next step is to run the training process on rice leaf images into the fit model. In Figures 4, 5, and 6, the results of the fit model generator can be observed for each architecture, where from epoch 1 to epoch 25, there is an increasing trend in accuracy values for both the training data and testing data.

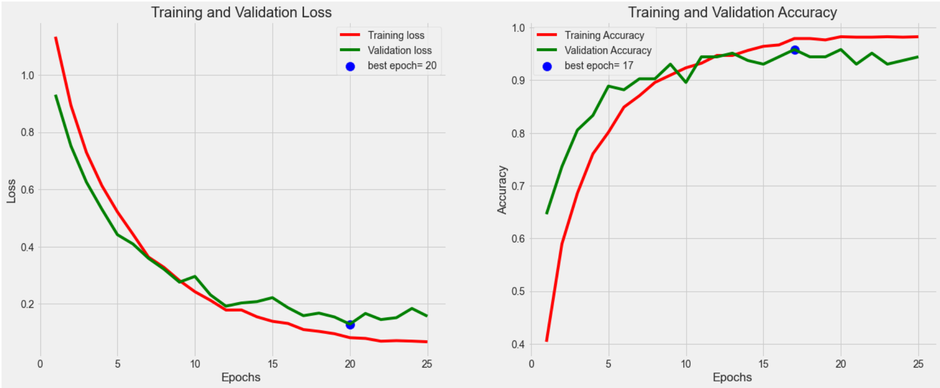


Figure 4 - Graph of Training and Validation Data Accuracy Values from the VGG16 Architecture

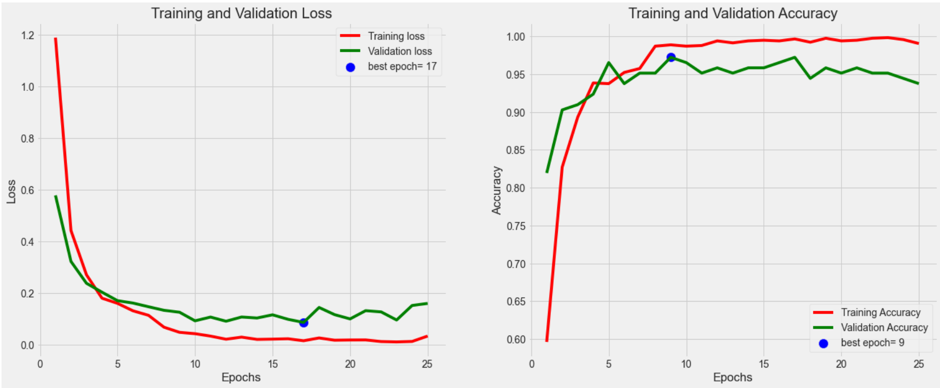


Figure 5 - Graph of Training and Validation Data Accuracy Values from the NASNetMobile Architecture

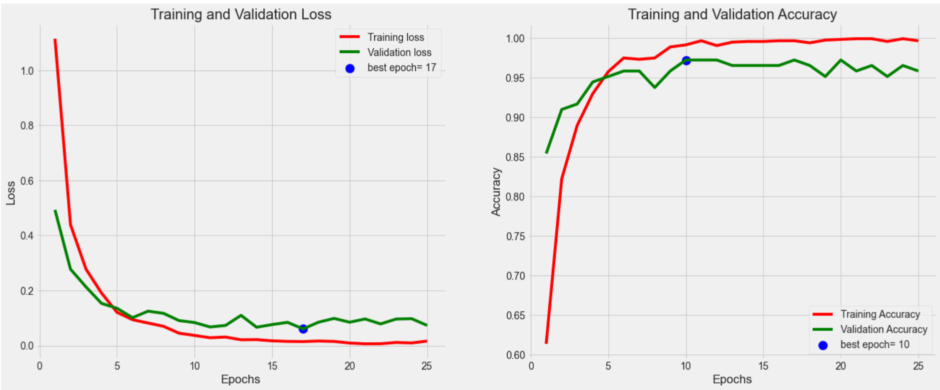


Figure 6 - Graph of Training and Validation Data Accuracy Values from the Xception Architecture

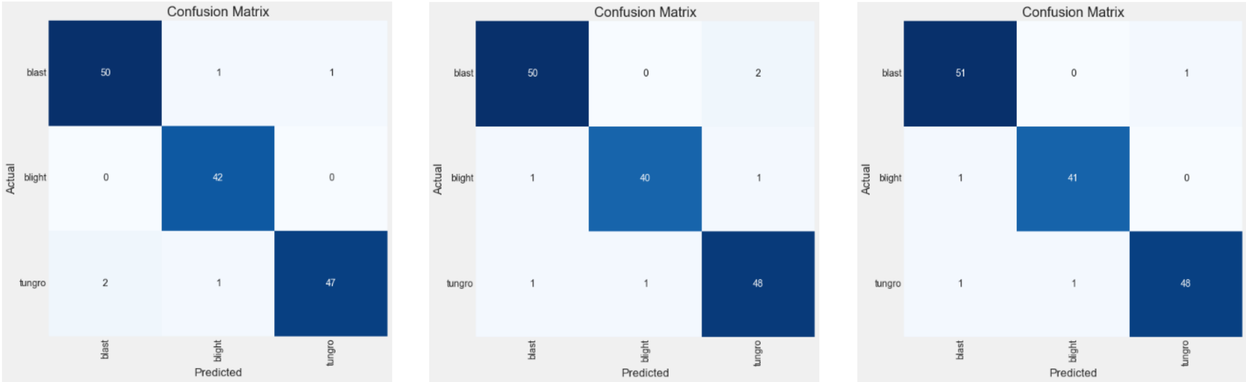
The best results for training, validation, and testing data for each model architecture from epoch 1 to 25 can be seen in Table 2.

Table 2 – Recap of Model Fit Results

Architecture	**Best Epoch Acc**	**Loss**	**Val Loss**	**Accuracy**	**Val Acc**	**Test Acc**
VGG16	17	0.1101	0.1586	0.9792	0.9583	96.53 %
NASNetMobile	9	0.0471	0.1250	0.9887	0.9722	95.83 %
Xception	10	0.0368	0.0837	0.9913	0.9722	97.22 %

Based on Table 2, the VGG16 architecture had the best validation accuracy at epoch 17 with a training accuracy of 0.9792, validation accuracy of 0.9583, and testing accuracy of 96.53%. The NASNetMobile architecture had the best validation accuracy at epoch 9 with a training accuracy of 0.9887, validation accuracy of 0.9722, and testing accuracy of 95.83%. Lastly, the Xception architecture had the best validation accuracy at epoch 10 with a training accuracy of 0.9913, validation accuracy of 0.9722, and testing accuracy of 97.22%.

A confusion matrix is commonly used to measure the performance of the model testing against the dataset. The classification confusion matrix results for each architecture model in this study can be seen in Figure 7.



(a) (b) (c)

Figure 7 - (a) Confusion Matrix VGG16; (b) Confusion Matrix NASNetMobile; (c) Confusion Matrix Xception

5. Conclusion

Based on the implemented training, validation, and testing models on a dataset of 1440 rice leaf images, it can be concluded that this study has produced good results. The best result was obtained using the Xception architecture, with a training accuracy of 99.13%, a validation accuracy of 97.22% at epoch 10, and a testing accuracy of 97.22%. Suggestions for future research are to try using other larger datasets and various other architectures.

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