

Comparison of MobilenetV2 and EfficiennetB3 Method to Classify Diseases on Corn Leaves

Slamet Riyadi^{1,*}, Rezka Mulya¹ and Aulia Nabila Realisti¹

¹Department of Information Technology, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta, Indonesia

Abstract. Corn is an important commodity in Indonesia and one of the world's staple foods. According to FAO in 2017, disease problems often hamper corn production. The main problems that affect crop yields are diseases that damage corn leaves, including rust, spot, blight and downy mildew. Manual disease identification on corn leaves has limitations in consistency and scalability. A digital image processing system is needed to increase the speed and accuracy of recognition. Classification of types of corn leaf disease is needed so that farmers can distinguish types of corn leaf disease. Therefore, to identify four forms of maize leaf disease, this study tested a CNN model using the EfficientNetB3 and MobileNetV2 architectures. The data used to evaluate these two models is divided into training and testing subsets. Based on test results with 50 epochs, EfficientNetB3 obtained 93.20% accuracy with a loss of 0.0850, while MobileNetV2 obtained 92.48% accuracy with a loss of 0.19020. When the test data is evaluated, EfficientNetB3 performs better than MobileNetV2. MobileNetV2 has limitations in handling complex feature representation on very complex data. On the other hand, although it provides better results, EfficientNetB3 has the disadvantage of high computing and memory resource requirements, which can hamper efficiency in practical implementation. Based on these findings, EfficientNetB3 is recommended because it performs better in maize leaf disease classification, shows smaller losses and higher accuracy than MobileNetV2. By using this model, corn plant diseases can be identified efficiently and precisely, thereby improving disease control and producing more productive corn plants.

1 Introduction

Following rice and wheat as the world's two most essential dietary staples, corn is also a major necessity in Indonesia. Without requiring a lot of air, corn plants grow effectively in both hot and cold climates with enough rainfall and irrigation [1]. As of the end of 2017, Indonesia was the world's greatest producer of corn, according to the Food and Agriculture Organization (FAO). Low corn yield was, however, caused by disease-related reasons. On maize leaves, there are four primary disease types: downy mildew, leaf rust, leaf spot, and leaf blight. Reddish-yellow patches on the leaves of corn plants afflicted with leaf rust disease resemble the color of rust on iron. The fungus *Puccinia polyspora* is the source of this illness.

* Corresponding author: riyadi@umy.ac.id

The fungus *Helminthosporium maydis* is the cause of leaf spot disease in corn plants [2]. Brownish-yellow patches that are oval or elongated are the hallmarks of this condition. The fungus *Peronosclerospora maydis* is the cause of downy mildew disease, also known as corn downy mildew. This disease is very common among farmers and is characterized by a thick layer of white on the leaf surface that is followed by chlorotic lines. *Rhizoctonia solani*, the disease that causes leaf blight on corn plants, is characterized by the emergence of stunted, oval-shaped patches that eventually enlarge and take on an elliptical shape before developing into the necrotic form known as blight [3].

Because diseased maize leaves change color, it is possible to manually identify illnesses on corn plant leaves using the human eye [4]. The sorting that the farmers have been doing all this time is still using the conventional way, that is, with the sense of sight. This conventional method seems to be less effective because it takes a lot of energy, takes a long time, and there are different perceptions between farmers [5]. However, if the plants need to be identified in big quantities and take a long period, there are limitations to using the human sense of sight to distinguish the color of maize leaves. Besides, everyone's perception of color is unique. A digital image processing system is required to facilitate the identification process efficiently and precisely.

Numerous strategies and techniques for recognizing, comprehending, and managing illnesses that impact corn plant growth have been highlighted by earlier studies on the disease classification of maize leaves [6]. Numerous investigations have looked into the use of digital image analysis and image-sensing technology to find early illness symptoms in maize leaves, such as wrinkles, curling, and spots. These investigations have looked for distinctive patterns in photos of diseased maize leaves.

Previous studies used EfficientNetB3 to categorize illnesses on corn leaves. An accuracy of 0.3051, or 30%, and a loss of 1.6613 are produced by the EfficientNetB3 epoch 50 optimizer Adamax [7]. Because EfficientNetB3 has a bigger network with more breadth, depth, or resolution, which tends to produce higher accuracy, it is a CNN model that can reliably predict and categorize items [8].

For the Android-based maize leaf disease classification, MobileNetV2 was chosen for several significant reasons. Unlike other deep learning algorithms, which are frequently quite complex, such as EfficientNetB3 and ResNet-50, MobileNetV2 is computationally efficient on mobile devices, ensuring efficient performance with low processing power consumption. MobileNetV2 can respond quickly and effectively in Android device contexts with limited processing power [9]. Second, one advantage of MobileNetV2 is its capacity to learn efficient transmission. Even with limited formal datasets, MobileNetV2 can be readily adapted for Android-based corn leaf disease classification tasks by leveraging existing knowledge from models trained on large-scale datasets like ImageNet. Furthermore, real-time systems are supported by MobileNetV2's quick estimate speed, which is essential for the prompt and precise identification of plant diseases in the field. This becomes more crucial in agricultural settings when prompt action is necessary. Therefore, when mobile device resources are restricted, MobileNetV2's combination of computational economy, adaptive learning, and high prediction rate make it a suitable choice in environments based on Android and effectively demands a corn leaf disease classification system [10].

The disease classification on corn leaves using EfficientNetB3 and MobileNetV2 algorithms is not compared. The purpose of comparing the EfficientNetB3 and MobileNetV2 approaches for classifying diseases on corn leaves is to determine which system is more effective and precise at identifying different diseases that impact corn plants by analyzing leaf images [11]. This project intends to assess and comprehend the effectiveness of both approaches in resolving the issue of identifying illnesses in Cassava plants by conducting this comparison. To select the most effective and efficient approach for managing maize plant

diseases, it is intended that the comparison's outcomes will offer comprehensive insight into the efficacy and efficiency of each technique.

This proposed topic presents novelty by proposing a comparison of disease classification on corn leaves using two relevant methods, namely MobileNetV2 and EfficientNetB3. The uniqueness of this project lies in its focus on comparing two different neural network architectures: MobileNetV2, which is designed specifically for computational efficiency on mobile devices, and EfficientNetB3, which prioritizes performance and efficiency at scale. Previous research may involve a single method or focus on a particular aspect, while this project examines differences in the performance of the two in the context of maize foliar disease classification.

The uniqueness of this project also lies in the choice of EfficientNetB3 as one of the comparison methods. EfficientNetB3 has an innovative architecture with careful parameter optimization, enabling more efficient use of resources. The selection of this method is expected to contribute to a better understanding of the potential of EfficientNetB3 in handling corn plant disease classification tasks [12]. This comparison allows for a more thorough understanding of the benefits and drawbacks of each approach in the particular context of maize disease classification, which opens up new possibilities for the selection and improvement of these approaches in agricultural applications.

There could be a lot of short- and long-term advantages to the Corn Leaf Disease Classification Project Using the MobileNetV2 Method. Shortly, farmers may directly profit from this project by being able to identify disease indications in maize plants early on, allowing for faster and more accurate application of control and preventive measures [13]. It is anticipated that these potential benefits will decrease production losses due to disease attacks and raise total crop yields by implementing a fast and precise categorization system.

This initiative could have major long-term benefits in addition to its immediate advantages. By reducing reliance on the use of pesticides and other chemicals, this effective and adaptable classification method can enhance soil health and environmental sustainability. Additionally, farmers can implement more effective and sustainable agricultural methods by adopting a responsive classification system to better understand the state of their crop overall [14].

This research has the potential to significantly improve global food security and the sustainability of food production overall, in addition to the immediate benefits for farmers. This research has the potential to significantly contribute to the stability of the world's food supplies, lower volatility in food prices, and eventually increase food availability for people everywhere by preventing and lowering losses due to disease in maize harvests. As a result, this project's possible advantages extend well beyond the agricultural sphere and have a significant influence on promoting agricultural sustainability and global food security.

2 Research method

Data augmentation is a stage of pre-processing that involves multiple operations, including rotation, flip transformation, rescaling, and more. Additionally, data augmentation is carried out to expand the training set's size and produce a wide variety of images. The process of gathering data involved choosing pictures of maize leaves from an existing dataset, including both healthy and diseased leaf photographs. Data pre-processing was done using pixel intensity leveling and data augmentation to increase dataset variation before the model training phase. The dataset is separated into sections for testing, validation, and training. Pre-trained weights on ImageNet are used to configure the MobileNetV2 and EfficientNetB3 classification models, with the output layer adjusted for maize leaf classification [15].

The next step in the model training process is to optimize the number of epochs, batch size, and learning rate, among other hyperparameters. If there is a GPU available, it can be

used to speed up this procedure. To avoid overfitting, the model is tested on a different dataset that wasn't used for training after it has been trained using a validation subset. Model performance is assessed for each illness class using evaluation criteria like accuracy, precision, recall, and F1-score.

After that, the classification outcomes from EfficientNetB3 and MobileNetV2 were compared, and misclassification analysis was done to determine how well the model could distinguish between leaves that were disease-infected and those that weren't. To make sure the results are genuine and consistent, this process can be repeated. In the framework of this project, comments or suggestions for additional development or research are offered alongside the categorization comparison's conclusions [16].

There are various variations of the CNN architecture called EfficientNet. This system makes use of a scaling technique that uses combined coefficients to scale all dimensions evenly. The specs of the EfficientnetB3 design include two convolution layers, seven mobile bottleneck convolution layers, one pooling layer, and one fully linked layer, for a total of 12M parameters. The only distinction between the EfficientNetB0 and EfficientNetB3 layer structures is the number of layers [17].

One of the convolutional neural network methodology's architectures, MobileNetV2, is also referred to by its acronym, CNN. It is a technique that can be utilized to remove the need for excessive computer resources or those that require high computing. The main distinction between CNN architectures generally and the MobileNetV2 architecture is that the latter uses convolution layers or layers whose filter thickness is the same as the thickness of the input picture. Convolution is split into two categories by MobileNet: depthwise convolution and pointwise convolution. In the meantime, two additional capabilities are added by MobileNetV2: shortcut connections between bottlenecks and linear bottlenecks. Furthermore, the study's findings demonstrate how size data augmentation is used by the ADAM type optimizer on the MobileNetV2 architecture to generate good accuracy during training and testing [18].

There are various variations of the CNN architecture called EfficientNet. This system makes use of a scaling technique that uses combined coefficients to scale all dimensions evenly. The specs of the Efficientnet B3 design include two convolution layers, seven mobile bottleneck convolution layers, one pooling layer, and one fully linked layer, for a total of 12M parameters. Except layer count, the Efficientnet B3 layer structure is essentially the same as the Efficientnet B0 layer structure.

All convolution layers start as shown in Figure 1 below with a convolutional process using a filter value of 24 kernels 3×3 . This is followed by a ReLU process, a Max Pooling process using filter 32, and a convolution process using filter 32 and 3×3 kernels. The ReLU activation function mechanism comes next. The procedure continues in the same manner until layer 7 convolution with filter 384 and max pooling 384 is reached. The fully connected process will use 1 layer and SoftMax after the convolution, ReLU activation function, and Max Pooling are finished. The purpose of this method is to categorize the acquired features to generate an output representing the class of the image under examination [19], as shown in the EfficientNetB3 design in Figure 1.

One of the CNN architectures, MobileNetV2, is a convolutional neural network technique that can be utilized to remove the need for excessive computer resources or those that require high computation. CNN is also widely abbreviated as CNN. The use of layers or convolution layers with a filter thickness that matches the thickness of the input image is the primary distinction between the CNN architecture in general and the MobileNetV2 architecture in particular. Convolution is split into two categories by MobileNet: depthwise convolution and pointwise convolution [20].

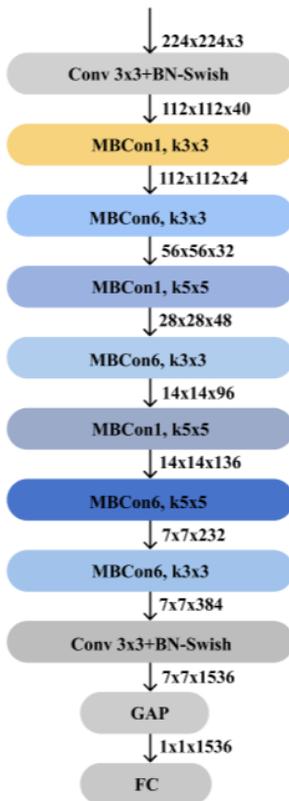


Fig. 1. EfficientNetB3 Architecture [19]

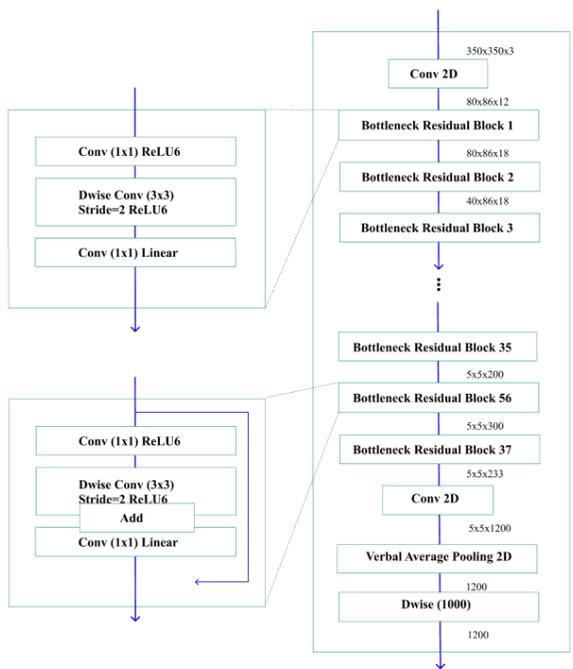


Fig. 2. MobileNetV2 Architecture [21]

In the meantime, two additional capabilities are added by MobileNetV2: shortcut connections between bottlenecks and linear bottlenecks. Aside from that, the study's findings demonstrate that during the training and testing phases, the ADAM type optimizer on the MobileNetV2 architecture employing data size augmentation generates good accuracy. as shown in the MobileNetv2 design in Figure 2.

The picture will be input in the first step of the MobileNet-V2 model's usage. Next, a 2D layer will be used by MobileNet-V2, and the process will continue with 17 blocks in the following step. Blocks 0–16 can be clustered together, or bottleneck 1–17. As is well known, MobileNet-V2 includes more features in section 2's bottleneck layer. The two blocks use distinct methods, including bypass, which is referred to as residue. The Global Average Pooling (GAP) layer will then see the procedure after it is finished. The MobileNet-V2 model essentially consists of ± 150 layers altogether, one layer for each block.

3 Results and discussion

The training and testing datasets for the EfficientNetB3 and MobileNetV2 models are separated into 4 classes within the testing process dataset. 3,350 training datasets and 838 testing datasets make up the total amount of datasets in the EfficientNetB3 model. In the meantime, there are 3349 training datasets and 838 testing datasets altogether in the MobileNetV2 model.

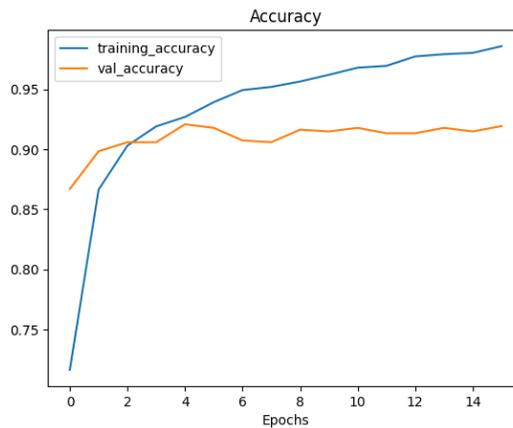


Fig. 3. MobileNetV2 Training Accuracy

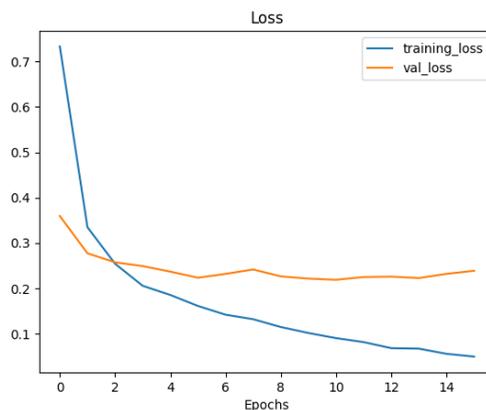


Fig. 4. MobileNetV2 Training Loss

Graphs showing the results of accuracy and loss from the training and validation data used to create the model are shown in Figure 3 and Figure 4. The ratio of accurate predictions positive and negative from all available data for each class is known as accuracy [22]. In the meantime, the prediction's accuracy can be ascertained by the loss function model. Figure 3 explains that the total accuracy is 92.48% and Figure 4 explains that the total loss of 0.19020 is produced by the accuracy achieved by MobileNetV2 epoch 50. The probability values derived from each class show how accurately the identification of different fruit leaf kinds is measured. If the probability value for the image under test is around 1, meaning that it falls between 0 and 1, then the model's accuracy for that image will be good.

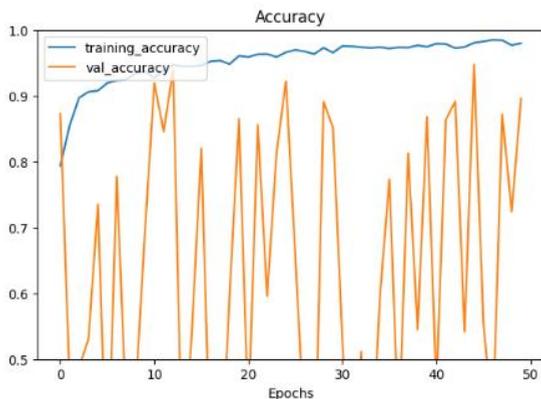


Fig. 5. EfficientNetB3 Training Accuracy

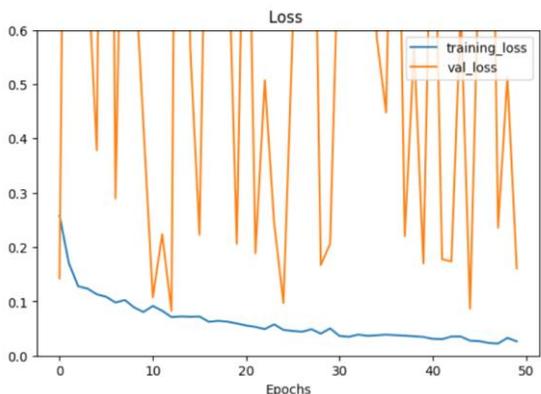


Fig. 6. EfficientNetB3 Training Loss

Graphs showing the accuracy and loss results of the training and validation data used to create the model are shown in Figure 5 and Figure 6. The ratio of accurate predictions positive and negative from all available data for each class is known as accuracy. In the meantime, the prediction's accuracy can be ascertained by the loss function model. The loss value was kept low during the model's creation. Figure 5 explains that the total accuracy is 93.20% and Figure 6 explains that the total loss of 0.0850 was obtained using EfficientNetB3 epoch 50. The probability values derived from each class show how accurately the identification of different fruit leaf kinds is measured. If the probability value for the image under test is around 1, meaning that it falls between 0 and 1, then the model's accuracy for that image will be good.

Confusion matrix is a method in the form of visualization that is used to measure the level of success or model performance in the classification process in machine learning. The

confusion matrix is also often called the error matrix which provides information about the success and error of predictions regarding the data being tested [23]. Figure 7 and Figure 8 are a confusion matrix representation of model performance which is evaluated on test data by displaying actual data and predicted data made by the model.

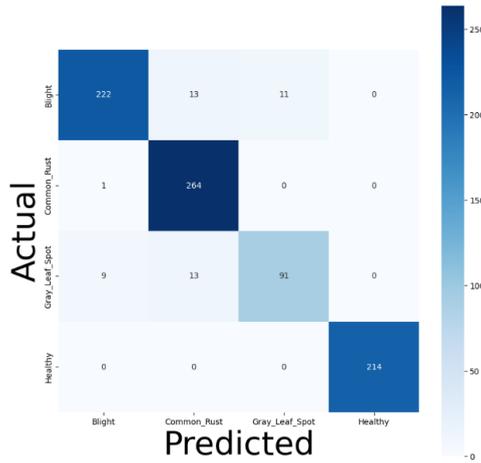


Fig. 7. Confusion Matrix EfficientNetB3

The prediction results from the model with the highest accuracy, epoch 50 in the EfficientNetB3 model, were then compared to each class in the test data, and the results were fairly satisfactory, as seen in the graphic above. 222 data points for the first class, the blight class, were accurate forecasts. The algorithm produced multiple prediction errors: 13 data points were incorrectly identified as common rust, 11 data points as gray leaf spots, and 0 data points as healthy. Common_rust forecasts yielded 264 accurate predictions. 1 information was identified as Blight and 0 data points as Gray_leaf_spot and healthy. The algorithm produced a prediction error, with data points being incorrectly identified as healthy. Next, the Gray_Leaf_spot prediction produced a valid prediction for 91 data points. The model made several predictions that turned out to be incorrect. For example, it projected that 9 piece of data would be blight, 13 pieces would be common rust, and 0 pieces would be healthy. Healthy's predictions yielded 214 accurate predictions. No prediction mistakes for blight, common rust, dan gray_leaf_spot were found.

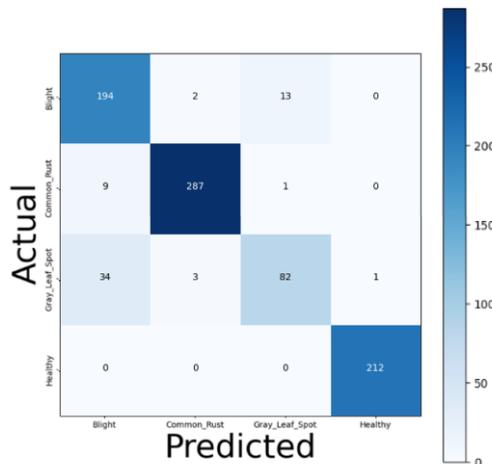


Fig. 8. Confusion Matrix MobilenetV2

When the prediction results from the model with the highest accuracy MobileNetV2 model's epoch 50 were compared to each class in the test data, they outperformed EfficientNetB3 as seen in the above image. 194 data were accurate predictions for the first class, or the blight class. The model produced several prediction mistakes, including two predictions for common rust, thirteen predictions for gray leaf spots, and no predictions for healthy. 287 of the predictions made in Common_rust were accurate. The algorithm produced many prediction errors: nine data points were expected to be blight, one as gray-leaf-spot, and zero as healthy. Next, 82 accurate data predictions were achieved by the Gray_Leaf_spot prediction. The model produced several incorrect predictions, including 34 data that were assumed to be blight, 3 data that were assumed to be common rust, and 1 data that was assumed to be healthy. Healthy's predictions yielded 212 accurate predictions. The model has not produced any forecast mistakes.

The model is then tested or evaluated against the testing data following the completion of the training procedure (Table 1 and Table 2). Numerous metrics are measured during this review process, including F-Score values, Precision, and Recall[24]. Weighted metrics are a notion that is used in the value calculation; typically, weighted metrics are employed in multiclass classification. When all projected values or outcomes are accurate or positive, precision is a positive prediction measurement. The ratio of correctly predicted (positive) data to all correct data from each class is known as recall or sensitivity. F-Score, on the other hand, compares the average of Precision and Recall. The model that has been trained using testing data has yielded the following evaluation findings.

Table 1. Model Evaluation MobileNetV2

	Precision	Recall	F1-score	Support
Blight	0.81	0.92	0.86	209.00
Common-Rust	0.98	0.96	0.97	297.00
Gray_Leaf_Spot	0.85	0.68	0.75	120.00
Healthy	0.99	1.00	0.99	212.00
Accuracy	0.92	0.92	0.92	0.92
Macro avg	0.91	0.89	0.90	838.00
Weighted avg	0.92	0.92	0.92	838.00

Table 2. Model Evaluation EfficientNetB3

	Precision	Recall	F1-score	Support
Blight	0.96	0.90	0.93	246.00
Common-Rust	0.91	0.99	0.95	265.00
Gray_Leaf_Spot	0.89	0.81	0.85	113.00
Healthy	1.00	1.00	1.00	214.00
Accuracy	0.94	0.94	0.94	0.94
Macro avg	0.94	0.92	0.93	838.00
Weighted avg	0.94	0.94	0.94	838.00

4 Conclusion and recommendation

Using the EfficientNetB3 and MobileNetV2 architecture, we have built a Convolutional Neural Network algorithm in this research. One of these models, namely the MobileNetV2 model which aims to categorize four types of corn leaf diseases by producing output in the form of the names of corn leaf diseases, has been successfully implemented and provides better results compared to the EfficientNetB3 model. The results of the research using the MobileNetV2 and EfficientNetB3 models by varying various parameters such as epoch 50 were then obtained for each model, namely EfficientNetB3 with an accuracy of 93.20% and a loss of 0.0850. Meanwhile, the accuracy of the MobileNetV2 model is 92.48% with a loss

of 0.19020. Therefore, based on the results, EfficientNetB3 is highly recommended due to its better accuracy performance when compared to MobileNetV2.

Acknowledgments. The author expresses gratitude to Mr. Eka for their invaluable direction and support, without which the scientific work would not have been completed. The author also acknowledges the Muhammadiyah University of Yogyakarta for providing funding for this endeavor.

References

- 1 S. Kurniawan, R. S. T. Putra, and ..., "Android-Based Corn Plant Disease Diagnosis Application," ... *Teknologi & Sains* ..., vol. 2, pp. 51–58, 2023, [Online]. Available: <https://proceeding.unpkediri.ac.id/index.php/stains/article/download/2853/1988>
- 2 M. Khoiruddin, A. Junaidi, and W. A. Saputra, "Classification of Rice Leaf Diseases Using Convolutional Neural Network," *Journal of Dinda : Data Science, Information Technology, and Data Analytics*, vol. 2, no. 1, pp. 37–45, 2022, doi: 10.20895/dinda.v2i1.341.
- 3 F. Ikorasaki and M. B. Akbar, "Detecting Corn Plant Disease with Expert System Using Bayes Theorem Method," *2018 6th International Conference on Cyber and IT Service Management, CITSM 2018*, no. Citsm, pp. 9–12, 2019, doi: 10.1109/CITSM.2018.8674303.
- 4 A. Hidayat, U. Darusalam, and I. Irmawati, "Detection of Disease on Corn Plants Using Convolutional Neural Network Methods," *Jurnal Ilmu Komputer dan Informasi*, vol. 12, no. 1, p. 51, 2019, doi: 10.21609/jiki.v12i1.695.
- 5 N. A. Utama, W. I. Triyani, S. Riyadi, and C. Damarjati, "Discrete Curvelet Transform Feature Extraction for Mangosteen Fruit Surface Damage Detection," *Emerging Information Science and Technology*, vol. 5, no. 1, pp. 46–51, 2024, doi: 10.18196/eist.v5i1.22602.
- 6 B. Mehlig, "Convolutional Networks," *Machine Learning with Neural Networks*, pp. 141–156, 2021, doi: 10.1017/9781108860604.008.
- 7 F. Adnan, M. J. Awan, A. Mahmoud, H. Nobanee, A. Yasin, and A. M. Zain, "EfficientNetB3-Adaptive Augmented Deep Learning (AADL) for Multi-Class Plant Disease Classification," *IEEE Access*, vol. 11, no. July, pp. 85426–85440, 2023, doi: 10.1109/ACCESS.2023.3303131.
- 8 H. Farman, J. Ahmad, B. Jan, Y. Shahzad, M. Abdullah, and A. Ullah, "Efficientnet-based robust recognition of peach plant diseases in field images," *Computers, Materials and Continua*, vol. 71, no. 1, pp. 2073–2089, 2022, doi: 10.32604/cmc.2022.018961.
- 9 C. Buiu, V. R. Dănilă, and C. N. Răduță, "MobileNetV2 ensemble for cervical precancerous lesions classification," *Processes*, vol. 8, no. 5, 2020, doi: 10.3390/PR8050595.
- 10 A. S. Ardiansyah and A. Nugroho, "Classification of Coffee Leaf Diseases Using MobileNetV2 Architecture," *Journal of Computer Science and Business*, vol. 14, no. 1, pp. 66–73, 2023, doi: 10.47927/jikb.v14i1.622.
- 11 M. Akay *et al.*, "Deep Learning Classification of Systemic Sclerosis Skin Using the MobileNetV2 Model," *IEEE Open J Eng Med Biol*, vol. 2, pp. 104–110, 2021, doi: 10.1109/OJEMB.2021.3066097.
- 12 D. Putri Ayuni, Jasril, M. Irsyad, F. Yanto, and S. Sanjaya, "Data Augmentation in the Implementation of Convolutional Neural Network Efficientnet-B3 Architecture for

- Classification of Rice Leaf Diseases," *ZONAsi: Journal of Information Systems*, vol. 5, no. 2, pp. 239–249, 2023, doi: 10.31849/zn.v5i2.13874.
- 13 B. Widiyanto, E. Utami, and D. Ariatmanto, "Identification of Corn Plant Diseases Based on Leaf Image Using Convolutional Neural Network," *Techno.Com*, vol. 22, no. 3, pp. 599–608, 2023, doi: 10.33633/tc.v22i3.8425.
 - 14 A. B. Prakosa, Hendry, and R. Tanone, "Implementation of a Deep Learning Convolutional Neural Network (Cnn) Model on Corn Leaf Disease Images," *Jurnal Pendidikan Teknologi Informasi (JUKANTI)*, vol. 6, no. 1, pp. 107–116, 2023.
 - 15 T. S. Winanto, C. Rozikin, and A. Jamaludin, "Performance Analysis of Transfer Learning Architecture for Identifying Leaf Diseases in Food Plants," *Journal of Applied Informatics and Computing*, vol. 7, no. 1, pp. 68–81, 2023, doi: 10.30871/jaic.v7i1.5991.
 - 16 S. Aravind, S. Harini, and V. K. kumar A, "Cassava leaf disease classification using Deep Learning," *Volatiles & Essent. Oils*, vol. 8, no. 5, pp. 9375–9389, 2021.
 - 17 M. I. Rosadi and M. Lutfi, "Identify Types of Corn Leaf Disease Using Deep Learning Pre-Trained Model," *Jurnal Explore IT!*, vol. 13, no. 2, pp. 36–42, 2021, [Online]. Available: <https://doi.org/10.35891/explorit>
 - 18 R. Mawarni, R. Wulaningrum, and R. Helilintar, "Implementation of the CNN Method in Corn Disease Classification," vol. 7, pp. 1256–1263, 2023.
 - 19 J. Cai *et al.*, "Improved EfficientNet for corn disease identification," *Front Plant Sci*, vol. 14, no. September, pp. 1–17, 2023, doi: 10.3389/fpls.2023.1224385.
 - 20 Y. Gulzar, "Fruit Image Classification Model Based on MobileNetV2 with Deep Transfer Learning Technique," *Sustainability (Switzerland)*, vol. 15, no. 3, 2023, doi: 10.3390/su15031906.
 - 21 B. Syamsuri and G. P. Kusuma*, "Plant Disease Classification using Lite Pretrained Deep Convolutional Neural Network on Android Mobile Device," *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, no. 2, pp. 2796–2804, 2019, doi: 10.35940/ijitee.b6647.129219.
 - 22 E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans Leaf Diseases Classification Using MobileNet Models," *IEEE Access*, vol. 10, pp. 9471–9482, 2022, doi: 10.1109/ACCESS.2022.3142817.
 - 23 A. Of, "Tomato Leaf Disease Detection Using Cutting-Edge Deep Learning," vol. 66, no. 1, pp. 4320–4332, 2023.
 - 24 Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," *Ecol Inform*, vol. 61, no. October 2020, p. 101182, 2021, doi: 10.1016/j.ecoinf.2020.101182.