Classification of Coffee Leaf Diseases using the Convolutional Neural Network (CNN) EfficientNet Model

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Abstract

Coffee leaf disease is a problem that needs attention because it affects the quality and productivity of the coffee harvest and is detrimental to farmers. Therefore, a system is needed to identify types of coffee leaf diseases using artificial intelligence. There are four types of coffee leaf diseases, namely Miner leaf, Phoma leaf, Rust leaf, and Nodisease leaf. The research used the EfficientNet Architecture Convolutional Neural Network (CNN) method to detect types of disease on coffee leaves. This method was chosen because it is capable and reliable in processing digital images for pattern recognition. The dataset used is 1,464 images with dimensions of 2048 x 1024 pixels with RGB type which are divided into 1,264 training data and 400 testing data. Several architectures used in EfficientNet are EfficientNet B0, EfficientNet B1, EfficientNet B2, EfficientNet B3, EfficientNet B4. Parameters used are Lanczos resampling, Epoch 25, Learning Rate 0.0001, Loss Function Sparse Categorical Cross Entropy, Optimizer Adam. The results of training data testing, namely the CNN EfficientNet B1 Architecture Model method, got the best accuracy of 97% and a loss of 0.1328 and testing data testing got an accuracy of 0.97% and a loss of 0.1328. The architecture of the EfficientNet B1 model is better than other architectural models, namely VGG16, ResNet50, MobileNetv2, EfficientNet B0, EfficientNet B2, EfficientNet B3, EfficientNet B4, EfficientNet B5, EfficientNet B6, EfficientNet B7.

***Keywords**: Identification, Coffee Leaf Disease, Convolutional Neural Network (CNN), EfficientNet*

1. Introduction

Coffee has a very significant role in the agricultural sector and is a major contributor to foreign exchange earnings in the Indonesian economy. According to data from the Central Statistics Agency (BPS), coffee production in Indonesia reached its highest peak in recent years in 2021. On the other hand, coffee production reached its lowest level in 2017 with a total of 716.10 thousand tons, then experienced an increase in 2018 of 756 thousand tons. Furthermore, coffee production continued to increase successively in 2019 and 2020, reaching 752.5 thousand tons and 762.4 thousand tons respectively. In 2021, there will be another increase with total production reaching 786.2 thousand tons [1].

When coffee plant leaves are attacked by pests or diseases, the impact will be felt on the overall growth of the coffee plant [2]. Various types of diseases such as Miner, Rust, Phoma, and Cercospora can infect coffee plant leaves [3]. To increase effectiveness in disease control, it is necessary to recognize the severity of disease in coffee plants [4][5]. Measuring the level of severity can be done through observation and assessment of the condition of the leaves on Robusta and Arabica coffee plants [6].

Diseases in coffee plants can be detected through changes in leaf color and morphology. Several types of diseases that can be identified by observing the leaves on coffee plants involve leaf rust

(Hemileia Vastatrix), leaf miner (Leucoptera Coffeella), and leaf blight (Phoma Costaricensis) [7]. These diseases can be caused by various factors such as fungi, microbes, and viruses, so identifying the type of disease with the naked eye can be a complicated task. Additional obstacles arise from the large area of coffee plantations and the abundance of plants, which makes it difficult for farmers to identify diseases accurately. Therefore, the development of special methods for disease identification on coffee plant leaves is very important. Implementation of this method can help farmers improve the quality and quantity of coffee production in Indonesia [7].

In the current era, the agricultural sector does not only rely on artificial intelligence [8]. The use of advanced technology in agricultural practices is believed to increase productivity and quality of agricultural products [9]. In particular, the combination of artificial intelligence and computer vision has proven to be very effective in its applications in agriculture, especially for plant disease detection [10]. Significant advances in artificial intelligence, especially in Machine Learning, have resulted in the concept of Deep Learning (DL). Even though artificial intelligence has limitations in applying some intuition to its knowledge, the concept of deep learning is a solution used to overcome these obstacles [11].

Research related to identifying coffee leaf diseases. using the CNN VGG16 method results in 89% accuracy [12]. Unet for Segmentation and ResNet50 for classification produces an accuracy rate of 97.07% [13]. ResNet50 for disease classification in robutsa coffee multiclass 88.98% and binary class 92.88% [14]. The Local Binary Pattern and Random Forest methods produce the best accuracy rate of 95.83% [15]. ResNet 50 and MobileNet methods using Loss Function categorical cross entropy LR 0.001 Epoch 20 Batch Size 32 produce accuracy of 99.89% and 98.96% [16]. the Haralick feature extraction method, Color Histogram and Random Forest classification produces an accuracy of 98.83% but 2 classification classes are Rust and Miner [17]. YOLOv7 method uses augmentation, annotation, labeling with parameters 300 epochs, 8 workers, 16 bath size, optimizer SDG F-1 Score 0.93, Precision 0.92, recall 0.932 for all classes [18]. The Convolutional Neural Network (CNN) method based on Android hyperparameters 50 epochs, bath size 32, Adam optimizer produces an accuracy of 94.33% [19]. The EfficientNet B-0 method, Adam optimizer and RMSProp produce 91% accuracy [20]. The EfficientNet model uses Scaling its performance is very effective surpassing state-of-the-art accuracy with orders of magnitude fewer parameters and FLOPS [21]. This method is able to outperform other Deep Learning methods ResNet, DenseNet, NASNet, Inception [21].

Based on the background above, the focus of this research is identifying types of coffee leaf disease based on leaf images using the Deep Learning Convolutional Neural Network (CNN) EfficientNet Model Architecture method [22]. It is hoped that this research will help farmers identify coffee leaf diseases using artificial intelligence. So it can reduce losses to the quality and results of coffee production caused by diseases in coffee plants [23].

2. Research Methods

This research uses several stages, namely image input, sharing of training and testing data, resampling, classification and evaluation [24].

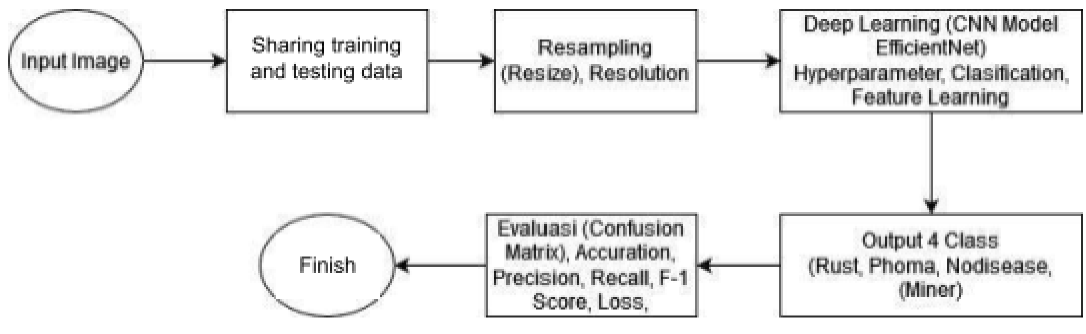


Figure 1. Research Flow

2.1 Efficient Net Models dan Hyperparameter

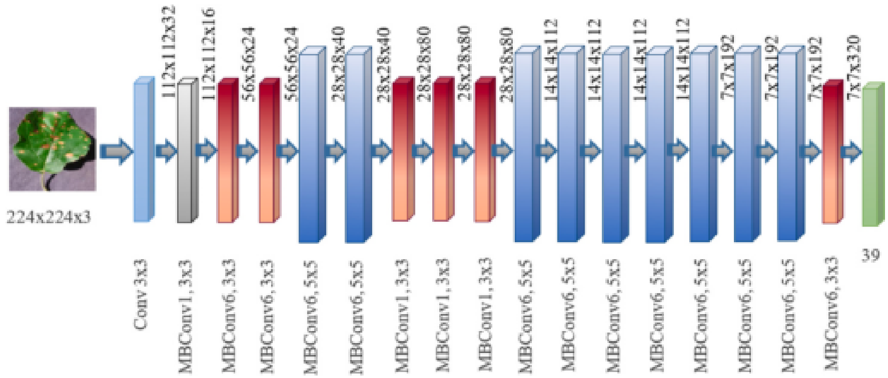


Figure 2. EfficientNet Model Architecture

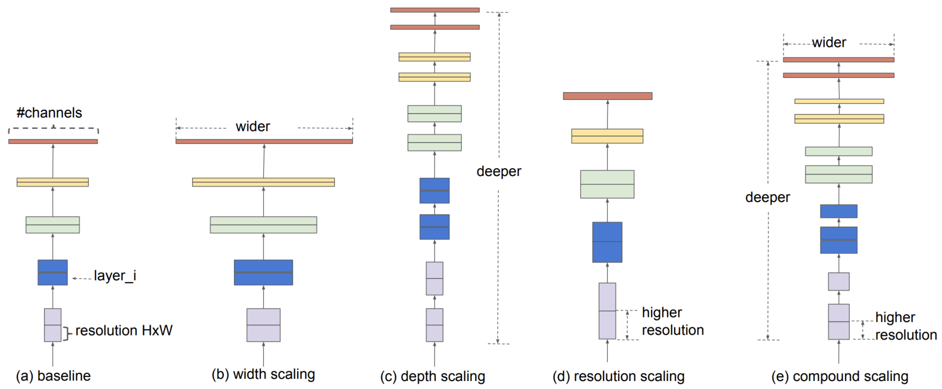


Figure 3. Scaling Model on EfficientNet

Table 1. Image Input Shape and parameters for each model

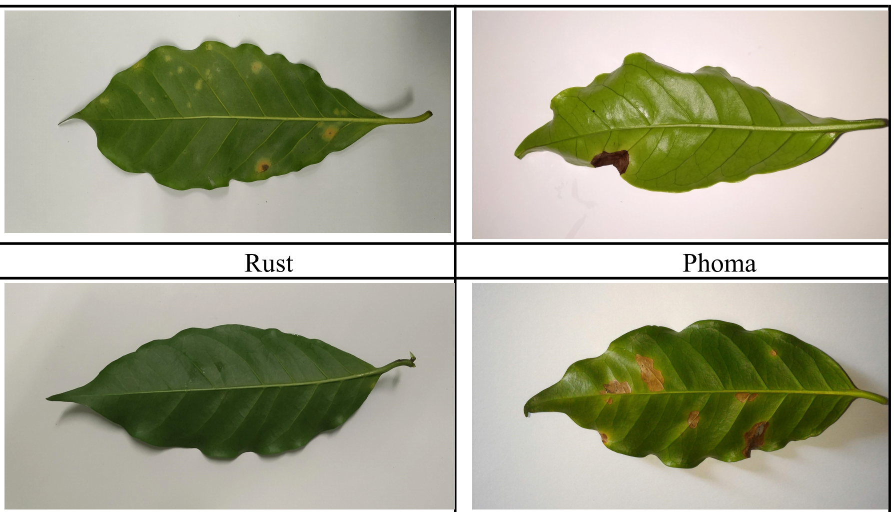
Model	Resolution (NxN)	Total Parameters
EfficientNetB0	224	5,330,571
EfficientNetB1	240	7,856,239
EfficientNetB2	260	9,177,569
EfficientNetB3	300	12,320,535
EfficientNetB4	380	19,466,823
EfficientNetB5	465	30,562,527
EfficientNetB6	528	43,265,143
EfficientNetB7	600	66,658,687

Table 2. Model Parameters

Resampling	Lanczos
Epoch	25
Learning Rate	0,0001
Loss Function	Sparse Categorical CrossEntropy
Optimizer	Adam

2. 2 Dataset

In this research, a secondary dataset is used which comes from the open source Kaggle [25]. This dataset contains information about four types of diseases on coffee plant leaves, namely Miner leaf, Phoma leaf, Rust leaf, and Nodisease leaf [26]. Each image in the dataset has dimensions of 2048 x 1024 pixels with RGB color mode, and the total number of images is 1.464, as detailed in Table 3. This dataset can be accessed via the following link: https://www.kaggle.com/datasets/gauravduttakiit/coffee-leaf-diseases.



Rust | Phoma

Nodisease | Miner

Figure 4. Types of Coffee Leaf Diseases

Table 3. Dataset details

Type	Training	Testing
Miner	332	128
No Disease	284	116
Phoma	388	96
Rust	260	60
Total	**1.264**	**400**

2.3 Evaluation

Evaluation is a critical step to obtain performance from model results [27][28]. This evaluation process utilizes a matrix, an evaluation method used to assess classification methods [29][30]. In this research, model performance is measured using parameters such as accuracy, precision, recall and f1-score, with the formula listed in Table 4.

Tabel 4 Confusion Matrix

Matrix	Formula
Accuracy	$A = \frac{(TP+TN)}{(TP+TN+FP+FN)}$
Precision	$P = \frac{(TP)}{(TP+FP)}$
Recall	$R = \frac{(TP)}{(TP+FN)}$
F1-Score	$F1 = 2x\frac{(PxR)}{(P+R)}$

3. Research Results and Discussion

3.1 Experimental Tools

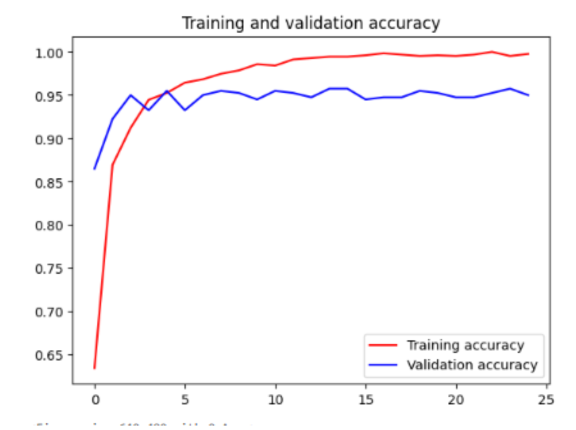
The research uses the EfficientNet architecture with Kaggle Notebooks tools, the Python programming language and the Keras and Tensorflow libraries.

3.2. Results

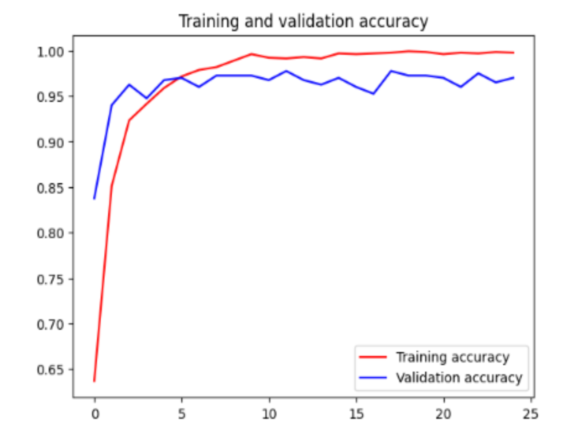
Table 5. EfficientNet Model Measurements on training and testing data

Model	Validation Accuracy	Validation Loss	Train Accuracy	Loss Train
Efficient NetB0k	0.95	0.1509	0.95	0.1509
Efficient NotE 1	0.97	0.1328	0.97	0.1328
Efficient NotE 2	0.93	0.2004	0.93	0.2004
Efficient NotE 3	0.96	0.1567	0.96	0.1567
Efficient NotE 4	0.95	0.2389	0.95	0.2390
Efficient NotE 5	0.94	0.1351	0.94	0.1352
Efficient Net B6	0.90	0.2842	0.90	0.2842
Efficient NotE 7	0.93	0.2163	0.93	0.2164

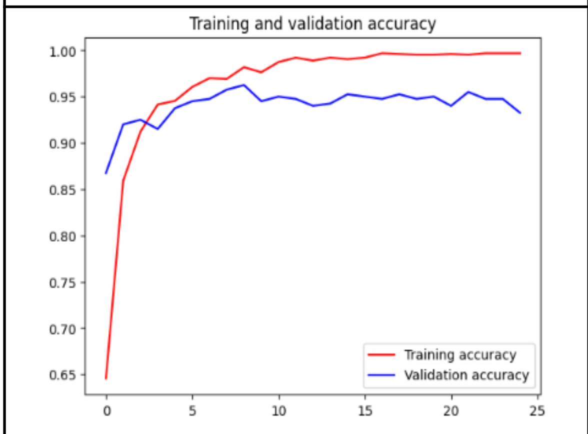
Based on table 5, the highest accuracy results use the EfficientNet B1 model, the accuracy of the training data is 97% and the testing data is 97%, the training data loss is 0.1328 and the testing data loss is 0.1328. A comparison graph of the accuracy of each model is presented in Figure 5 and the loss results for each model in Figure 6.



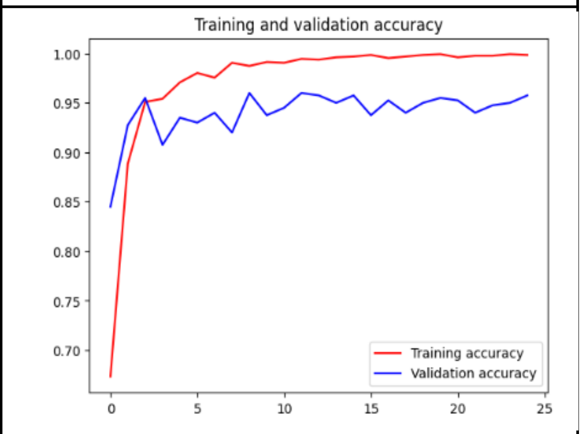
Efficient Net B0



Efficient Net B1



Efficient Net B2



Efficient Net B3

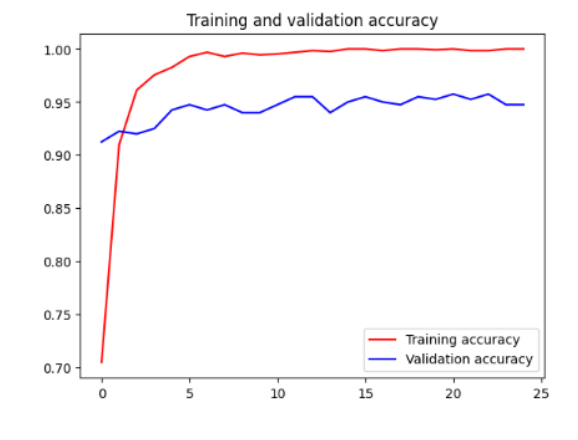
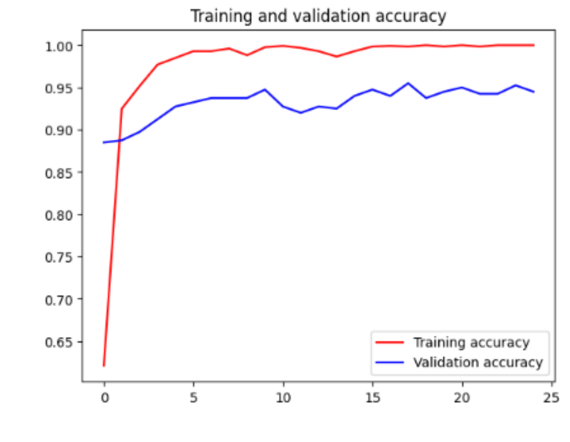
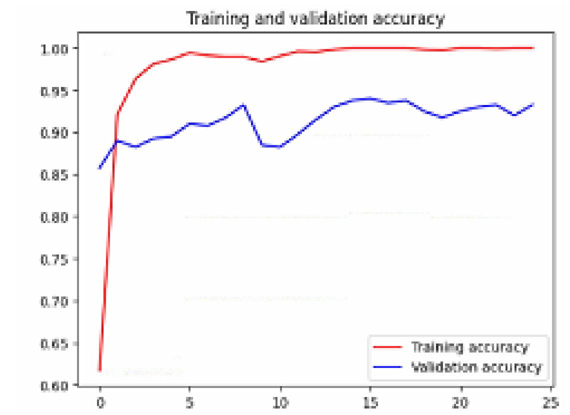
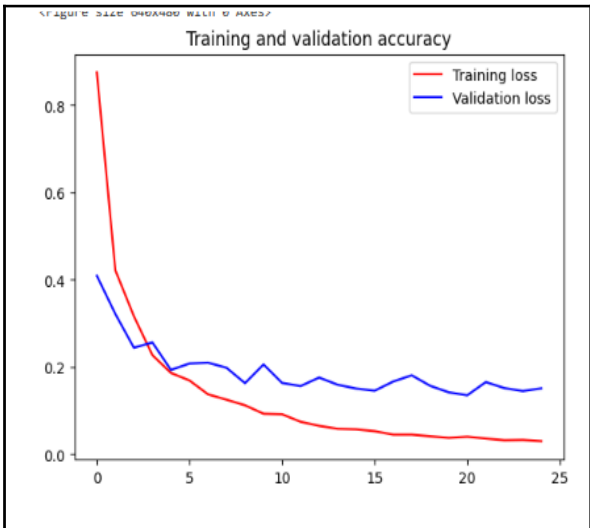
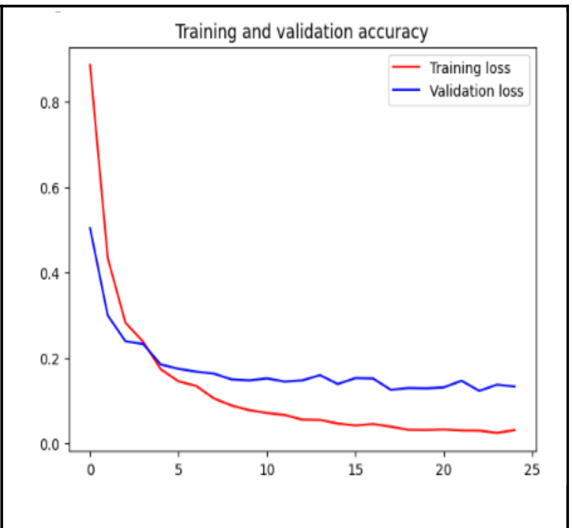
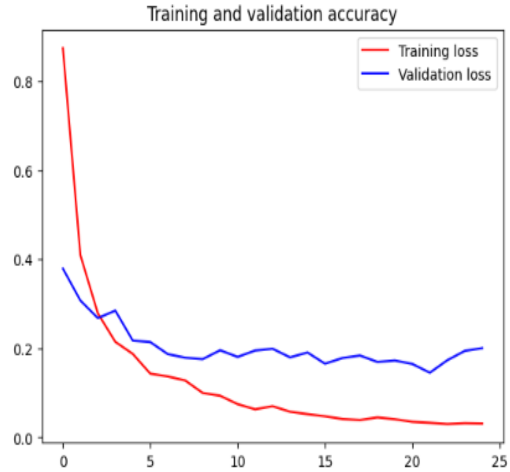
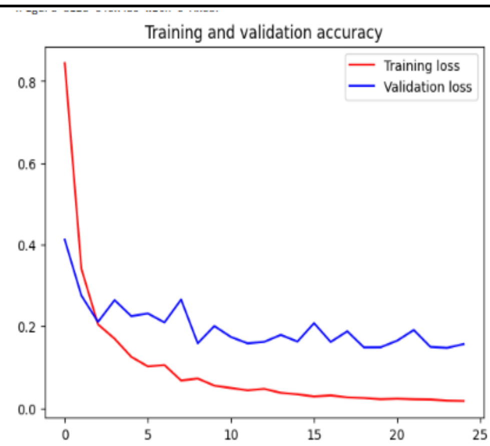
	
Efficient Net B4	Efficient Net B5
	
Efficient Net B6	Efficient Net B7

Figure 5. Results of measuring the accuracy of the EfficientNet Model

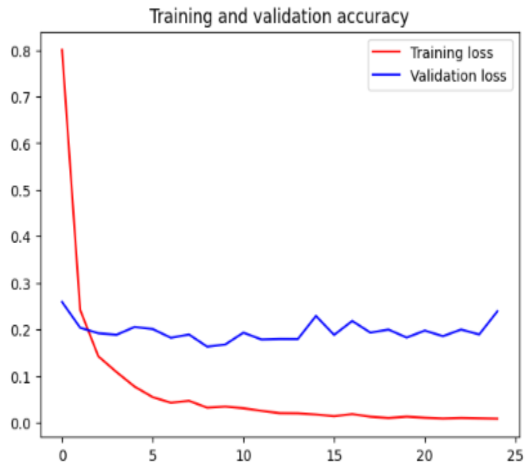
	
Efifi saintNet B0	Epifise interNet B1



Epifise interNet B2

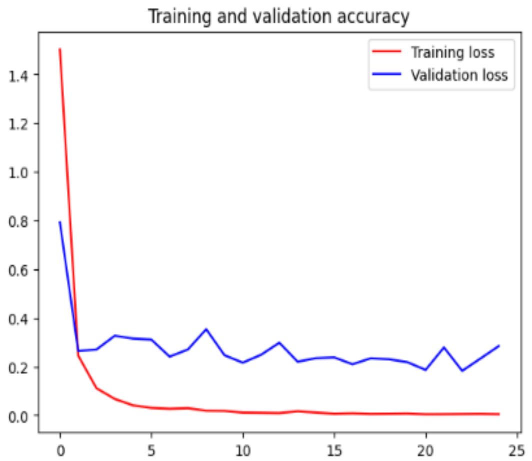


Efifi saintNet B3

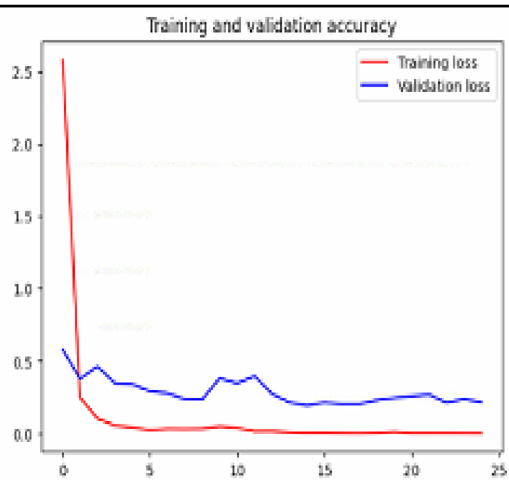


Epifise interNet B4

Epifise interNet B5

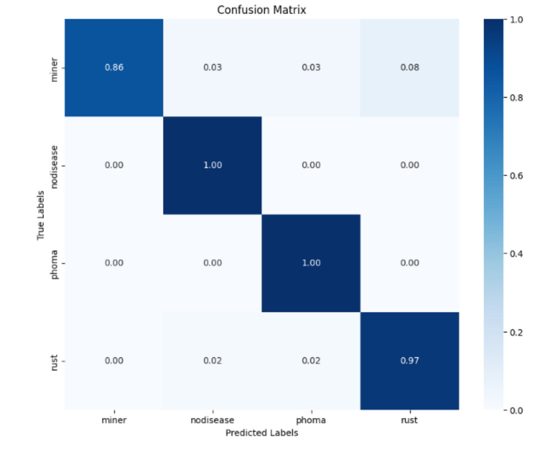


Epifise interNet B6

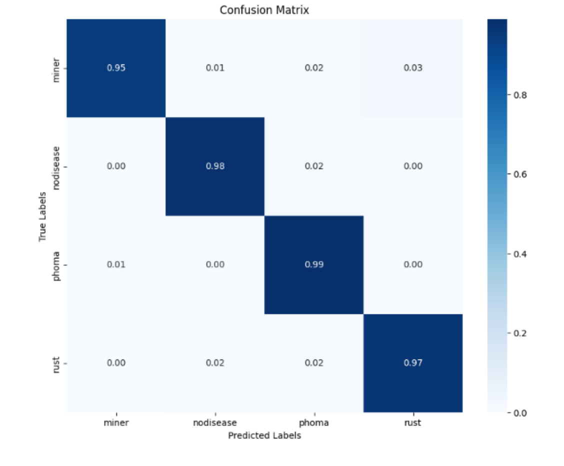


Epifise interNet B7

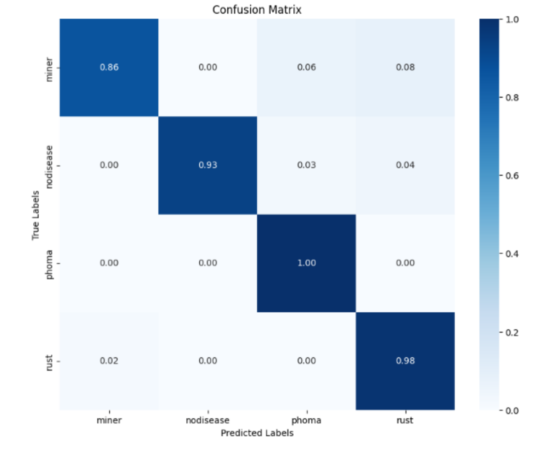
Figure 6. EfficentNet Model Loss Measurement Results



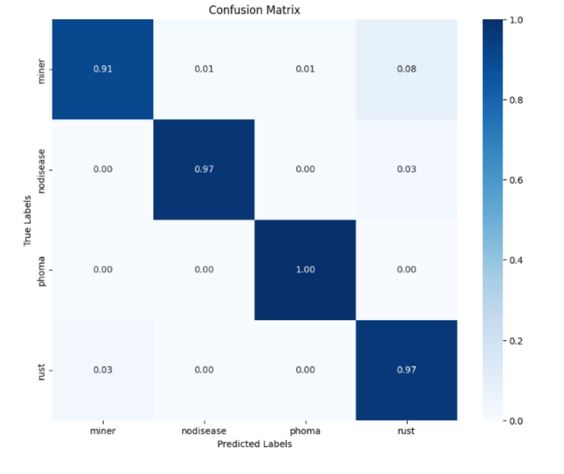
EfifisentNet B0



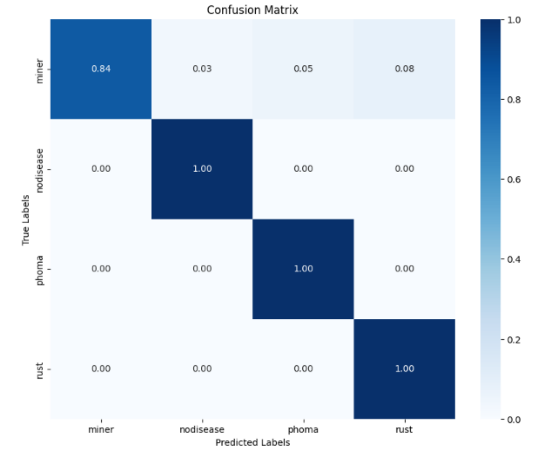
EfifisentNet B1



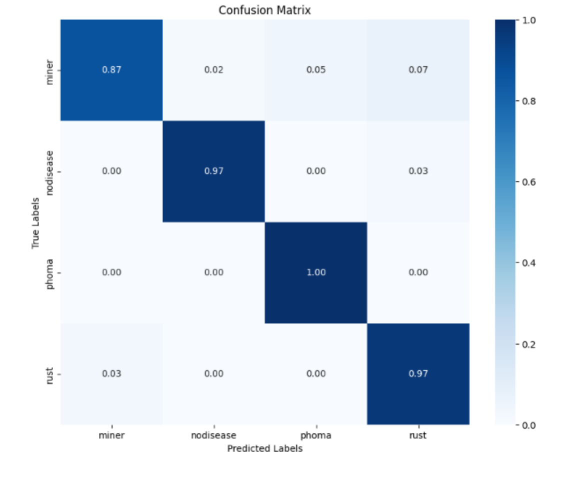
EfifisentNet B2



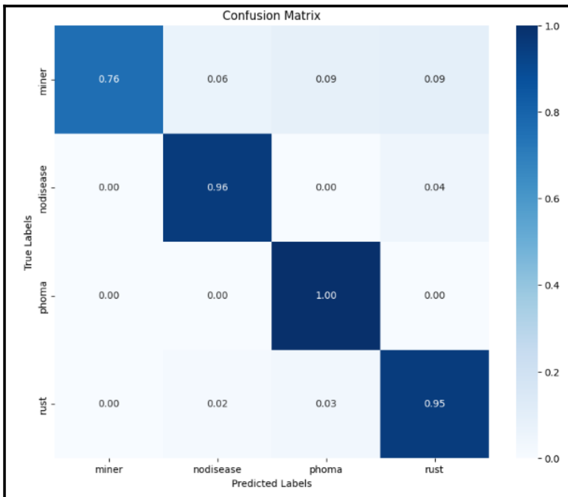
EfifisentNet B3



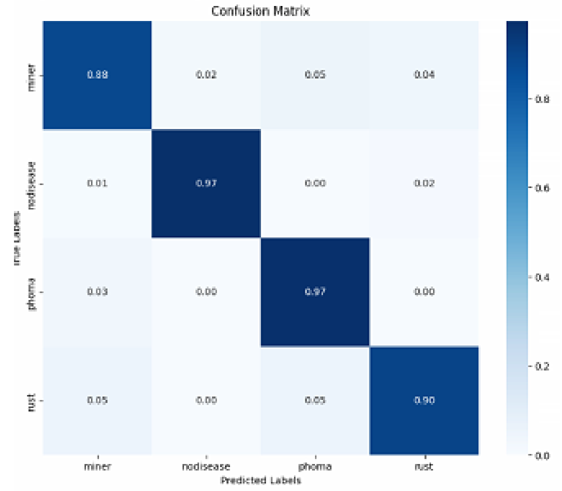
EfifisentNet B4



EfifisentNet B5



EfifisentNet B6



EfifisentNet B7

Gambar 7. Hasil Convolution Matrix model EfficientNet

13/13 [==============================] - 6s 492ms/step

	precision	recall	f1-score	support
0	1.00	0.86	0.92	128
1	0.96	1.00	0.98	116
2	0.95	1.00	0.97	96
3	0.85	0.97	0.91	60
accuracy			0.95	400
macro avg	0.94	0.96	0.95	400
weighted avg	0.95	0.95	0.95	400

EfifisentNet B0

13/13 [==============================] - 7s 559ms/step

	precision	recall	f1-score	support
0	0.99	0.95	0.97	128
1	0.98	0.98	0.98	116
2	0.95	0.99	0.97	96
3	0.94	0.97	0.95	60
accuracy			0.97	400
macro avg	0.97	0.97	0.97	400
weighted avg	0.97	0.97	0.97	400

EfifisentNet B1

13/13 [==============================] - 18s 1s/step

	precision	recall	f1-score	support
0	0.99	0.86	0.92	128
1	1.00	0.93	0.96	116
2	0.90	1.00	0.95	96
3	0.80	0.98	0.88	60
accuracy			0.93	400
macro avg	0.92	0.94	0.93	400
weighted avg	0.94	0.93	0.93	400

EfifisentNet B2

13/13 [==============================] - 21s 2s/step

	precision	recall	f1-score	support
0	0.98	0.91	0.94	128
1	0.99	0.97	0.98	116
2	0.99	1.00	0.99	96
3	0.82	0.97	0.89	60
accuracy			0.96	400
macro avg	0.95	0.96	0.95	400
weighted avg	0.96	0.96	0.96	400

EfifisentNet B3

13/13 [==============================] - 21s 2s/step

	precision	recall	f1-score	support
0	0.98	0.91	0.94	128
1	0.99	0.97	0.98	116
2	0.99	1.00	0.99	96
3	0.82	0.97	0.89	60
accuracy			0.96	400
macro avg	0.95	0.96	0.95	400
weighted avg	0.96	0.96	0.96	400

EfifisentNet B4

13/13 [==============================] - 5s 412ms/step

	precision	recall	f1-score	support
0	0.98	0.87	0.92	128
1	0.98	0.97	0.98	116
2	0.94	1.00	0.97	96
3	0.83	0.97	0.89	60
accuracy			0.94	400
macro avg	0.93	0.95	0.94	400
weighted avg	0.95	0.94	0.95	400

EfifisentNet B5

```
13/13 [==============================] - 170s 13s/step
              precision    recall  f1-score   support

           0       1.00      0.76      0.86       128
           1       0.93      0.96      0.94       116
           2       0.88      1.00      0.94        96
           3       0.77      0.95      0.85        60

    accuracy                           0.90       400
   macro avg       0.89      0.92      0.90       400
weighted avg       0.92      0.90      0.90       400
```

EfifisentNet B6

```
13/13 [==============================] - 322s 23s/step
              precision    recall  f1-score   support

           0       0.94      0.88      0.91       128
           1       0.97      0.97      0.97       116
           2       0.90      0.97      0.93        96
           3       0.89      0.90      0.89        60

    accuracy                           0.93       400
   macro avg       0.93      0.93      0.93       400
weighted avg       0.93      0.93      0.93       400
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EfifisentNet B7

Figure 8. Results of measuring Precision, Recall, F-1 Score of the EfficientNet model

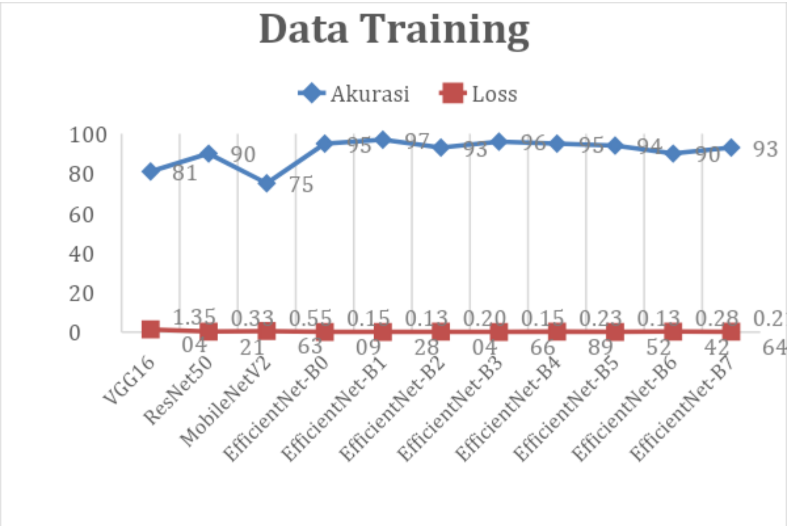

Figure 10. Comparison of accuracy and loss results on training data

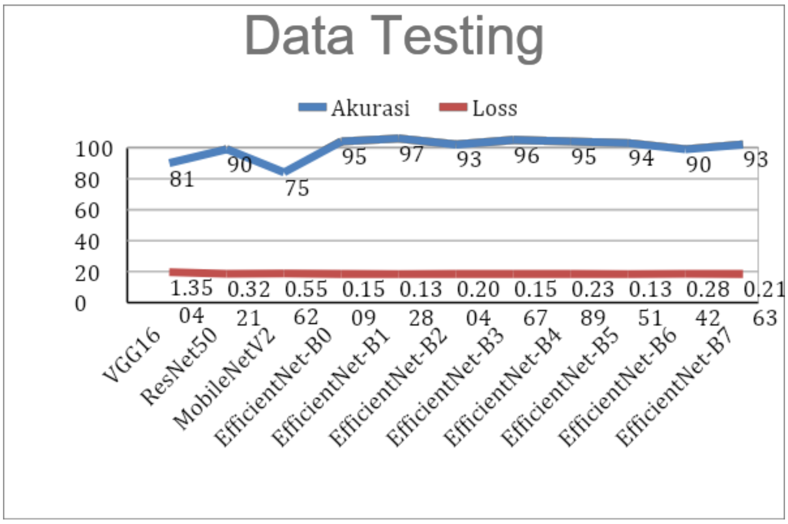

Figure 11. Comparison of accuracy and loss results on testing data

3.2. Discussion

Based on experiments on training and testing data, the use of the CNN method, the EfficientNet model, is very good based on the accuracy value of each model being above 90% compared to the VGG16 method 81%, ResNet50 90% and MobileNetV2 75%. In addition, in the precision, recall, and

F1-Score processes, there is an insignificant difference between these values as a whole. This shows that the use of the EfficientNet model to balance data distribution can increase the accuracy of evaluation in each class, as seen in Figure 8. In this context, the classification system developed is able to identify diseases well. Based on the Loss value of each training and testing data using the EfficientNet model, it produces a very good Loss value, namely below 1.3504. Apart from that, the use of Lanczos resampling can help improve the quality of the input image, but must also be considered carefully regarding the available computing and resources.

4. Conclusion

Based on research on the identification of 4 types of coffee leaf disease, namely Miner leaf, Phoma leaf, Rust leaf, No disease leaf using the EfficientNet Architecture Convolutional Neural Network (CNN) method. Testing on 1,264 training data and 400 RGB image testing data using size resizing according to the efficientNet model, Lanczos resampling parameters, Epoch 25, Learning Rate 0.0001, Loss Function Sparse Categorical Crossentropy, Optimizer Adam obtained the training data test results, namely the CNN EfficientNet Architecture Model method -B1 gets the best accuracy of 97% and Loss 0.1328 and data testing gets an accuracy of 0.97% and Loss 0.1328. The architecture of the EfficientNet-B1 model is better than other Architectural Models, namely VGG16, ResNet50, MobileNetv2, EfficientNet-B0, EfficientNet-B2, EfficientNet-B3, EfficientNet-B4, EfficientNet- B5, EfficientNet-B6, EfficientNet-B7. For further research, it is recommended to use hyperparameters, namely adding epochs, using a Loss Function other than Sparse Categorical Cross Entropy, Learning Rate Value, SGD Optimizer, RMSProp to produce a more optimal model. Furthermore, this research can be developed for web or Android-based implementation on plantations so that it can be used by coffee farmers to identify types of coffee leaf diseases.

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