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Implementation of pretrained VGG16 model for rice leaf disease classification using image segmentation

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Abstract

Rice is an agricultural sector that produces rice which is one of the staple foods for the majority of the population in Indonesia. In the cultivation of rice plants there are also factors that affect rice production and are not realized by farmers causing that they are late in handling and diagnosing symptoms and making rice production decline. Therefore, it is necessary to have an early diagnosis of rice plants to identify them correctly, quickly and accurately. Machine learning is one of the classification techniques to detect various plant diseases such as rice plants. There are several studies on machine learning using the Convolutional Neural Network with the VGG16 model to classify rice leaf diseases and using Image Segmentation techniques on rice leaf datasets for make the image becomes a form that is not too complicated to analyze. The data used in this research is Rice Leaf Disease which consists of 3 classes including Bacterial leaf blight, Brown spot, and Leaf smut. Then segmentation is carried out using two techniques, namely threshold and k-means. Then data augmentation for make dataset used has a large and varied number and training using VGG16 model with hyperparameter value optimizer RMSProp and Learning rate 0.001 and obtained 91.66% accuracy results for scenarios with the k-means dataset.

1. Introduction

Rice is a rice-producing food crop product which is one of the staple foods of the majority of the population in Indonesia. This agricultural sector is one of the useful production products to meet the food of the population [1]. In the cultivation of rice plants, there are also factors that affect rice production such as diseases that attack. The disease that attacks rice plants is unnoticed by farmers and that it is late in handling and diagnosing symptoms and makes rice production decrease. Therefore, it is necessary to have an early diagnosis for farmers can recognize the types of diseases in rice plants to identify and implement appropriate, fast and accurate control, quickly and accurately [2]. Machine learning is one of the classification techniques to detect various plant diseases such as rice plants. There are several studies on machine learning using the Convolutional Neural Network (CNN) algorithm which is the most efficient algorithm [3].

Various studies that have been carried out previously to detect diseases in rice leaves and various plants, one of which is a study conducted by Panuwat Mekha and et al which uses the classification method of Random Forest, Decision Tree, Gradient Boosting and Naïve Bayes with the result random forest algorithm with an accuracy value of 69.44% [4]. The research conducted by Radhika Wadhawan which detects rice leaf disease using datasets from UCI Machine Learning with the Convolutional Neural Network (CNN) with an accuracy value of 85.7% [5]. In other studies, there are also those who use the KNN classification method with an accuracy value of 97.9167% in a study conducted by kawcher ahmed [6]. Research conducted by Md. Mafiul Hasan Martin, et al. The study which detects rice disease using the AlexNet Classification technique with an accuracy value of 99.42% [7]. The research conducted by Krishnamoorthy et al in the study compares two classification methods, namely simple CNN and inceptionResNetV2 with highes accuracy from inceptionResNetV2 with accuracy 95.67% [8]. In a study conducted by Malliga et al performed hyperparameter optimization with the VGG16 model for leaf disease classification [9]. Then the research conducted by Sk Mahundul Hassan et al. Identifying plant leaf disease with pre-trained models such as InceptionV3, InceptionResnetV2, MobilenetV2, and EfficientNetB0 [10].

Several recent studies have also used pre-trained models for the classification of rice leaf disease such as in the study conducted by Vimal K. Shirivastava et al. conducting classification with several CNN pre-trained models with the most superior pre-trained model research results being VGG16 with an accuracy value of 93.11%. Because this model has more parameters that help adjust to the new data [11]. And also a study conducted by Ghosal et al implemented deep learning with the CNN model with transfer learning VGG16 with an accuracy result of 92.46% [12].

In several previous studies, researchers also used the Image Segmentation Technique for the classification of plant diseases such as research conducted by Md. Arifur Rahman et al. The one performs detection by implementing the Image Segmentation method with the HSV color Thresholding technique. This technique is effective because it does not require heavy computing [13]. And also on the research conducted by D.Bandara et al detects using SVM by implementing the Disease Segmentation method with k-means clustering techniques. This technique is suitable for feature extraction in leaf disease images [14].

So, in this study, the proposed method is the Convolutional Neural Network (CNN) for the classification of rice leaf disease using Rice leaf Disease data. This study used the VGG16 pre-trained model by adding a fully connected layer by implementing several image segmentation techniques as a test scenario including using image segmentation data with thresholding techniques and k-means techniques. This study proposes implementing the Image Segmentation technique and classification using model petrainded VGG19 with hyperparameter tuning, and it is hoped that propose method can improve the accuracy results obtained from previous research.

2. Research Method

In this study, the testing stages that will be carried out for the classification of rice leaf disease start from collecting datasets, image segmentation processes, preprocessing, training, and evaluation of the proposed method. The method to be used uses the Convolutional Neural Network model pretrained VGG16 and the implementation of Image Segmentation. The flowchart of the study can be seen in Figure 1.

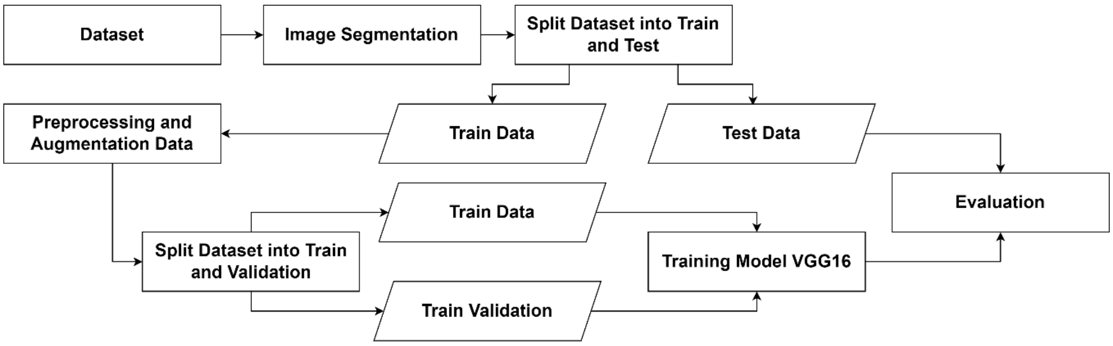


Figure 1. Graph of Research Method

2.1 Dataset

The dataset used in this study was Leaf Rice Diseases obtained from the open source UCI Machine Learning dataset which contained 120 rice leaf image data on a white background divided into 3 classes including Bacterial leaf blight, Brown spot, and Leaf smut with each class totaling 40 images. Some examples of images of rice leaves with spots on their surface can be seen in Figure 2.

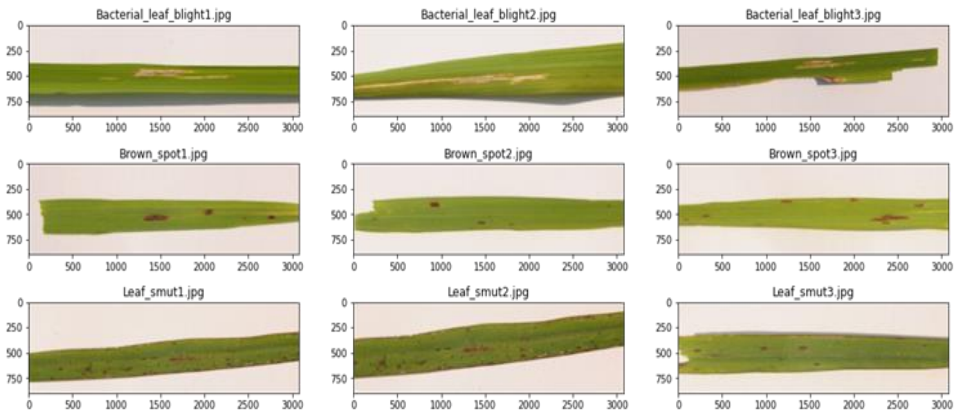


Figure 2. The example of image in the rice leaf disease dataset

2.2 Image Segmentation

The main purpose of the image segmentation technique use to convert the texture of the image into a shape that is not too complicated to analyze and that it serves to obtain the spot of the disease in rice leaf disease[15]. Image segmentation is the process of separating important objects from the background of an image[16].The following is an image that has been segmented can be seen in Figure 3.

Normal image After Segmented

Figure 3. The example resuls of image segmentation

Some segmentation techniques such as Thresholding is one of the easiest techniques for image segmentation and is mainly categorized into global, local and adaptive thresholding. Thresholding can create binary images by converting all pixels to 0 and 1. Pixels that reach the threshold value are converted to one and below the threshold value to zero. Obtaining binary images at an early stage can reduce the complexity of the data and make detection and classification a simple process [13]. The threshold technique Equation 1 can be seen as follows.

$$dst(x,y) = \begin{cases} maxval & if\ src(x,y) > thresh \\ 0 & otherwise \end{cases} \quad (1)$$

Where the value of the image pixel is symbolized by x and y if the value reaches the threshold value, it will be changed to 1 and if not to 0.

The K-menas technique is also a segmentation technique by grouping the color components by the specified number of groups and the selected group parts that need to be used and the unselected ones will be removed [14]. The k-means technique Equation 2 can be seen as follows.

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)} - c_j\right\|^2 \quad (2)$$

Where k is the cluster that will be assigned to each pixel value data point symbolized n to the nearest centroid and then will be calculated and assigned a new centroid from each cluster. In this study, the dataset used will be carried out 2 segmentation techniques including thresholding techniques and k-means techniques and then produce 2 datasets as test scenarios and then the next process is carried out.

2.3 Preprocessing

Image preprocessing is important and has been widely used in the field of image mining[17]. Preprocessing on the image is necessary to remove noise from the image. It is also necessary to normalize the intensity value of an image. Preprocessing is the process of improving image quality by removing background noise and normalizing the intensity of various image elements before the computational process is applied to them[18]. One of the preprocessing processes is to perform data augmentation on the image to be able can add image variation[19] by rotating, flipping, resizing the original image[20]. To do data augmentation, you can use the Image Data Generator with parameters such as rotation image, zoom range and horizontal flip and and others[21]. Some of the image data generator parameters that will be carried out for augmentation in the rice leaf disease dataset in this study are shown in Table 1 below.

Table 1. The Parameter of Image Data Generator

No	Parameter	Value
1	Zoom range	30
2	Rotation range	0.4
3	Horizontal flip	True

2.4 Convolutional Neural Network

Convolutional Neural Network is an effective machine learning technique of deep learning[22]. This method was developed from a neural network that can be used in data in the form of images to detect an object image, CNN has several parts such as the convolution layer which is a process of taking a matrix called the kernel through an image and changing based on kernel values. The convolution Equation 3 can be seen as follows.

$$G[i,j] = \sum_{u=-k}^{k}\sum_{u=-k}^{k} H[u,v]F[i-u,j-v] \quad (3)$$

Where the kernel is symbolized by H and F and the row and column indexes are symbolized i and j. Maxpooling is a hidden layer on CNN this layer serves to combine and that the image can greatly reduce the number of calculations but will not lose the main features of the image[23]. Dense layer to receive input from neurons layered earlier. Dropout Layer to prevent overfitting and combining many neural network architectures[14].

The Convolutional Neural Network model that will be used in this study is the VGG16 pretrained model. VGG16 is one of the excellent model architectures because it has a large network that has more than 138 million parameters[24]. The proposed model architecture is VGG16 which has convolutional layers consisting of 5 blocks of convolution layers and maxpooling layer as feature extraction and also a fully connected layer consisting of Flaten, Batch Normalization, Dropout, and Dense as a Classifier. The architecture of the VGG16 model is shown in Figure 4. In the architecture of the model made the resolution of the image uses a size of 224 x 224 pixels. For the activation layer value used using elu and a dropout value of 0.5. The model traing process is done using Hyperparameter tuning to find the best performance for each scenario with the parameters shown in Table 2. With a loss value using categorical consetropy and an epoch amount of 100.

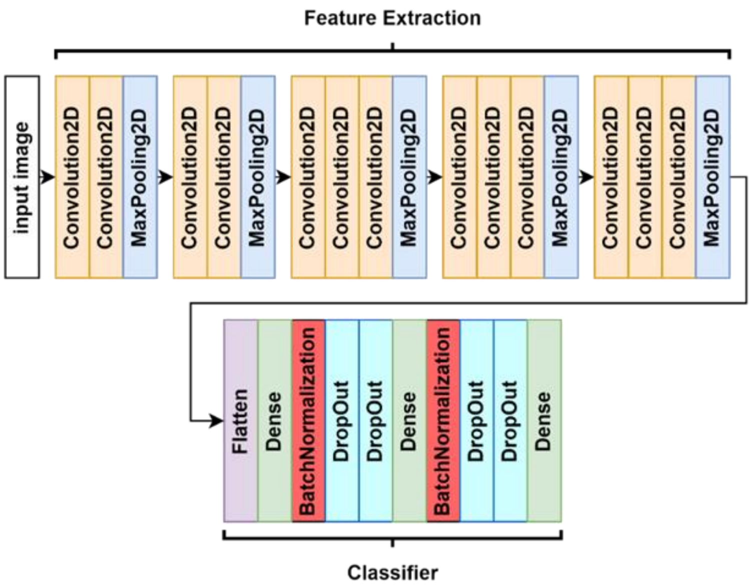


Figure 4. The VGG16 Model Architecture

Table 2. The Hyperparameter tuning

No	Parameter	Value
1	Optimizer	Adam, RMSProp, SGD
2	Learning Rate	0.001, 0.01, 0.1

2.5 Model Evaluation

Evaluation of the model from several proposed scenarios on the segmentation data using thresholding and k-means with the results in the form of performance calculations. Then the evaluation results are in the form of a validation loss and validation accuracy graph to determine the accuracy and loss performance. Also evaluation is in the form of a confusion matrix to measure the performance of the model to find out how accurately the model predicts [25]. Not only that, the evaluation of the model is also shown in the form of a classification report in the form of calculating the performance of accuracy, precision, recal, and f1-score [26]. The formula for calculating model performance such as Accuracy Equation 4, Precision Equation 5, Recall Equation 6, and F1-score Equation 7 is as follows.

$$Accuracy = \frac{True\ Positive\ + True\ Negative}{True\ Positive\ + False\ Positive + True\ Negative + False\ Negative} \tag{4}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{5}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{6}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

2.6 Test Scenario

In this study, two test scenarios will be carried out based on datasets that will be carried out image segmentation techniques with thresholding techniques and k-means techniques on rice leaf disease datasets. Furthermore, the dataset is carried out in the splitting stage with a data train ratio of 70% and test data of 30%. From the data train, preprocessing and augmentation were carried out after which splitting 80% of the data train and 20% of data validation. The results of spriting can be seen in the following Table 3.

Table 3. The Result of Dataset Spliting Dataset

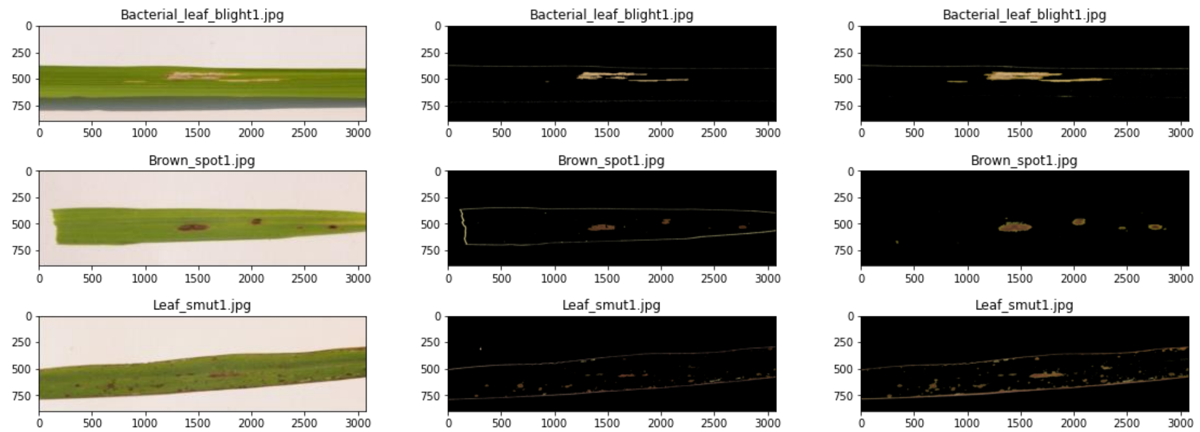
Dataset	Class			Total
	Bacterial leaf blight	Brown spot	Leaf smut	
Train	22	22	22	66
Validation	5	5	5	15
Test	12	12	12	36

From the dataset that has been split, data augmentation will be carried out with the aim of increasing the variety of images in the dataset during model training. then data training is carried out using the VGG16 architectural model. And also using categorical consetropy for loss value and epoch 100 then can compare the results of both with the results of the evaluation with test data.

3. Results and Discussion

3.1 Image Segmentation

In this study, the dataset used for the study was Rice Leaf Disease from UCI Machine Learning. This dataset will be subjected to an image segmentation process which will produce 2 datasets, namely a dataset with a threshold segmentation that has been segmented using a threshold technique and a dataset with a k-means segmentation that has been segmented using the k-Menas technique with a value of k = 10. The results of the dataset image segmentation can be seen in Figure 5.



Normal Segmentation using Threshold Segmentation using K-means

Figure 5. The Result of Image Segmentation using Threshold and K-means

3.2 Test Result

There are two test scenarios performed on this paper. The first scenario uses datasets that have been segmented using the thershold technique. Then training was carried out using the CNN pretrained model VGG16 with the application of hyperparameter tunning[9].

Table 4. The Result of Accuracy from the Hyperparamater in First Scenario

No	Hyperparameter		Accuracy
	Optimizer	Learning Rate	
1	Adam	0.001	80,55%
2	Adam	0.01	75,55%

3	Adam	0.1	72.22%
4	RMSProp	0.001	**83.33%**
5	RMSProp	0.01	72.22%
6	RMSProp	0.1	80.55%
7	SGD	0.001	77.77%
8	SGD	0.01	72.22%
9	SGD	0.1	80.55%

In Table 4 above, the comparative results of the accuracy of each hyperparameter showed that the rice leaf dataset with threshold segmentation technique using the Optimizer meter = RMSProp and Learning rate = 0.001 was shown. Got the highest accuracy value of 83,33%. Furthermore, Figure 6 shows a graph of accuracy and loss from training with an epoch count of 100 that still has overfiting and in Figure 7 is intended to be the result of a confusion matrix of 3 classes in the dataset that can be seen there are 6 incorrect predictions, especially the most prominent of the brown spot actual data and the leaf smut predict data.

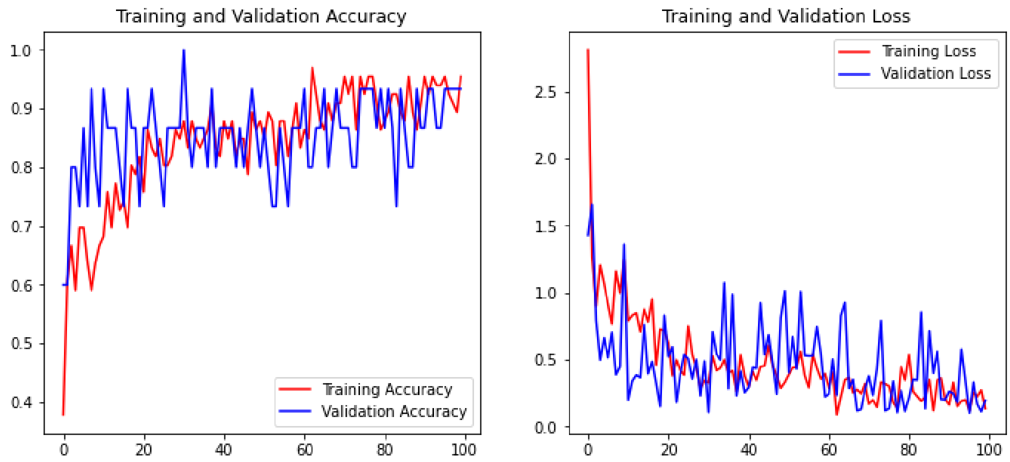


Figure 6. The Graph of Accuracy and Loss from First Scenario

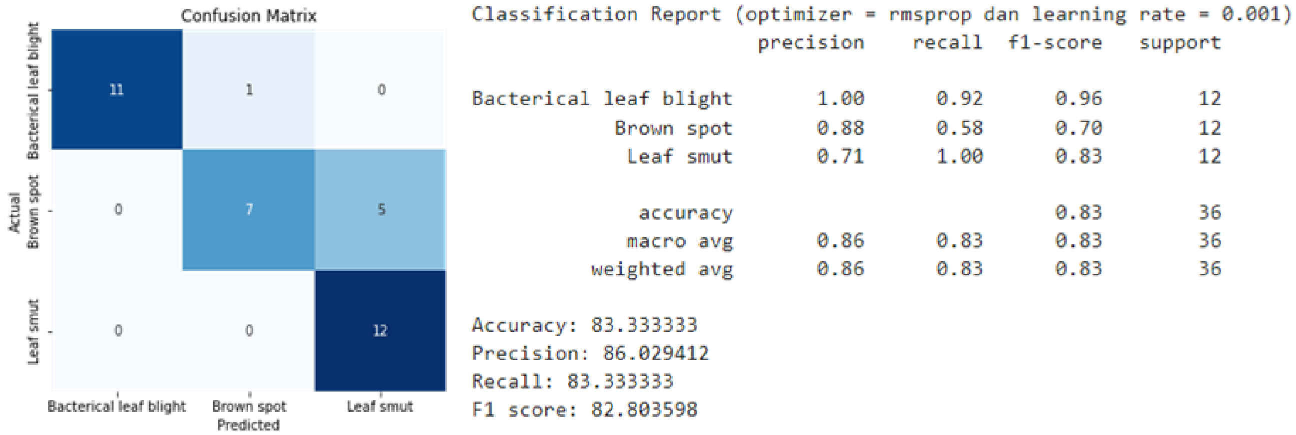


Figure 7. The Confusion Matrix and Classification Repot from First Scenario

Just like in the first test scenario, this test was conducted training using the CNN pretrained model VGG16 with the application of hyperparameter tunning on different datasets, namely datasets that have been segmented using the K-means technique. The results of this test in Table 5 show that the test using optimizer parameters = RMSProp and Learning Rate = 0,001 obtained the highest value of 91,66%. This parameter is the same as the result used in the first scenario. Furthermore, in Figure 8, the results of the accuracy and loss graph can be seen as not too overfitting as in the first test . Figure 9 shows the results of the confusion matrix of classes in the dataset used which can be seen as having a series of incorrect predictions.

Table 5. The Result of Accuracy from the Hyperparamater in Second Scenario

No	Hyperparameter		Accuracy
	Optimizer	Learning Rate	
1	Adam	0.001	86.66%
2	Adam	0.01	88.88%
3	Adam	0.1	83.33%
4	RMSProp	0.001	**91.66%**
5	RMSProp	0.01	77.77%
6	RMSProp	0.1	88.88%
7	SGD	0.001	83.33%
8	SGD	0.01	77.77%
9	SGD	0.1	83.33%

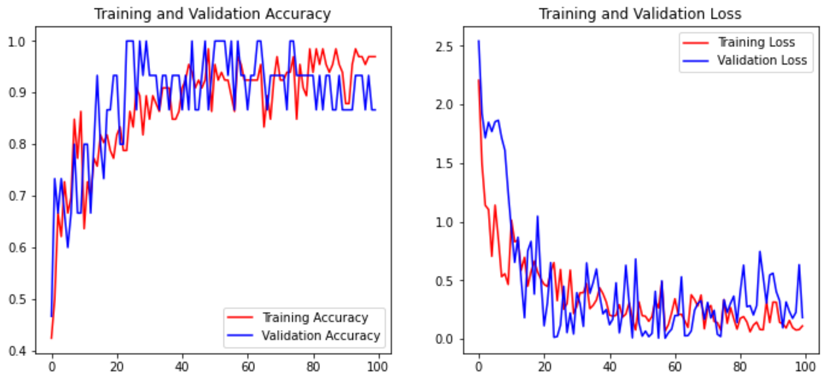
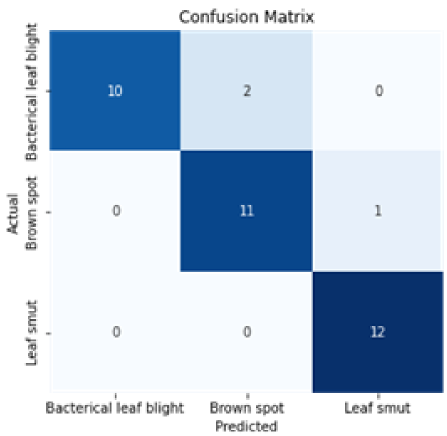


Figure 8. The Graph of Accuracy and Loss from Second Scenario




```
Classification Report (optimizer = rmsprop dan learning rate = 0.001)
                        precision    recall  f1-score   support

Bacterical leaf blight       1.00      0.83      0.91        12
            Brown spot       0.85      0.92      0.88        12
             Leaf smut       0.92      1.00      0.96        12

              accuracy                           0.92        36
             macro avg       0.92      0.92      0.92        36
          weighted avg       0.92      0.92      0.92        36

Accuracy: 91.666667
Precision: 92.307692
Recall: 91.666667
F1 score: 91.636364
```

Figure 9. The Confusion Matrix and Classification Repot from Second Scenario

In the tests carried out the classification of the VGG16 model using the Rice Leaf Disease dataset. With the results obtained from second scenario, it gets superior performance with an Accuracy value of 91,66% with an RMSprop optimizer paremeter and learning rate of 0,001. Compared to first scenario which gets low performance with an Accuracy value of only 83,33% with the same hyperparamater value.

4. Conclusion

Based on the scenario conducted from this study, it can be implied that the VGG16 model with implementation of Image segmentation using the k-means technique obtained an accuracy performance result of 91,66% with hyperparameter optimizer RMSProp and learning rate 0,001. The results obtained in this study were able to surpass the performance of previous studies. In the scenario carried out with the VGG16 model and Image segmentation with two kmenas techniques, it is able to increase the accuracy of scenarios that use threshold segmentation techniques. This proves that the classification method using the VGG16 pretrained model with the Image Segmentation Technique is have not been able to go beyond some previous studies. there is a need for further research in further research by conducting data augmentation and other segmentation methods..

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