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DEVELOPMENT RICE PLANT DISEASE CLASSIFICATION USING CNN WITH TRANSFER LEARNING

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Abstract: The rice plant, Oryza sativa, is a major food source in Indonesia. This plant is processed into rice, a staple food for the Indonesian people. Rice growth is crucial to ensure the rice produced is of good quality. One part of the rice plant that is susceptible to disease is the leaves, which can inhibit growth and reduce rice quality. Therefore, early detection and accurate classification of rice diseases are crucial to minimize these negative impacts. This has driven the development of a Deep Learning model capable of high-performance automatic classification. This study aims to create a rice leaf classification model using the CNN algorithm and several transfer learning architectures such as ResNet101, VGG16, and Xception. A dataset of 859 rice leaf images collected from the Kaggle website was then processed using augmentation techniques to a total of 2,439 images, plus 215 smartphone photos for external data validation. Thus, the total dataset increased to 2,656 images, covering four categories: leafblast, brownspot, healthy, and hispa. The model was processed in two stages: on the initial dataset (Non-Augmented Dataset) and the Augmented Dataset. The best experimental results were obtained using the ResNet architecture, with a training accuracy of 96.17% and a validation accuracy of 95.22%. Based on the research results, the rice plant disease classification model using deep learning demonstrated good performance.

Keywords: convolutional neural network; deep learning; fine-tuning; image classification; res-net; rice plant

Abstrak: Tanaman padi, Oryza sativa, merupakan sumber pangan utama di Indonesia. Tanaman ini diolah menjadi beras, makanan pokok bagi masyarakat Indonesia. Pertumbuhan padi sangat penting untuk memastikan beras yang dihasilkan berkualitas baik. Salah satu bagian tanaman padi yang rentan terhadap penyakit adalah daunnya, yang dapat menghambat pertumbuhan dan menurunkan kualitas beras. Oleh karena itu, deteksi dini dan klasifikasi penyakit padi yang akurat sangat penting untuk meminimalkan dampak negatif tersebut. Hal ini mendorong pengembangan model Pembelajaran Mendalam (Deep Learning) yang mampu melakukan klasifikasi otomatis dengan kinerja tinggi. Penelitian ini bertujuan untuk membuat model klasifikasi daun tanaman padi menggunakan algoritma CNN serta beberapa arsitektur transfer learning seperti ResNet101, VGG16, dan Xception. Pengumpulan dataset sebanyak 859 citra daun tanaman padi yang diambil melalui situs web Kaggle, kemudian diolah dengan teknik augmentasi menjadi total 2.439 citra, ditambah 215 foto smartphone untuk validasi data eksternal. Dengan demikian, total dataset bertambah menjadi 2.656 gambar, yang mencakup empat kategori: leafblast, brownspot, sehat, dan hispa. Model diproses dalam dua tahap: pada dataset awal Dataset Non-Augmented dan Dataset Augmented. Hasil eksperimen terbaik diperoleh menggunakan arsitektur ResNet, dengan akurasi pelatihan 96,17% dan akurasi validasi 95,22%. Berdasarkan hasil penelitian, model klasifikasi penyakit tanaman padi menggunakan deep learning menunjukkan kinerja yang baik.

Kata kunci: convolutional neural network; deep learning; fine-tuning; klasifikasi citra; resnet; tanaman pad

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INTRODUCTION

Indonesia is an agricultural country, meaning the agricultural sector plays a vital role in the overall national economy. This is evident in the large population and workforce employed in the agricultural sector [1]. Rice farming plays a significant role in contributing to food security in many countries, including Indonesia. This situation encourages Indonesia to continuously innovate to ensure an abundant and secure rice supply [2]. During the rice cultivation process, pests and diseases are often attacked, which can disrupt rice growth and even cause crop failure. Farmers must regularly monitor rice growth to determine growth developments from the planting season to harvest [3]. Detecting rice plant diseases requires rapid, accurate, and precise action to prevent damage to rice plants that can result in reduced yields.

Deep learning has become a hot topic in the world of machine learning due to its ability to model various complex data, such as images and sounds. Convolutional Neural Network (CNN) is currently the most effective deep learning method for image recognition because its function is similar to human neural networks, where computer programming receives image information to learn, recognizes each visual part in the image, and understands the patterns, which allows the computer to recognize images [4].

CNN can achieve a high level of accuracy by using leaf images with controlled lighting and background conditions [5]. Although the presence of AI helps in the rapid detection of rice diseases, the presence of experts is still needed as a comparison in the process of determining disease detection results.

Identification of rice plant disease symptoms can be done through leaf color because leaves will have certain characteristics according to the type of pest and disease. According to Ramesh [6]in 2020, there are four types of leaves based on the disease (brownspot, leafblast, hispa, and healthy). These types of infected leaves can be identified and classified using deep learning algorithms to find certain characteristics that differentiate them from each other. The algorithm used is a Convolutional Neural Network (CNN).

Research conducted by Asif Shahriar Arnob et al. in 2025 discussed a comparison of CNN architectures used to classify cauliflower diseases using 1753 augmented images, resulting in the ResNet architecture having the highest accuracy rate of 90.85%. According to him, this finding shows that deep learning approaches, especially ResNet, and their proposed model can detect diseases effectively in tropical regions. Therefore, this study specifically uses the ResNet CNN architecture because ResNet has been proven to be able to classify images quite well [7].

In a 2021 study conducted by Purbasari and colleagues, researchers detected rice plant diseases using CNNs, utilizing a dataset of 2,239 images of rice leaf diseases taken from public sources. This study successfully automatically detected diseases in leaf images with a training accuracy of 90%. These experimental results can be improved by experimenting with more variations of CNN architectures and performing image augmentation [8].

In 2021, AA JE VeggyPriyangka and colleagues conducted a study to develop an application that can classify rice diseases based on leaf color and texture by utilizing the Convolutional Neural Network method and performing data augmentation on a specific data set. They

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tested various variations of epoch parameters and data augmentation and successfully achieved a test accuracy of 91.24%. However, this study used a data set that was too small, consisting of only 108 images, resulting in poor performance for the three image criteria used in the testing process [9]. Another study conducted by SunuJatmika et al. in 2022 discussed the application of CNN deep learning methods in identifying rice leaf diseases using 800 images, resulting in a good accuracy of 87%. Other models only achieved 62% accuracy. However, this study has limitations because the dataset only consisted of 800 images and other models had lower accuracy [10].

According to previous research, CNN models often struggle to produce output that reflects real-world conditions. Several challenges arise, including a lack of sufficiently representative datasets and suboptimal model design based on the data provided. CNN models also often face efficiency challenges, particularly in the long training time required [11].

METHOD

Research Flow

This research comprises several stages in the rice disease classification process, starting from problem identification, data collection, data pre-processing, algorithm and method selection, data augmentation, fine-tuning, data training, model evaluation, selecting the best model, and drawing conclusions. Figure 1 shows the research flow.

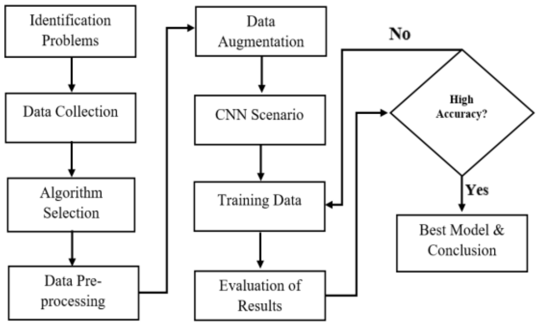
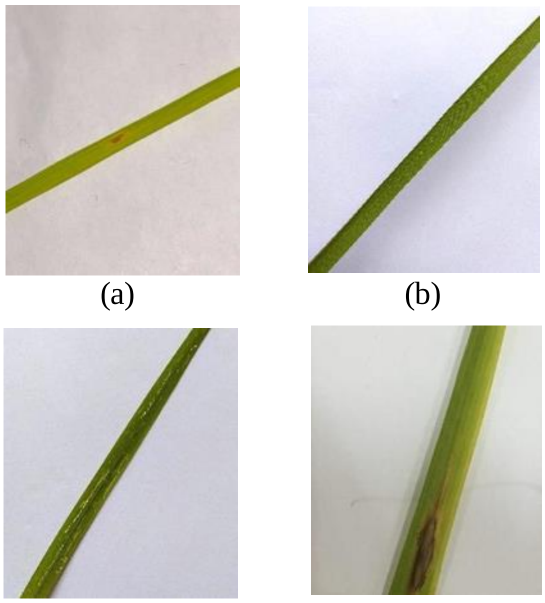


Figure 1. Research Flowchart

Data Collection

Data collection is the stage of collecting the dataset that will be used in the research. The dataset used is secondary data on rice leaf diseases taken from a public Kaggle dataset called Rice Leaf Diseases with the URL dataset www.kaggle.com/datasets/tedisetiady/leaf-rice-disease-indonesia. The dataset consists of 4 image classes, namely Brownspot, Leafblast, Healthy and Hispa, which have a total of 859 images of rice plants in the .jpg file extension [12]. Examples of image data for each class used are shown in Figure 2.



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

Figure 2. (a) Brownspot; (b) Healthy; (c) Leafblast; (d) Hispa

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Data Augmentation

This stage is part of the preprocessing process, which involves image augmentation, or the creation of new images by increasing brightness, resizing, warp shifting, adding noise, and blurring. Thus, the augmented data, combined with the original dataset and an external validation dataset using 217 smartphone photos, resulted in a dataset initially containing 859 images before augmentation, expanding to 2,656 images. An example of the original image with augmentation is shown in Figure 3.

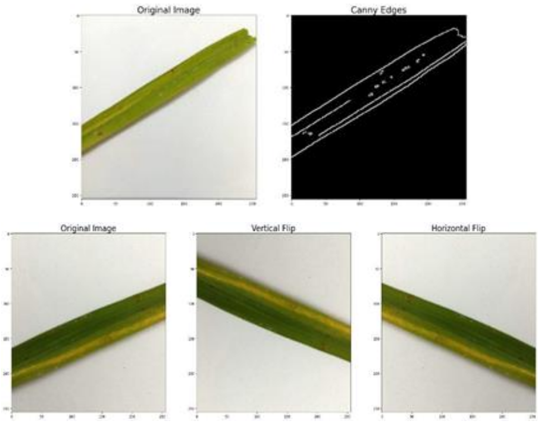
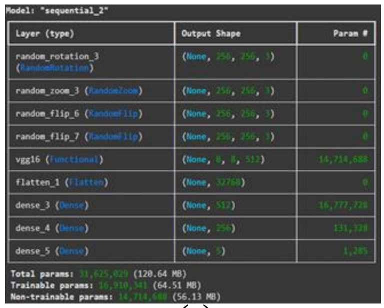


Figure 3. Image Augmentation Results

Model Architecture

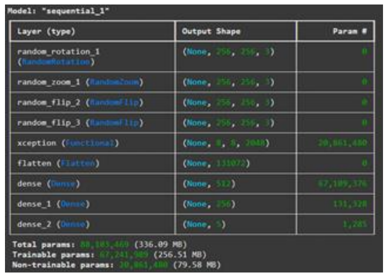
CNN, short for Convolutional Neural Network, is a type of deep neural network commonly used for image recognition and processing. CNN is often used to recognize objects or detect specific features in images [13]. The development of the CNN architecture will adopt transfer learning from three popular architectures, namely ResNet101, VGG16, and Xception. Then, from the transfer learning model, 1 convolutional layer, max pooling, dropout, flatten, and finally a dense layer are added to each model. The model summary is in Figure 4.


Model: "sequential_2"

Layer (type)	Output Shape	Param #
random_rotation_3 (RandomRotation)	(None, 256, 256, 3)	0
random_zoom_3 (RandomZoom)	(None, 256, 256, 3)	0
random_flip_6 (RandomFlip)	(None, 256, 256, 3)	0
random_flip_7 (RandomFlip)	(None, 256, 256, 3)	0
vgg16 (Functional)	(None, 8, 8, 512)	14,714,688
flatten_1 (Flatten)	(None, 32768)	0
dense_3 (Dense)	(None, 512)	16,777,728
dense_4 (Dense)	(None, 256)	131,328
dense_5 (Dense)	(None, 5)	1,285

Total params: 31,625,029 (120.64 MB)
Trainable params: 16,910,341 (64.51 MB)
Non-trainable params: 14,714,688 (56.13 MB)

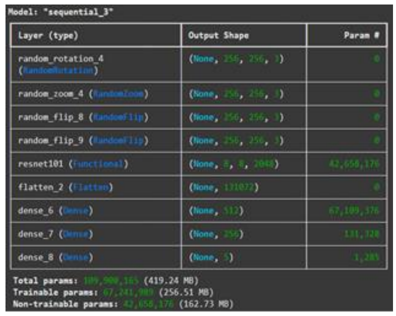
(a)


Model: "sequential_1"

Layer (type)	Output Shape	Param #
random_rotation_1 (RandomRotation)	(None, 256, 256, 3)	0
random_zoom_1 (RandomZoom)	(None, 256, 256, 3)	0
random_flip_2 (RandomFlip)	(None, 256, 256, 3)	0
random_flip_3 (RandomFlip)	(None, 256, 256, 3)	0
xception (Functional)	(None, 8, 8, 2048)	20,861,480
flatten (Flatten)	(None, 131072)	0
dense (Dense)	(None, 512)	67,109,376
dense_1 (Dense)	(None, 256)	131,328
dense_2 (Dense)	(None, 5)	1,285

Total params: 88,103,469 (336.09 MB)
Trainable params: 67,241,989 (256.51 MB)
Non-trainable params: 20,861,480 (79.58 MB)

(b)


Model: "sequential_3"

Layer (type)	Output Shape	Param #
random_rotation_4 (RandomRotation)	(None, 256, 256, 3)	0
random_zoom_4 (RandomZoom)	(None, 256, 256, 3)	0
random_flip_8 (RandomFlip)	(None, 256, 256, 3)	0
random_flip_9 (RandomFlip)	(None, 256, 256, 3)	0
resnet101 (Functional)	(None, 8, 8, 2048)	42,658,176
flatten_2 (Flatten)	(None, 131072)	0
dense_6 (Dense)	(None, 512)	67,109,376
dense_7 (Dense)	(None, 256)	131,328
dense_8 (Dense)	(None, 5)	1,285

Total params: 109,900,165 (419.24 MB)
Trainable params: 67,241,989 (256.51 MB)
Non-trainable params: 42,658,176 (162.73 MB)

(c)

Figure 4. (a) Model Summary VGG16; (b) Model Summary Xception; (c) Model Summary ResNet101

Confusion Matrix

The confusion matrix is used as a tool to assess the performance of a classification model, which consists of four main elements. True Positive (TP) refers to the number of cases where the model successfully predicts data as positive. True Negative (TN) reflects the number of correct predictions when the model identifies data as negative. False Positive (FP) occurs when the model incorrectly identifies negative data as positive. Meanwhile, False Negative (FN) indicates the number of errors when the

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model fails to recognize positive data and instead classifies it as negative [14]. Based on these four components, model performance can then be evaluated through various evaluation matrices [15].

$$Accuracy = \frac{\text{Number Correct Predict}}{\text{Total Data}} \quad (1)$$

$$Precision = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + False\ Positive\ (FP)} \quad (2)$$

$$Recall = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + False\ Negative\ (FN)} \quad (3)$$

$$F1 - Score = 2.\frac{\text{Presisi . Recall}}{\text{Presisi + Recall}} \quad (4)$$

RESULTS AND DISCUSSION

Model Performance Evaluation

This study used two training scenarios for rice leaf image datasets: one with and one without augmented data. The augmentation process involved improving the dataset by applying horizontal flips and vertical flips, increasing brightness, resizing, warp shifting, and adding noise. During model training, several key settings affected how the model learned from the data.

One of them is the number of epochs, which represents the number of times the model processes the entire dataset, set at 30 epochs in this study. The batch size, which refers to the number of data samples processed together, is set at 32, which affects the speed and efficiency of the model's learning process. Furthermore, the learning rate, set at 0.0001, determines the magnitude of adjustments made during training to improve model predictions. Figures 5 and 6 show the corresponding model evaluation results for each scenario before and after data augmentation.

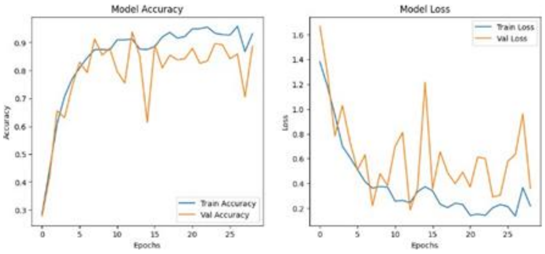

Figure 5. Accuracy Graph Results Before Data Augmentation

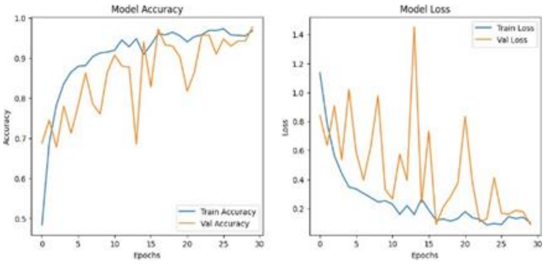

Figure 6. Accuracy Graph Results After Data Augmentation

Figure 5 shows the accuracy and loss results for the training and validation data when testing the original image before image augmentation. This graph shows that the highest accuracy value was achieved at epoch 27, with a training accuracy of 0.9318 and a validation accuracy of 0.8589. These accuracy values are considered good, but have not yet reached 1. Furthermore, in Figure 6, after image augmentation, the graph shows that the best accuracy value was achieved at epoch 30, with a training accuracy of 0.9450 and a validation accuracy of 0.9512. A table summarizing the accuracy in each comparison scenario is presented in Table 1.

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Table 1. Amount of Accuracy Improv ment

Method	**Training Accuracy**	**Validation Accuracy**
Non-Augmented Dataset	93.18%	85.72%
Augmented Dataset	94.50%	95.12%

Comparison of Each Architecture

The comparison of the effectiveness of various layers within the CNN architecture used in this study aims to assess the success of the CNN architecture in the classification models created. In Figures 7, 8, and 9, the results of the development of relevant models can be seen for each architecture, where from epoch 1 to epoch 30, there is a tendency for increasing accuracy values for both training and testing data.

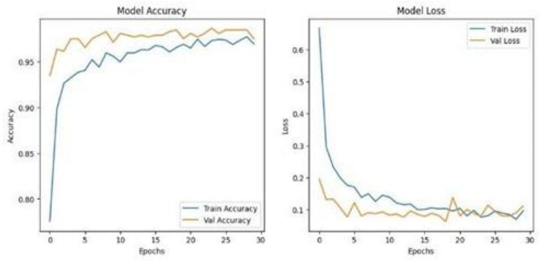


Figure 7. Accuracy Graph of Training and Validation Data of ResNet101 Architecture

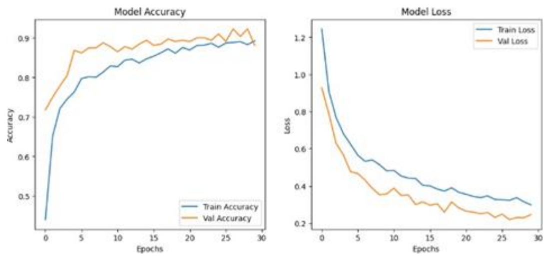


Figure 8. Accuracy Graph of Training and Validation Data of VGG16 Architecture

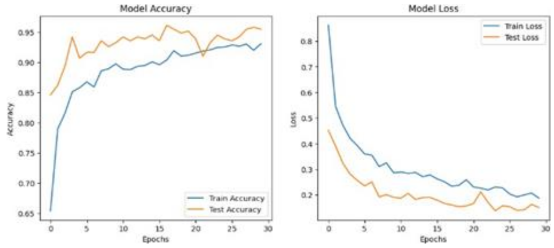


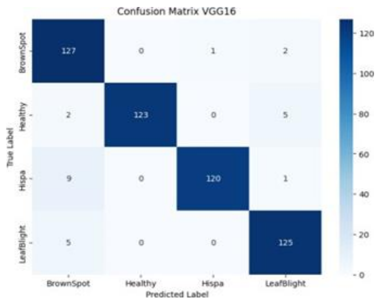
Figure 9. Xception Architecture Training and Validation Data Accuracy Graph

Table 2 shows the best results from training and validation data for each model architecture from epoch 1 to 30.

Table 2. Architectural Comparison

Architecture	**Best Epoch Acc**	**Loss**	**Acc**	**Val Acc**
VGG16	28	0.3246	0.8950	0.9231
Resnet101	12	0.1471	0.9617	0.9522
Xception	30	0.1784	0.9424	0.9615

Based on Table 2, the VGG16 architecture has the best validation accuracy at epoch 28 with a training accuracy (Acc) of 0.8950 and a validation accuracy of 0.9231. The ResNet101 architecture has the best validation accuracy at epoch 12 with a training accuracy (Acc) of 0.9617 and a validation accuracy of 0.9522. Finally, the Xception architecture has the best validation accuracy at epoch 30 with a training accuracy (Acc) of 0.9424 and a validation accuracy of 0.9615.The results of the confusion matrix are shown in Figure 10.



(a)

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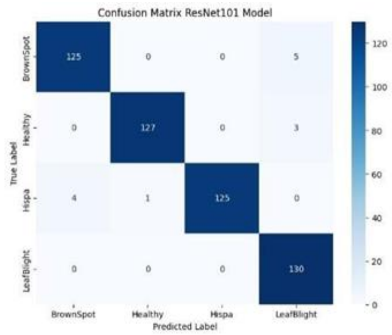
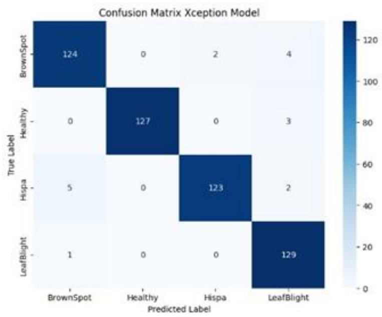


(b)



(c)

Figure 10. (a) Confusion Matrix VGG16; (b) Confusion Matrix Resnet101; (c) Confusion Matrix Xception

CONCLUSION

This research successfully developed and refined the CNN model, especially ResNet101, in classifying rice plant diseases with good accuracy. Through a series of experiments and scenarios, this model achieved 96.17% accuracy in diagnosing four different types of rice diseases. This performance outperforms previous research demonstrating the effectiveness of individual CNN architectures. However, this study has several limitations. Namely, the model's performance has not been extensively tested on datasets collected from diverse environmental conditions, which may affect its generalizability to real-world scenarios. Suggestions for further research include using larger datasets, further exploring the model, applying it to other agricultural fields, and using different architectures.

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