Optimizing Deep Learning Models with Optuna for Accurate Rice Leaf Disease Classification

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Abstract. Rice diseases significantly affected the production of rice in Indonesia, where rice is their main food source. This research paper proposes a deep learning approach to detect and classify rice leaf diseases using deep learning models. This dataset contains 10.776 labeled images with 5 categories which were preprocessed, augmented, and splitted 8:2 for training and validation. Using pre-trained convolutional neural network models such as VGG16, VGG19, and ResNet50, The dataset was fine-tuned using transfer learning and optimized with Optuna for hyperparameter tuning. The result of each model gained similar accuracy, with ResNet50 performing the best by achieving 91.79% validation accuracy, followed by VGG19 with 91.69% validation score, and lastly VGG16 with 91.09% validation score. ResNet50 get 0.94 precision, 0.93 recall, and 0.93 F1_score, followed by VGG19 with 0.92 precision, 0.92 recall, and 0.92 F1_score, and lastly VGG16 with 0.91 precision, 0.91 recall, and 0.91 F1_score. This research demonstrates the potential of deep learning in predicting and enabling early accurate rice disease detection, which could support many Indonesian farmers in reducing agricultural losses and improving crop yields in the future. This research contributes to improving food security and farmers wellbeing by improving crop health, reducing crop loss, and supporting agricultural sustainability.

Keywords: Rice Disease Detection, Deep Learning, Computer Vision, VGG16, VGG19, ResNet50, Optuna, Zero Hunger

1 Introduction

Indonesia is one of the countries where rice is their main food source, with a high level of rice consumption[1]. According to data from the Central Bureau of Statistics, in 2024, it is estimated that each person in Indonesia consumes 1,521 kg of rice per week [2]. In the same year, Indonesia produced 30,34 million tons of rice for consumption[3] and imported 3,85 million tons of rice between January to November 2024. Rice production in 2024 is reduced by 757,13 thousand tons or equal to 2,43% of production in 2023.

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However, despite Indonesia's significant rice consumption and production, many rice farmers struggle to earn sustainable income with their average salary of only Rp 15.199 per day[4]. Meanwhile, the World Bank has reported that the price of rice in Indonesia is 20 percent higher than the price of rice in the global market. Between 2010-2017, it was even estimated that the price of rice in Indonesia was 60% more expensive than the international price.[5] One of the main reasons is the high cost of production, which includes the rising price of fertilizers, pesticides, and equipment. In addition, Indonesia's unpredictable weather condition also further affects the rice plant to be more vulnerable to diseases such as Bacterial Blight, Brown Spot, and Leaf Smut.

Detecting rice diseases poses a unique challenge for farmers, particularly in larger rice fields where it is more difficult to detect diseases in rice plants. Rice diseases like Bacterial Blight, Brown Spot, and Leaf Smut are difficult to detect manually, therefore technology can play a crucial role in earlier disease detection and support more effective disease management before the disease spreads[6].

Technologies like computer vision and machine learning can help farmers detect rice leaf diseases. Deep learning as part of machine learning and computer vision has been developed to improve Artificial Intelligence performance in detection and classification images. Some deep learning models for photo detection and classification have been developed and used in many sectors to increase productivity and reduce risk, including agriculture and farming. It can detect what type of disease from the disease symptoms images on the leaf and other parts of the plant. This research study is aimed to make a new optimized deep learning model with the help of Optuna, and determine which deep learning model is compatible for rice disease detection and classification. The goal is to help farmers detect diseases more effectively, therefore improving crop health, reducing crop loss, and supporting agricultural sustainability.

2 Literature Review

In the last 15 years, computer vision has developed quite significantly with deep learning. Deep learning has been used to solve problems in computer vision, including image classification, image classification with localization, object detection, object segmentation [7]. The most important factors that boost deep learning development are large, high-quality, publicly available labelled datasets, along with the empowerment of parallel GPU computing, which enables faster computation with GPU based training[8]. Compared to traditional methods, features in deep learning models can be automatically learned from big data, while we need to manually design the parameters in the traditional method to get better accuracy. Deep learning models also contain more parameters than the traditional method, making it more expressive[9] so that it can reach higher accuracy.

As the number of computer vision in agriculture sector publication has increased and provided larger dataset, this helped farmers to implement computer vision for their crops production and proved the usefulness of computer vision for plant disease detection. More models have been created and upgraded to improve the accuracy, such as VGG-16, VGG-19, Resnet, and many others.

During the deep learning era, CNN method has been commonly used due to its feature which can automatically learn the features of images at different levels[10]. CNN models are generally used in supervised learning like image classification. [11]Later, in 2014, more sophisticated CNN models like VGGNet (Visual Geometry Group Network) were developed, resulting in two distinct versions. One of them is VGG-16 with 16 weight layers[12]. VGG-16 with a deeper architecture than other models like MobileNetV3-Small, the model was more powerful but struggled with dataset's size or learning rate. This suggests strong performance during validation but poor performance during testing. [13]. In the previous publications, VGG-16 performed a 91,66% of accuracy value[14], 97.77% of accuracy[15], and 97.91% of accuracy which is better than other models like Inception V3 and VGG-19[16].

The VGG-16 model is designed to process color images (R, G, B) with dimension 224x224x3 pixels, which are processed through several convolutional layers[17]. The VGG-16 architecture consists of 13 convolutional layers and 3 fully connected layers[18].

The other version of VGG is VGG-19 which was also introduced in 2014. The difference with VGG-16 is in their architecture where VGG-19 uses 19 weighted layers with a smaller convolutional filter size of 3×3[19]. The VGG-19 adds one more convolutional layer after the second, the third, and the fourth pooling layer[20]. Previous publications have reported various results using VGG19 in terms of comparison with other models like VGG16. Some reported that VGG-19 has better accuracy[16], while the others reported it has lower accuracy than VGG-16[21].

Another popular deep learning model is Residual Neural Network (ResNet), a groundbreaking deep learning structure that addresses the problem of vanishing gradient in very deep layers by introducing residual connections, which allow for the training of much deeper layers than previously possible[22]. However, a deeper layer means gradients can diminish significantly [23], here ResNet's primary innovation is the use of residual blocks, which include skip connections or shortcuts that bypass one or more layers[24]. These connections enable the network to learn residual functions rather than direct mappings, making it easier to optimize very deep networks[25]. The two popular variants of ResNet include ResNet-50 and ResNet-152, where the number indicates the depth of the network in terms of layers[26].

ResNet achieved a top 1 accuracy of 78.93% on the CIFAR-100 dataset, which was better than other models such as VGG-16 and GoogLeNet[27]. ResNet can be very deep without suffering from vanishing gradients and is great at classification tasks, but ResNet models require significant computational resources and can overfit on smaller datasets if not properly regularized[28].

ResNet has outperformed other architectures like VGG and Inception. For example, older publication shows ResNet-50 achieved a test accuracy of 70%, compared to 25% for VGG-16 on Diabetic Retinopathy dataset, which is a significant improvement. However, some studies have noted that ResNet can struggle with very small datasets or require careful tuning of hyperparameters to achieve optimal performance[28][29] and need high compute demands, which make it slightly difficult if we implement with low computational devices like mobile phone and drone[30].

Some publications have compared one model to another model, but only few of them tested the model using optimization. We will modify some components of the model such as epoch number, batch number, learning rate, and dropout rate to find the best model.

3 Methodology

Figure 1 shows the flow process of building the deep learning model.

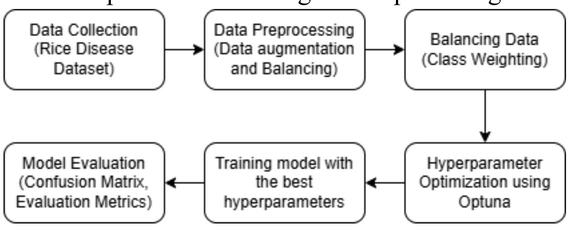

Fig 1. Flow process of model training

3.1 Data Collection and Acquisition

The dataset is collected from Mendeley Data which consists of 10766 images with 5 categories of Rice Diseases such as Bacterial Leaf Blight, Rice Blast, Rice, Tungro, and Healthy Leaf. This dataset has high resolution images of rice leaves that exhibit symptoms of the specified disease, aiding the deep learning image recognition task while also having the symptom description in the form of textual description outlining the major symptoms visible on the leaf.

3.2 Splitting Data

The dataset is splitted into training data and validation data with 8:2 ratio. Training data will be used to train the model and the validation data will be used to evaluate the model by using it to classify the validation data and compare with the label. This splitting process results around 8000 training images and 2000 test data

3.3 Data Augmentation

The dataset is augmented to increase data amount and make the model learn from various images. Some method used for data augmentation is to rescale pixel value of the image from the range [0, 255] to the range [0, 1], flip the image horizontally, rotate the images within range ± 20 degrees, and zoom it in or out by up to 20%.

3.4 Preprocessing Data

To ensure the performance of Convolutional Neural Networks (CNN) so that overfitting of model does not happen, proper image preprocessing is needed. The image preprocessing steps include image resizing where it resizes all images to a fixed input size which is 128x128 for VGG16, VGG19, and ResNet50

3.5 Class Weighting

Balancing the unbalanced distribution between classes by calculating class weight. Giving more importance to the underrepresented class during model training helps to achieve balanced distribution.

3.6 Deep Learning Models

The model that is used is a pre-trained VGG16, VGG19, and ResNet50 model with transfer learning to extract deep features from the rice leaf images. With the model architecture that consists of feature extraction where the initial layers of VGG16 and VGG19 are frozen to retain learned features from large scale dataset (ImageNet), this helps preserve general image representations that can be useful for rice disease classification. Then we did fine tuning, the fully connected layers are modified and retrained on the rice disease dataset and then several layers are unfrozen to allow the model to learn more specific patterns relevant to the rice diseases dataset. Finally, softmax classification is applied on the final layers which consist of 3 neurons corresponding to the disease categories.

3.7 Training Model with Optuna

The training process is using Optuna to tune the hyperparameter combination including dropout rates, dense units, optimizer, learning rate, and number of unfrozen layers. There will be 20 trials for VGG16 and VGG19 models and 12 trials for the ResNet50 model to find the best hyperparameter combinations.

3.8 Evaluation of the Models

The performance of the model is compared and given four categories. They were true positive (TP) which is correctly predicted the type of disease; false positive (FP) other type of disease that were predicted as positive; true negative (TN) which is correctly predicted that the rice plant don't have any disease; false negative (FN) which predict the plant does not have disease when the reality is the other way around.

4 Result And Discussion

This research uses an image dataset that has been divided by the ratio of 80% training data and 20% validation data. 3 CNN model is used for this model which includes VGG-16, VGG-19, and ResNet50 to classificate the image dataset into 5 classes: Bacterial Leaf Blight, Healthy leaf, Rice, Rice Blast, and Tungro. The best accuracy will be chosen among the trials with Optuna method for the hyperparameter tuning.

4.1 VGG-16

Table 1 contains the hyperparameter combination that got the highest accuracy with Optuna.

Table 1. Hyperparameter VGG16

Hyperparameter	Value
Epoch	20
Batch Size	32
Dense Unit	512
Optimizer	Adam
Learning Rate	1e-5
Dropout	0.3
Unfrozen Layers	11

Figure 2 and Figure 3 show the accuracy and loss from VGG16 shown by each epoch. Loss represents how well or poor the model can match the actual value. Accuracy represents how accurate the model can predict the class.

VGG16 reached 91.09% validation accuracy, 93.21% training accuracy, and validation loss 0.2414, and training loss 0.1492.

4.2 VGG-19

Trained with Optuna method in 20 trials. Table 2 contains the hyperparameter combination that has the highest accuracy.

Table 1. Hyperparameter VGG19

Hyperparameter	Value
Epoch	20
Batch Size	32
Dense Unit	256
Optimizer	Adam
Learning Rate	1e-5
Dropout	0.5
Unfrozen Layers	20

Figure 4 and Figure 5 show the accuracy and loss from VGG19 shown by each epoch. Loss represents how well or poor the model can match the actual value. Accuracy represents how accurate the model can predict the class.

VGG19 reached 91.69% validation accuracy, 92.29% training accuracy, 0.2371 validation loss, and 0.1679 training loss in the 12th trial with Optuna.

4.3 ResNet50

Table 3 contains the hyperparameter which resulted in the best accuracy with ResNet 50 in 12 trials.

Table 3. Hyperparameter ResNet50

Hyperparameter	Value
Epoch	15
Batch Size	32
Dense Unit	512
Optimizer	Adam
Learning Rate	0.0001
Dropout	0.3
Unfrozen Layers	40

Figure 6 and Figure 7 show the accuracy and loss from ResNet50 shown by each epoch. Loss represents how well or poor the model can match the actual value. Accuracy represents how accurate the model can predict the class.

ResNet50 reached 91.79% validation accuracy, 92.32% training accuracy, 0.2384 validation loss, and 0.1583 training loss.

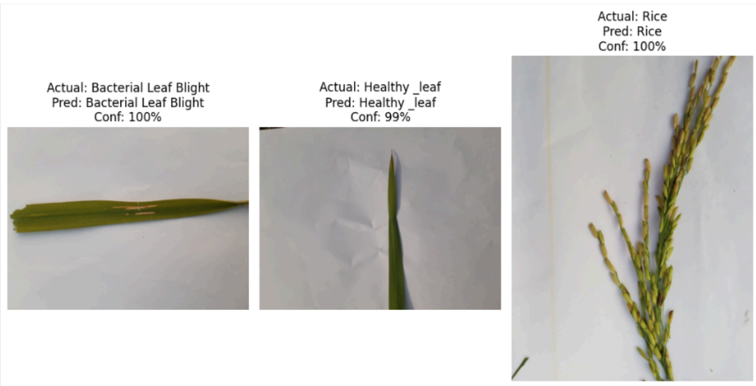

Fig 8. Implementation of Model

Figure 8 represents the implementation of ResNet50, using the best model we implement in a real case scenario using pictures of rice leaf diseases. This model is implemented and plotted using matplotlib while also showing its confidence level for each prediction of the images.

Figure 9, 10, and 11 shows the confusion matrix for each model.

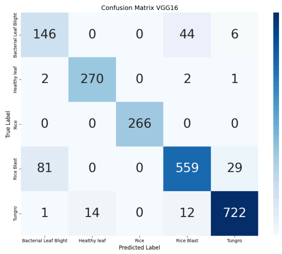

Fig 9. Confusion Matrix of VGG16

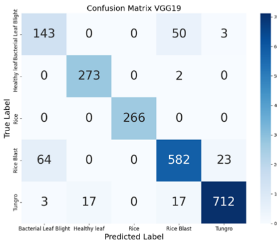

Fig 10. Confusion Matrix of VGG19

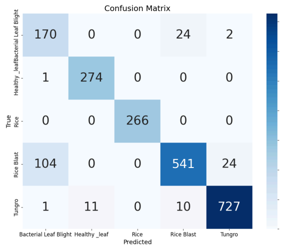

Fig 11. Confusion Matrix of ResNet50

ResNet50 performs the best in all classes except the Rice Blast class. The models work well with rice class with the accuracy of 100%. This is because the rice images have unique features such as color and pattern resulting in a different shape with the other classes. It contains brown oval-shaped grains of rice that are different and unique with any other classes that consist of leaf images. Meanwhile, all models misclassified a lot of images in Rice Blast and Bacterial Leaf Blight because of their similarity in features like color and shape. Below are the sample images of Rice Blast and Bacterial Leaf Blight.

Fig 12. Rice Blast

Fig 13. Bacterial Leaf Blight

From the images above, we can see the similarity between the two classes of leaf with characteristics such as brown spots. However, the dataset lacks sufficient close up shots of rice leaves which makes it more difficult for the model to recognize the differences between similar diseases. It is because models classify images based on visual features like color patterns, making it difficult for all models to tell the differences between similar diseases such as Rice Blast and Bacterial Leaf Blight.

Table 4. K-Fold Result

Number of Fold	VGG16	VGG19	ResNet50
1	0.8688	0.87	0.8663
2	0.8531	0.8612	0.8521
3	0.8885	0.8902	0.874
4	0.8699	0.8769	0.8615
5	0.874	0.8821	0.8474

ANOVA (Analysis of Variance) method is used to compare each model performance with K-Fold accuracy. This test results in a P-value of 0.1284 which is much greater than the threshold of 0.05. This means we fail to reject the null hypothesis and indicate no significant differences between the models based on their cross validation accuracies with K-Fold.

Both of the models are performing so well with 91% of validation accuracy. This shows Optuna did a good work to determine the best hyperparameter for each model. The medium dataset works well for each model and helps them to perform a high accuracy. ResNet50 models show a higher but not significant accuracy due to its deeper architecture and the use of residual (skip) connections. These connections help prevent vanishing gradients during backpropagation and allow the model to retain low level features that are crucial for detecting subtle texture differences in diseased leaves. Despite the moderate dataset size which could favor VGG16 and VGG19, ResNet50's structural advantages bring the model to match the VGGs performance. However, ResNet50 usually outperformed VGG's model with the skip connections features but it needs to be fine tuned properly to bring out its advantages.

VGG16 and VGG19 rely on a linear stacking of convolutional layers without mechanisms to address optimization challenges. Their early use of max pooling also reduces detail retention, which can draw down the performance. Moreover, VGG models tend to perform poorly in early training, making them less compatible with Optuna, since Optuna picks winners based on early metrics. While ResNet50 was superior in this study, further fine tuning might allow VGG models to catch up. Future research should aim for more general systems that can classify more various rice leaf diseases.

5 Conclusion

This research demonstrates that all 3 models have similar results in the range of 91%. ResNet50 yields the highest performance on the dataset achieving 91.79% accuracy, followed by VGG19 with 91.69% accuracy, and VGG16 with 91.09% accuracy. All models were optimized using Optuna, which significantly increased the model performance on the given dataset. With the automation of key hyperparameters, Optuna enabled each model to reach its optimal configuration.

Even though each model achieved similar results, ResNet50 has the biggest potential for further improvement. The model has the ability to mitigate vanishing gradient problems and retain subtle details due to its deep architecture combined with skip connection. This model's performance can still be improved with longer training and deeper tuning.

While VGG16 and VGG19 are still effective, they rely on a simpler architecture like linear stacking of convolutional layers without mechanisms to address optimization challenges. Although they can benefit from extended training or deeper tuning, their performance ceiling is usually lower than ResNet50.

Future work should extend this study by including a more diverse dataset of rice disease to enhance robustness across real-world scenarios. Practical deployment strategies such as integrating models into drone systems can also be explored for real time rice disease detection.

6 Data Availability

Data used in this paper can be accessed using the following link. https://data.mendeley.com/datasets/g7tcwvshff/1

7 Paper Similarity

The following is the similarity report of the paper generated by Turnitin. Paper Similarity

8 Authorship Statement

0009-0009-9781-8215 - Marcello Evan Wijaya - Experiment, writing, review, and editing
0009-0002-5469-2666 - Okky Sudibyo Rades - Experiment, writing, review, and editing
0009-0006-8790-1216 - Hans Christian Soebroto - Experiment, writing, review, and editing
0009-0007-9670-4828 - Bakti Amirul Jabar - Data collection and ideation
0000-0001-8297-3428 - Jurike V Moniaga - Data collection and ideation

9 References Manager

Mendeley is used to manage references and maintain consistent citation formatting

10 References

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