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Rice Plant Disease Detection System Using Transfer Learning with MobilenetV3Large

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Abstract: In this study, we address that foliar diseases of rice (Oryza sativa L.) pose a serious threat to agricultural productivity and propose an effective method for disease detection using Convolutional Neural Network (CNN). We use transfer learning on the MobilenetV3Large model to improve the model's performance. Our study involves a curated dataset containing images of infected rice leaves, followed by a careful preprocessing step. This dataset is then used to train a CNN model. The results show a commendable accuracy rate of over 90% and almost reaching 95% when the model is trained over 200 epochs. The model performance graph shows a consistent upward trend in accuracy coupled with decreasing loss during the training process. Furthermore, the classification results highlight the ability of the model to discriminate between different types of diseases affecting rice leaves. This study demonstrates the effectiveness of our proposed method and positions it as a valuable tool for leaf disease detection in rice. By providing faster and more accurate control measures, our approach has the potential to significantly improve agricultural productivity. The successful application of the CNN model using MobilenetV3Large highlights its adaptability and robust performance in addressing the pressing problem of rice leaf diseases and provides a promising path for future advances in precision agriculture.

Keywords: Convolutional Neural Network (CNN), Disease detection, MobilenetV3Large, Oryza sativa L., Rice leaf disease

INTRODUCTION

In the realm of agriculture, particularly concerning rice plants, diseases on plant leaves pose a significant threat to both farmers and the overall plant growth, impacting productivity. Recognizing the crucial role of rice as a staple food in Indonesia, the research focuses on addressing this issue through an object detection method utilizing deep learning.Deep learning is used based on several factors, including the use of large amounts of training data. The model for deep learning techniques is Convolutional Neural Network (CNN) (TiaraSari & Haryatmi, 2021). The rice plant (Oryza sativa L.) is a producer of rice which is one of the staple foods consumed by many Indonesians, so the plant has become one of the agricultural fields that are favored in most parts of Indonesia. However, disease in rice plants is influenced by environmental and genetic factors. High air and soil humidity and genetic sensitivity play a major role. Disease control requires quick action to prevent further spread and damage, supporting optimal crop yields. The Convolutional Neural Network (CNN) method is a deep learning method for developing Multilayer Perceptron (MLP) used to process data such as images. The CNN method can learn directly from images so that the burden of programming can be reduced (Sri Rahmadhani & Lysbetti Marpaung, 2023). In deep learning, this CNN method is often used in solving problems related to image classification. From several reviews of the CNN method, it is considered to have good performance in image data classification by promising high performance for various agricultural problems (Parti Astuti et al., 2023). This choice is pivotal in overcoming the challenges posed by the need for extensive training data in deep learning applications.

Addressing existing research gaps, the research distinguishes itself by focusing on the unique combination of transfer learning, the MobilenetV3Large model, and CNN for rice plant disease detection. While similar studies have employed CNN for image classification in agriculture, the emphasis on the specific application to rice plants, the use of transfer learning, and the MobilenetV3Large model differentiate this research. This distinctive approach contributes to the existing body of knowledge by providing a specialized and effective solution tailored to the context of rice plant diseases.

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The research explicitly outlines its objectives and contributions, aiming to implement the CNN method with transfer learning using the MobilenetV3Large model to analyze images of infected rice leaves. The primary objective is to develop a robust disease detection system capable of quick and accurate identification, ensuring timely disease control and prevention of further spread. The overarching goal is to maintain the health of rice plants effectively, ultimately leading to increased productivity in rice cultivation.

In summary, this research provides a comprehensive exploration of the context, significance, and unique contributions within the realm of rice plant disease detection. By combining deep learning techniques, transfer learning, and a specialized model, the study aims to address existing research gaps and contribute to the development of efficient solutions for disease identification in rice plants, ultimately enhancing agricultural productivity.

LITERATURE REVIEW

A study conducted by Dicki Irfansyah et al. The study comes as many coffee trees as possible in Indonesia are suffering from diseases caused by pests, reducing coffee productivity. Therefore, the author implements his Alexnet convolutional neural network (CNN) architecture using the MATLAB programming platform to detect coffee tree diseases through images. A total of 300 datasets were used and classified into three classes: healthy, rust, and spider mite. The author's classification results in the learning process using 260 pieces of data were 69.44% to 80.56%. In the testing process, the accuracy value of his remaining 40 pieces of data was 81.6%. Based on the results of this study, the CNN-Alexnet architecture performs accurate coffee tree leaf pest classification (Irfansyah et al., 2021).

Research conducted by Rizal Amegia Saputra, et al. This research is based on the background of several rice leaf diseases that can cause a high risk of crop failure and a decrease in food value, so the authors developed a rice leaf disease detection application by applying the CNN algorithm and MobileNet architecture with feature extraction and feature map. The author's classification results produce very good accuracy with an accuracy value of 92% but with a small amount of data and the use of 100 epochs, which results in a higher validation error value than the error value during training, so the process will experience overfitting (Saputra et al., 2021).

In this study, we use CNN and CNN-ELM techniques to determine classification performance based on variations in input image size. In this study, we used a dataset obtained from Kaggle. This dataset consisted of his 1,583 normal images and 4,327 pneumonia images with an average size of 1000 x 1000 pixels, but the classification process was less effective. In the best-performing processing, the input image is reduced to 200x200 pixels, so the difference in accuracy between the CNN method and CNN-ELM method reaches 8.81%, and the difference in F1 score reaches 0.0729 (Nugroho & Yulia, 2021).

Research conducted by Atharizky Ade Santosa, et al. This research is based on the background of proper handling of diseases in rice plants by detecting them so that farmers can provide faster treatment. To detect diseases in rice plants, the author researched to create a digital image processing system with the CNN method. The system created by this author has been able to detect diseases in rice plants with as much as 3189 data with details of bacterial leaf blight with as much as 837 data, brown spot with as much as 837 data, leaf smut with as much as 767 data, and one class of healthy rice plants as much as 727 data. From this data, the best performance results that can be achieved provide an accuracy of 99.66% by using four hidden layers and the Adam optimizer (Santosa et al., 2023).

Research conducted by Hendry Fonda, et al. This research has a background to classify Riau batik models based on their characteristics so that they can distinguish which is Riau batik and not Riau batik. This study uses the CNN method to conduct training and testing of Riau batik models which produce classification results with an accuracy of 65%. The accuracy is due to the similarity between Riau batik motifs and not the difference lies in the color only (Fonda et al., 2020).

Despite significant advances in the application of Convolutional Neural Networks (CNN) for plant disease detection and cultural artifact classification, research on the integration of these technologies into comprehensive agricultural practices remains lacking. A large gap remains. Research is needed that considers the combined use of CNNs to identify and classify diseases in different crops, considering regional and environmental factors. Additionally, there is also an opportunity to extend CNN applications beyond traditional agriculture to address challenges in the preservation and classification of cultural artifacts such as batik. Filling this research gap could lead to the development of more robust and versatile models that meet the complex and diverse needs of both agriculture and cultural conservation.

METHOD

The purpose of this study is to apply Convolutional Neural Network (CNN) techniques to rice disease detection. Fig 1. shows the sequence of steps in the study.

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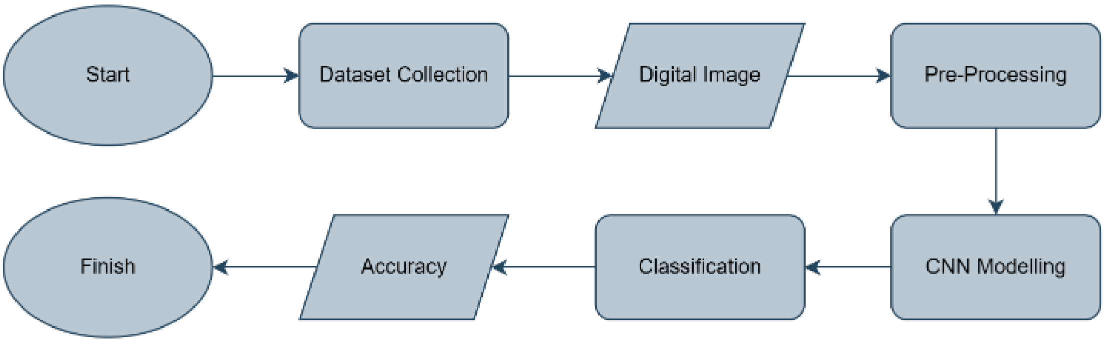

Fig. 1. Research Flow

Dataset Collection

The dataset collection process carried out was obtained from the Roboflow site. The number of datasets used in this study is 9687 images that will be classified consisting of five classes of rice plant diseases that will be classified are bacterial blight, blast, brown spot, leaf scald, and Tungro as well as one class for healthy rice plants and random image images. The dataset is then split into training data, validation data, and test data, with 75% of the total data distributed among training data, 15% validation data, and 10% test data. The following research dataset samples are used:

1) Healthy Rice Plants

The rice plant, Latin Oryza Sativa L., is one of the most important food crops because it produces rice, which is a staple food in agricultural countries, especially Indonesia, where almost everyone consumes rice as their daily staple food. Fig. 2 is an image of a healthy rice plant leaf.

Fig. 2. Healthy Rice Plants

2) Rice Plants Affected by Bacterial Blight

Bacterial plague is caused by the bacterium Xanthomonas campestri pv. Symptoms of the disease seen on leaves of rice plants affected by bacterial late blight include leaves turning gray in color and leaf blades drying out and folding along the leaf bones (Walascha et al., 2021). Fig. 3 is an image of the leaves of rice plants affected by bacterial blight.

Fig. 3. Rice Plants Affected by Bacterial Blight

3) Rice Plants Affected by Blast

Blast disease is caused by the fungus Magnaporthe oryzae. Symptoms of the disease that can be seen on the leaves of plants attacked by the blast are the presence of pointed spots on the tips of the leaves, and the edges of the leaves are brown and gray at the center of the spot. If left untreated the spots will continue to develop and be surrounded by pale yellow areas (Walascha et al., 2021). Fig. 4 is an image of a blast-affected leaf of a rice plant.

Fig. 4. Rice Plants Affected by Blast

4) Rice Plants Affected by Brown Spot

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Rice infected with brown spot disease is caused by a fungus called Cercospora oryzae. Symptoms of the disease on infected rice leaves include small brown spots on the leaf blade, dark brown spots in the center of the spots, and light brown spots at the edges of the spots (Walascha et al., 2021). Fig. 5 is an image of the leaves of rice plants affected by brown spots.

Fig. 5. Rice Plants Affected by Brown Spot

5) Rice Plants Affected by Leaf Scald

Leaf scorch is a rice disease caused by the fungus Microdochium oryzae, which causes the leaves to look like they are on fire. The main symptoms of this disease are divided into three stages: latent, chronic, and (Govindaraju et al., 2020). Fig. 6 is an image of a rice plant leaf affected by leaf scald.

Fig. 6. Rice Plants Affected by Leaf Scald

6) Rice Plants Affected by Tungro

Tungro disease is one of the most important diseases of rice due to its high damage potential. This disease is caused by an infestation of Green Wareng (Nephotettix virescens) (Landita et al., 2020). Symptoms suffered by infected leaf plants are yellowing and brownish leaf color, leaf drying, death, drooping, and less perfect plant growth (Matias Tobing et al., 2019). Fig. 7 is an image of the leaves of rice plants affected by Tungro.

Fig. 7. Rice Plants Affected by Tungro

Pre-Processing

Pre-processing is data cleaning and replacing data that has been collected and identified. After this stage, the data is ready to be used for the next process (Romli & Puspita Dewi, 2021). At this stage, pre-processing will resize the images input into the system to make the dataset size equal. In addition to resizing, this stage also removes disturbances in the image. Additionally, normalization is performed at this stage to ensure that the pixel values in the image are in the same range of values. In addition to regularization, this phase includes techniques such as data augmentation to reduce overfitting and improve model generalization.

CNN Modelling

Convolutional Neural Network (CNN) is a deep neural network algorithm, which is most used to analyze visual images. This CNN algorithm is a multilayer perception whose layers are connected to the next layer (Rasywir et al., 2020). The completion step is divided into feature extraction and image extraction. CNN algorithms generally have four components, namely the convolution layer, pooling layer, activation function, and fully connected layer (Passura Backar et al., 2023).

In this stage, model training is performed, which includes a CNN model training process using the preprocessed dataset. At this point, the dataset is also divided into three parts: training data, validation data, and test data.

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Training data is used to train the model, validation data is used to measure the model's performance during training, and test data is used to test the trained data.
The entire pre-shared dataset will be trained using the CNN method to make predictions on the test data and compare the results with the actual class labels to measure and evaluate its performance. Performance measurement and evaluation uses metrics such as accuracy, precision, recall, and F1 score in the detection and classification of diseases on rice plant leaves.
The accuracy metric is used to measure the correctness of the predictions of the overall model, the precision metric is used to measure the proportion of positive cases predicted correctly out of all the cases predicted as positive, and the recall metric is used to measure the proportion of correctly predicted examples. Positive Examples from all real positive examples. The F1 score metric is the average of the precision and recall metrics, so it provides a balanced measure of the model's performance. Fig. 9 is an illustration of the training architecture of the CNN model.

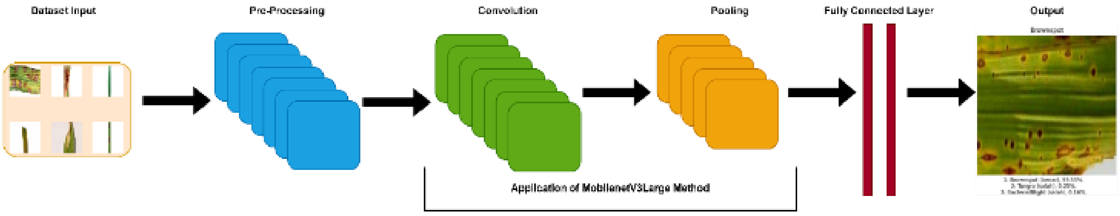

Fig. 8. CNN Model Training Architecture Illustration

Classification

CNN Model Training Architecture Classification is one of the methods used to predict an unknown class. Also, classification can be described as a method of detecting a data object as one of the types mentioned above (Alghifari & Juardi, 2021). In this phase, the model makes predictions on the test data and compares the predicted results with the actual class designation. The training and testing phases are important to evaluate and visualize how accurately the CNN model can identify rice diseases. After evaluation and visualization of the model and making predictions with the actual class, the pre-trained model will be converted to TensorFlow Lite format for size and latency optimization.

RESULT

In this study, we successfully evaluated a rice disease detection system based on convolutional neural networks using data used for classification. This system underwent testing to evaluate performance in providing accurate disease detection according to user preferences using the Google Colab tool. This research uses 9256 images to analyze diseases in rice plants. The image consists of 6985 datasets in train data, 1376 datasets in validation data, and 895 datasets in testing data stored on the Roboflow site.
Table I below is a summary result of the machine learning model used in this system. The augmentation performed is direct augmentation, not augmenting through Roboflow. This research also applies transfer learning using the MobilenetV3Large model which is then adjusted to make it more suitable and improve classification accuracy. The following is a more detailed explanation of the results in the table:

a) Gaussian Noise with output shape (None, 244, 224, 3). "None" indicates that the batch size is unspecified and can vary, the number "224" indicates the height and width dimensions of the image in pixels, while "3" indicates the number of colors in RGB. This layer has no parameters that can be reset.
b) Rescaling with the same output shape as Gaussian Noise, namely (None, 224, 224, 3). This layer also has no resettable parameters.
c) Random Flip with a fixed output shape, namely (None, 224, 224, 3). This layer randomly flips the image horizontally and has no resettable parameters.
d) Random Rotation has a fixed output shape of (None, 224, 224, 3). This layer randomly rotates the image and has no resettable parameters.
e) Random Zoom has a fixed output shape (None, 224, 224, 3). This layer performs random zoom on the image and has no resettable parameters.
f) Random Brightness has a fixed output shape (None, 224, 224, 3). This layer randomly changes the brightness of the image/image and has no resettable parameters.
g) MobilenetV3Large is a pre-trained model. Its output shape is (None, 960). The number "960" means it generates a feature vector of length 960 for each sample and has 2996352 resettable parameters.
h) There are two Dense Layers that each have an output shape and parameters of (None, 128) and 123008 resettable parameters and (None, 7) and 903 resettable parameters. The numbers "128" and "7" mean that this layer outputs feature vectors of length 128 and 7 for each sample.

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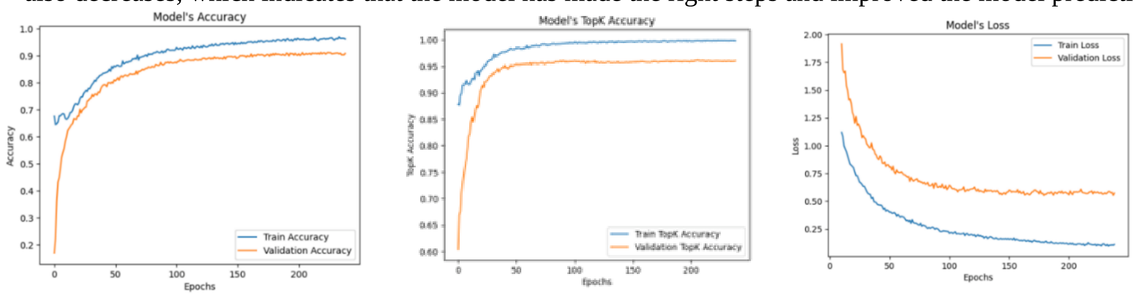
Table 1
Summary of Machine Learning Models

Layer (type)	Output Shape	Param #
gaussian_noise_1 (GaussianNoise)	(None, 224, 224, 3)	0
rescaling_1 (Rescaling)	(None, 224, 224, 3)	0
random_flip_1 (RandomFlip)	(None, 224, 224, 3)	0
Random_rotation_1 (RandomRotation)	(None, 224, 224, 3)	0
random_zone_1 (RandomZone)	(None, 224, 224, 3)	0
random_brightness_1 (RandomBrightness)	(None, 224, 224, 3)	0
MobilenetV3Large (Functional)	(None, 960)	2996352
dense_2 (Dense)	(None, 128)	123008

Results testing the accuracy of CNN methods in rice disease detection systems have already shown very high accuracy results above 90% and even close to 95% obtained using a model trained for 200 epochs. The following is a summary of each graph that shows an increase as the epoch increases, which means the model is learning and optimizing its performance:

a) Fig. 10 (a) is the accuracy result of the model accuracy, which is the calculation result of the correct prediction. In the graph, the train accuracy results continue to increase with increasing epochs until they reach 0.95. The validation accuracy also increases similarly to the training accuracy but stabilizes at the end.
b) Fig. 10 (b) is the accuracy result of the TopK model accuracy, which is a generalization of the accuracy value, but if one of the K scores has the highest prediction, then a prediction is considered correct. The meaning of "K" is the number of top classes taken to compare with the actual class. The graph shows that the train TopK accuracy increases as the epochs increase and reaches around 0.95. For validation, TopK accuracy also increases but is slightly lower than train TopK accuracy.
c) Fig. 10 (c) is the model's loss, there is a steady decrease as epochs increase in the train loss. The validation loss also decreases, which indicates that the model has made the right steps and improved the model prediction.



(a) (b) (c)

Fig. 9. CNN Model Performance (a) Accuracy (b) TopK Accuracy and (c) Loss

Here are some examples of the classification results generated by the machine learning model that has been created previously. The classification results are shown in Fig. 10.

a) Fig. 11 (a) is the classification result of rice plant leaves affected by the blast with an accuracy of 99.97% and not rice plant leaves affected by brown spot or bacterial blight.
b) Fig. 11 (b) is the classification result of the leaves of rice plants affected by brown spots with an accuracy of 99.55% and not the leaves of rice plants affected by Tungro or bacterial blight.
c) Fig. 11 (c) is the classification result of leaves of rice plants affected by bacterial blight with an accuracy of 99.62% and not the leaves of rice plants affected by Tungro or brown spots.

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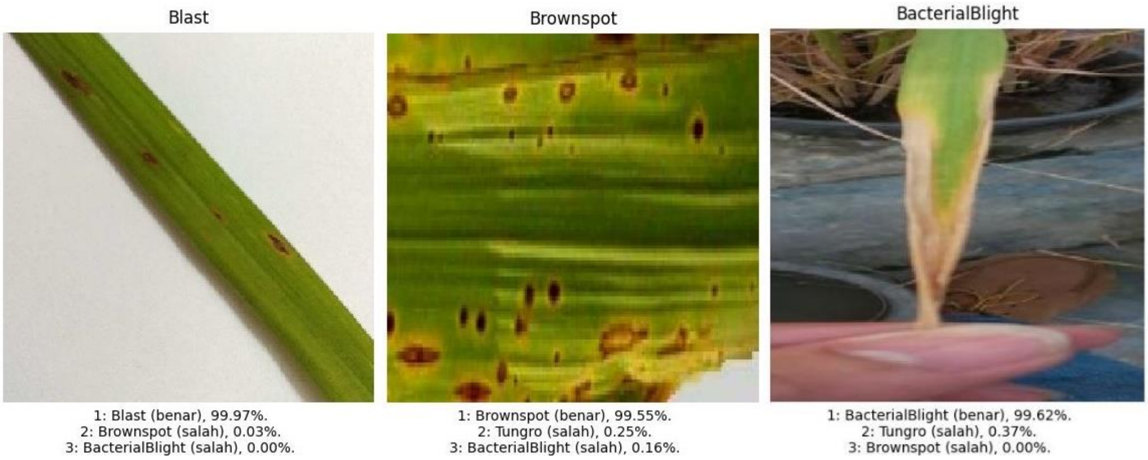

(a) (b) (c)

Fig. 10. Classification Results (a) Blast, (b) Brownspot, and (c) Bacterial Blight

CONCLUSION

Based on the results, this study successfully implemented a Convolutional Neural Network (CNN) using transfer learning using MobilenetV3Large for rice disease detection. It showed an excellent accuracy rate of over 90% with peak values reaching close to 95% when the model was trained for 200 epochs. The authors observed a steady improvement in the accuracy of the model and his TopK, demonstrating the effectiveness of his CNN method in accurately identifying and classifying various diseases in rice. did. A steadily decreasing model loss during the training process means a robust detection system with better predictive capabilities. However, it is important to recognize potential challenges such as data size, diversity, and generalization to different environmental conditions. To improve the applicability of the system, future studies can consider additional features and the integration of multimodal data sources to ensure the validity of the model in different agricultural environments. The goal of this study to develop a reliable disease detection system for rice using CNNs was nearly achieved, paving the way for continued advances and improvements in precision agriculture.

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