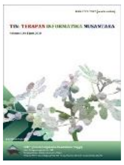

TIN: Terapan Informatika Nusantara
Vol 6, No 1, June 2025, page 45-54
ISSN 2722-7987 (Media Online)
Website https://ejurnal.seminar-id.com/index.php/tin
DOI 10.47065/tin.v6i1.7543

Comparative Study of Mobilenet and Resnet for Watermelon Leaf Disease Classification Using Deep Learning

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Abstract−Watermelon leaf diseases, caused by various factors such as fungi, viruses, and bacteria, can have a significant impact on agricultural yields. To increase the amount and quality of watermelon produced, early diagnosis of this disease is essential. This study aims to compare the performance of two Convolutional Neural Networks (CNN) architectures included in Deep Learning, namely MobileNet and ResNet, in classifying watermelon leaf diseases using a dataset taken from Kaggle. This dataset consists of 1000 watermelon leaf images with three conditions, namely Downy Mildew (380 images), Healthy (205 images), and Mosaic Virus (415 images).). 95% accuracy, 96% precision, 94% recall, and 95% f1-score are the results of the MobileNet model. In contrast, the ResNet model performs better, with 97% accuracy, 96% precision, 97% recall, and 97% f1-score. The study's findings show that ResNet outperforms MobileNet in the classification of watermelon leaf illnesses, despite both models' excellent and effective performance for automatic plant disease detection applications.

Keywords: Deep Learning; Convolutional Neural Networks (CNN); MobileNetv; ResNet; Watermelon Leaf Disease

1. INTRODUCTION

Watermelon leaf disease is one of the major threats in agriculture that can significantly reduce the quality and yield of crops(Nakib & Mridha, 2024)(Dauda et al., 2024)(Tian et al., 2024). This disease is caused by various factors such as viruses (Zhu et al., 2024), fungi (Gai & Wang, 2024), and bacterial infections that attack watermelon plants (Ferdous, 2024). Early detection of this disease is very important to reduce its negative impact on production(Demilie, 2024)(Brito & Hick, 2024)(Ozdemir, 2024). Conventional methods in identifying plant diseases still rely on manual observation by experts, which not only takes a long time but is also less efficient on a large scale(Saleem et al., 2024)(Kariyanna & Sowjanya, 2024)(González-Rodríguez et al., 2024). Therefore, the application of artificial intelligence-based technology, especially deep learning, is a promising solution in automatic plant disease classification(Shubhika et al., 2024)(Sow et al., 2024). Convolutional Neural Networks (CNN) have been proven effective in analyzing and recognizing patterns from digital images, including images of plants infected with diseases(Alim Murtopo et al., 2024)(Kurniawan et al., 2024)(Prince et al., 2024).

Watermelon leaf disease is the focus of this study because of its major impact on agricultural production and the need for a fast and accurate detection system. CNN was chosen as the primary method due to its ability to extract features from images with high efficiency, allowing the model to distinguish between healthy and infected leaves(Jouini et al., 2024)(Iftikhar et al., 2024)(Bouacida et al., 2024). MobileNet and ResNet were chosen as the models to be compared because they have different characteristics in terms of network depth and computational efficiency (Neshat et al., 2024)(Kumar Lilhore et al., 2024)(Arjun et al., 2024)(Hassan, 2024)(Careem et al., 2024). MobileNet is designed for resource-constrained devices(Kamath & Renuka, 2024)(Chang et al., 2024), while ResNet excels in handling deeper networks with higher accuracy(Hindarto, 2024)(Ejiyi et al., 2024)(Z. Xu et al., 2024)(Muhammad Yusuf et al., 2024). By comparing these two models, this study can identify the most suitable method for the application of automatic watermelon leaf disease classification using deep learning. Research has been conducted on the application of CNN for plant disease classification as conducted by (Muhammad Yusuf et al., 2024). In this study, an Android-based application was developed using the Central Neural Network (CNN) method with the VGG16 architecture to identify the type of disease in watermelon plants. The results showed that the accuracy of this study was 98% for precision, 98% for recall, and 98% for f1-score. Based on these results, the detection of diseases in watermelon plants was successful. The weakness of this study is that it only uses one architecture on CNN, namely VGG16, so it is necessary to conduct research using different architectures to determine the best architectural model for disease classification in watermelon plants.

Furthermore, other research that has been conducted in the application of CNN for plant disease classification conducted by (Pratama et al., 2022), this study uses the Convolutional Neural Network (CNN) method, assisted by Google Colab transfer learning, to facilitate the classification of banana leaf diseases. After the trained model experiences overfitting, dropout is used to perform regularization. The best model results were obtained using a ratio of 70:20:10 at the 80th epoch. The results show an accuracy score of 92%, a prediction of 92%, a sensitivity of 91%, and an f1 score of 91%. These results are validated and evaluated using a confusion matrix. This study produces a model that can accurately classify banana leaf diseases. The weakness in this study is that it is not mentioned what architecture is used and is not compared with other CNN architectures so it is not known which architecture model is most suitable for classifying plant diseases. Referring to the weaknesses in both studies, this study is useful for covering the weaknesses of both studies. This study focuses on comparing the two models to identify their respective advantages and

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ISSN 2722-7987 (Media Online)
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DOI 10.47065/tin.v6i1.7543

disadvantages. The main challenge in this research is to determine the most optimal model in detecting watermelon leaf diseases with a high level of accuracy and efficient processing speed. This research focuses on comparing the two models to identify their respective advantages and disadvantages. This analysis is expected to help develop a more accurate and efficient automatic detection system that can help nurses find plant diseases quickly. As part of this research, experiments will be conducted to measure the accuracy, training speed, and resource efficiency of MobileNet and ResNet in watermelon leaf disease classification. It is expected that the findings of this study will provide recommendations for the best model that can be used to implement real intelligent systems. This research is also expected to be a reference for further research on deep learning to detect plant diseases. This will not only help develop a watermelon leaf disease classification model but will also help apply deep learning technology in agriculture.

2. RESEARCH METHODOLOGY

To ensure that the results can be analyzed without bias, this research was conducted empirically, logically and structured, starting from formulating the problem to compiling the report (Tesfai et al., 2022). Figure 1 shows the structure of the proposed research stages.

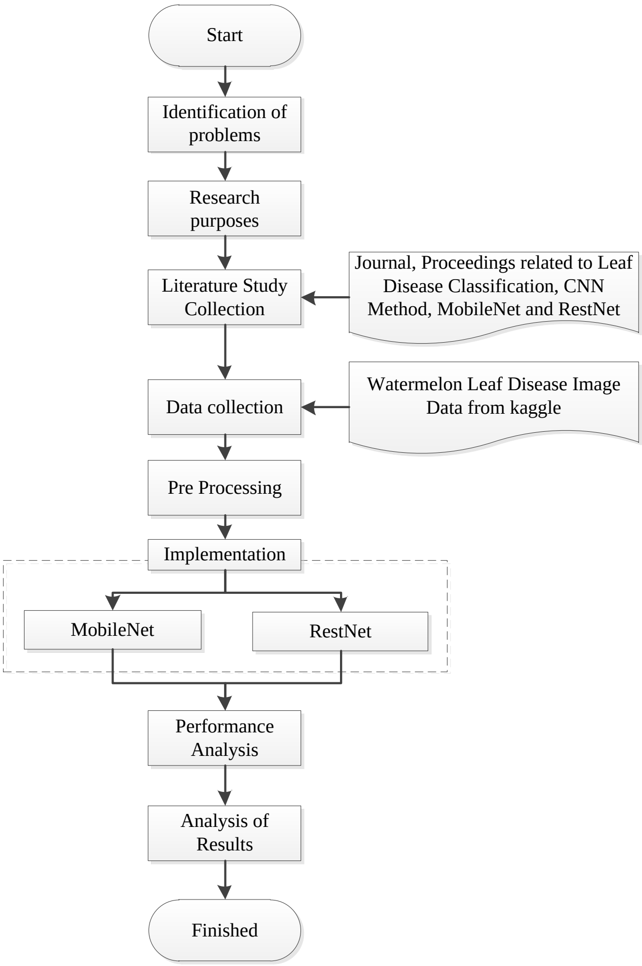

Figure 1. Research Stages

2.1 Identification of problems

Watermelon leaf disease detection still relies on slow and inaccurate manual observation, so an automated system based on deep learning is needed. Although CNN has been used in plant image classification, there has been no specific study comparing MobileNet and ResNet for watermelon leaf disease.

2.2 Research purposes

The purpose of this study is to compare the performance of MobileNet and ResNet in watermelon leaf disease classification using deep learning. By evaluating the accuracy, training speed, and computational efficiency of both models, this study is expected to identify a more optimal model for automatic disease detection. The results of this study are expected to contribute to the advancement of artificial intelligence-based agricultural technology, so that it can increase the effectiveness and efficiency in identifying diseases in the younger generation and develop faster and more accurate detection systems.

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2.3 Literature Study Collection

At the stage of collecting literature studies, previous research related to the classification of watermelon leaf diseases will be searched for, which will later become the Statement of DA (Statement of Data Analysis) or the basis for conveying statements or ideas and understanding related to the CNN, MobileNet and ShuffleNet models.

2.3.1 MobileNet

MobileNet is a Convolutional Neural Network (CNN) architecture designed to handle data-intensive devices, such as phones and systems(Tesfai et al., 2022)(Kirac & Ozbek, 2024)(Lokhande & Ganorkar, 2025)(Careem & Khatibi, 2024). Compared to conventional CNNs, MobileNet reduces the number of parameters and computations without compromising accuracy(Batool et al., 2025)(Al-funjan et al., 2024)(Chen et al., 2024).This architecture enables faster image processing with lower power requirements, making it well-suited for computer vision-based applications in mobile devices and edge computing(Xan et al., 2024)(Dembele et al., 2024).

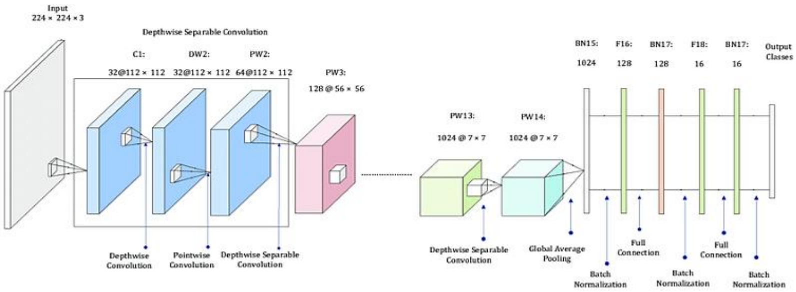

Figure 2. MobileNet architecture

2.3.2 RestNet

ResNet is a Convolutional Neural Network (CNN) architecture that uses the concept of residual learning to improve the training of very deep networks. Essentially, ResNet introduces shortcut connections (or skip connections), which allow gradients to flow more easily through the layers of the network, thus aiding the training of very deep models(W. Xu et al., 2023)(Zhou et al., 2024).

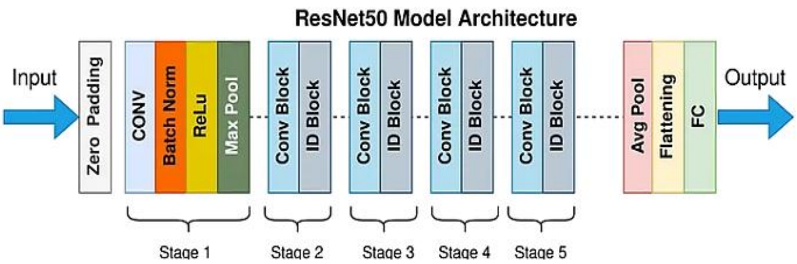

Figure 3. ResNet architecture

2.4.3 *Confusion Matrix*

Used as an evaluation tool, the Confusion Matrix measures the performance of a classification model by comparing the actual labels and predicted labels generated by the ground truth model with the labels predicted by the model (Chowdhury, 2024). The basic concept of the Confusion Matrix (Krstinić et al., 2024):

a. *True Positives (TP)*: occurs when the model predicts a positive outcome and labels it as such.
b. *False Positive (FP)* : When the model prediction is positive, the label is actually negative.
c. *False Negative (FN)*: When the model prediction is negative, the label is actually positive.
d. *Rue Negative (TN)*: The model prediction is negative, and the label itself is also negative.

2.4 Data collection

The first step of the data collection process is to obtain images from https://www.kaggle.com/datasets/nirmalsankalana/watermelon-disease-dataset. The focus of this study is three classes (conditions) of leaves, namely Downy Mildew, Healthy and Mosaic Virus. The total image data used is 1000, and the division is shown in Table 1.

Table 1. Number of Images

No	Leaf Condition	Number of Images
1	Downy Mildew	380
2	Healthy	205

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No	Leaf Condition	Number of Images
3	Mosaic Virus	415
	Total	1000

The data in table 1 is data sourced from kaggle, where the data has been divided based on its type. The following is an example of the image used from each watermelon leaf condition.

(a) (b) (c)

Figure 4. Image of Watermelon Leaf (a) Downy Mildew, (b) Healthy, (c) Mosaic Virus

3. RESULTS AND DISCUSSION

3.1 Image Data Preprocessing Results

At this stage, the data preparation stage is carried out before processing using the model. This stage includes cleaning data, as well as splitting data or dividing data into training, validation and testing data. At this stage, the data division is as follows:

Table 2. Image Data Division

No	Data Sharing	Class	Number of Images
1		Downy Mildew	266
2	Training	Healthy	143
3		Mosaic Virus	290
6		Downy Mildew	57
7	Validation	Healthy	31
8		Mosaic Virus	62
11		Downy Mildew	57
12	Testing	Healthy	31
13		Mosaic Virus	63

In this study, data sharing was done proportionally to ensure that the model could be trained, validated, and tested in the best way. Data training trains the model to recognize patterns from each class of watermelon leaf disease images, and data validation assesses the performance of the model during training to prevent overfitting. During the training phase, data analysis is used to assess the performance of the model after data that has not been collected or examined before.

A total of 699 images were used for instruction, 150 for validation, and 151 for research, so that the data set accurately reflects each class level. With this sharing strategy, the model is expected to achieve good generalization on the data.

3.2 Image Data Classification Results

At the modeling stage, two Convolutional Neural Network (CNN) architectures, namely MobileNet and RestNet, were used to train the model on watermelon leaf disease images.

3.3 *Image* Classification *Training Results*

The training process is monitored through loss and accuracy values. The following are the results of watermelon leaf disease image classification training.

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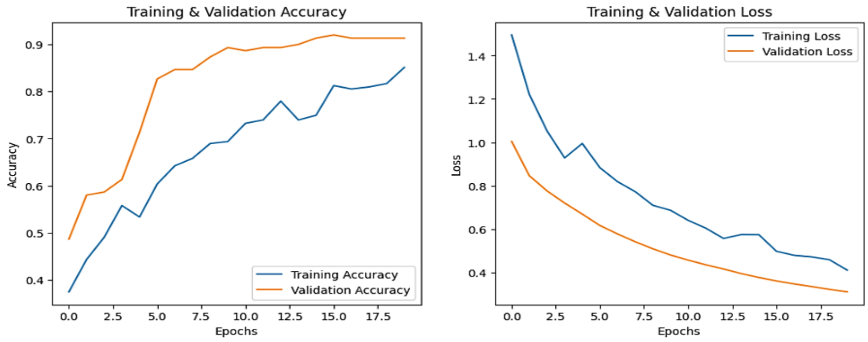
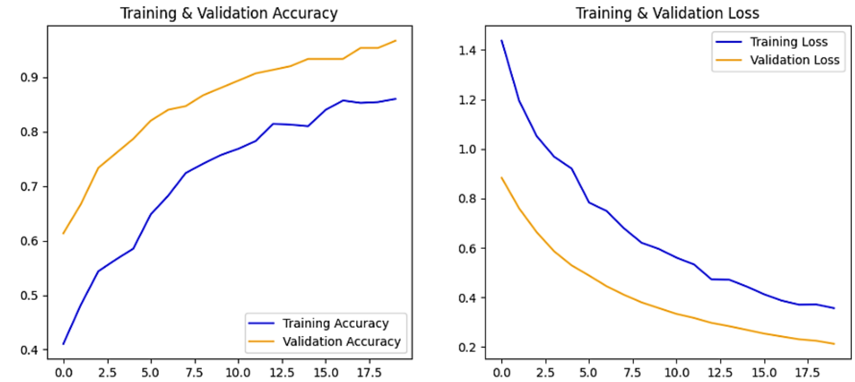


(a)

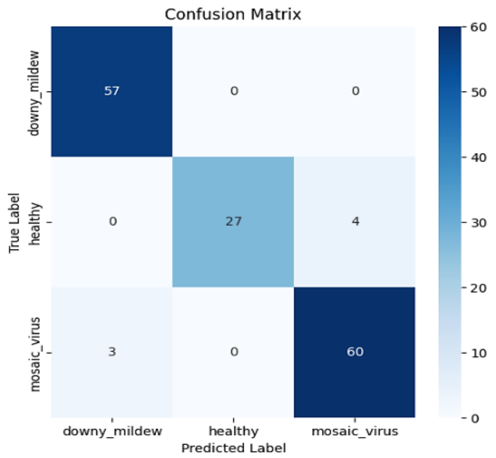


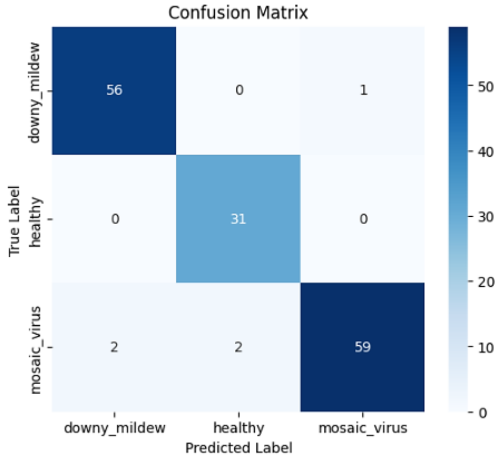
(b)

Figure 5. Training Loss and Accuracy Results of (a) mobilenet, (b) restnet

3.3.1 Image Classification Evaluation Results

The results of the image classification evaluation were analyzed using a confusion matrix, which functions to measure the extent to which the model successfully classifies watermelon leaf disease images. This analysis provides insight into the model's performance in identifying each class, including the number of correct predictions and errors that occur in each category.





(a) (b)

Figure 6. Confusion Matrix of (a) mobilenet, (b) restnet

The experimental results show that ResNet provides superior performance compared to MobileNet. ResNet achieves an accuracy of 97%, higher than MobileNet which achieves 95%. This shows that ResNet is more capable of classifying images correctly overall.

In terms of precision, both models have the same value, which is 96%, which means that when the model predicts a certain class, the prediction is likely to be correct. However, a more striking difference is seen in recall, where ResNet reaches 97%, higher than MobileNet which is only 94%. This shows that ResNet is better at recognizing all instances of each class, so that fewer cases are missed (false negatives).

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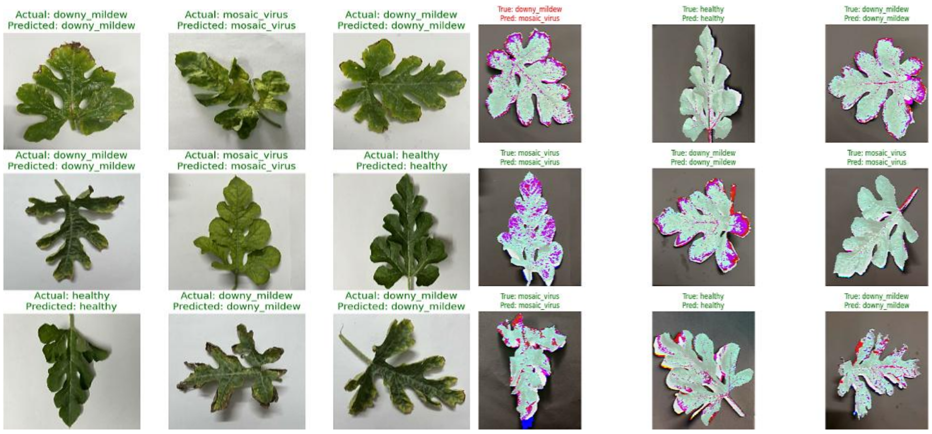
As a result of this difference, ResNet's F1-score is also higher, which is 97%, compared to MobileNet which has 95%. The higher F1-score in ResNet indicates a better balance between precision and recall, so this model is more stable and reliable in classifying watermelon leaf diseases.

3.3.2 Image Classification Prediction Results

Next, the MobileNet and RestNet models were tested on the data and given three images from each class of watermelon leaf disease images, namely Downy Mildew, Healthy and Mosaic Virus, resulting in an average correct prediction. Figure 7 shows the prediction findings with actual watermelon leaf disease images.



(a) (b)

Figure 7. Prediction results of testing with (a) MobileNet, (b) RestNet

The prediction results on MobileNet from 3 image samples from each class used were able to predict correctly overall. For RestNet from 3 image samples from each class used, there was 1 error in predicting, namely in the watermelon leaf disease image sample with Mosaic Virus conditions but had better accuracy than MobileNet.

3.4 Comparative Evaluation Results

The results demonstrate the superiority of RestNet in handling complex datasets with high inter-class similarity. While MobileNet offers a balance between performance and computational efficiency, the accuracy limitations of CNN underscore the need for more advanced architectures for similar tasks. The comparison is summarized in Table 3.

Table 3. Summary of Model Comparison

Model	Precision	Recall	F1 Score	Accuracy
MobileNet	96%	94%	95%	95%
RestNet	96%	97%	97%	97%

The following is a comparison chart of the four methods used:

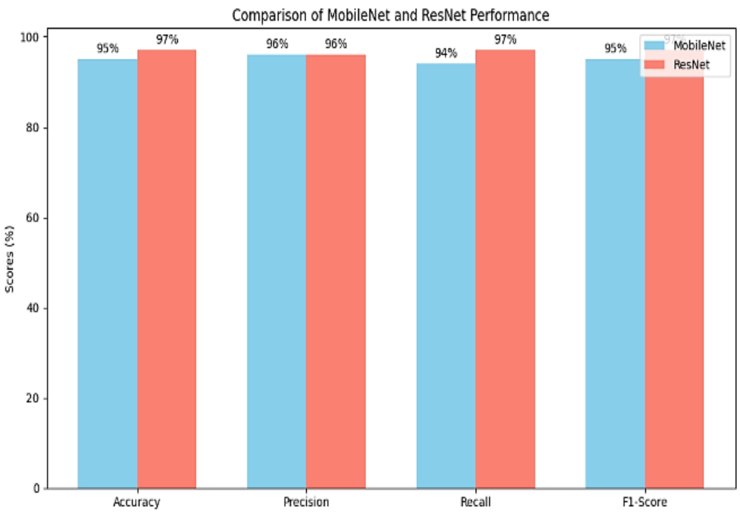


Figure 8. Comparison Chart of the Two Models

From Figure 8 it can be seen that RestNet has better results than MobileNet.

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ISSN 2722-7987 (Media Online)
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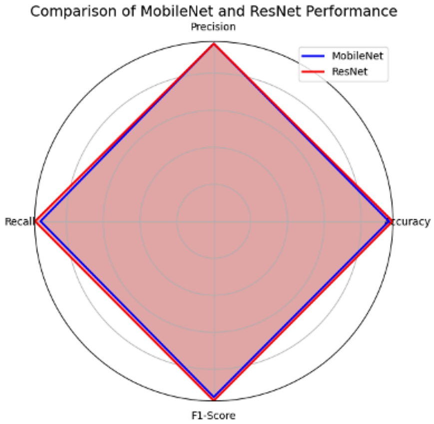

Figure 9. Radar Chat Comparison Models

The radar chart image compares the performance of MobileNet and ResNet based on accuracy, precision, recall and F1-score. The results show that ResNet is superior in accuracy, recall and F1-score, while the precision of both models is the same. The higher performance of ResNet especially in recall indicates its better ability to identify all instances of each class, resulting in fewer errors in classification. Thus, ResNet outperforms MobileNet in the task of watermelon leaf disease classification, although MobileNet remains a lighter and more computationally efficient choice.

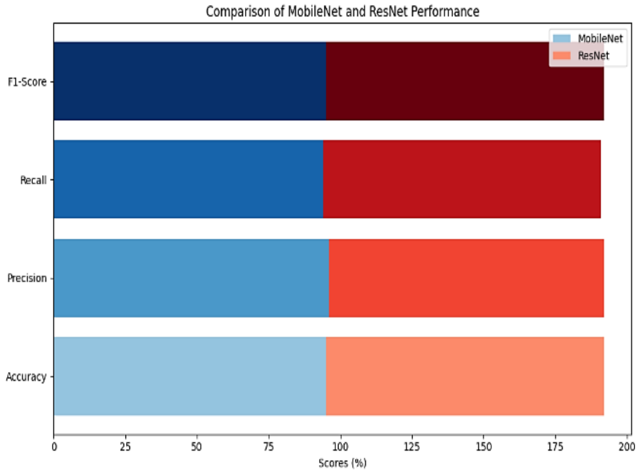

Figure 10. Horizontal Bar Chart Comparison of MobileNet and RestNet Methods

From this graph, it can be seen that ResNet has higher scores in almost all metrics compared to MobileNet, especially in Accuracy, Recall and F1-Score, indicating its better ability in classifying watermelon leaf diseases. However, the performance difference between the two models is not too significant, with MobileNet still showing competitive results, especially in Precision. This indicates that although ResNet is more accurate overall, MobileNet remains an efficient alternative with almost comparable performance.

3.4 Discussion

This study aims to compare the performance of two Convolutional Neural Network (CNN) architectures, namely MobileNet and ResNet, in classifying diseases on watermelon leaves. Based on the experimental results, the ResNet model demonstrated superior performance compared to MobileNet, achieving an accuracy of 97%, precision of 96%, recall of 97%, and F1-score of 97%. Meanwhile, MobileNet achieved 95% accuracy, 96% precision, 94% recall, and a 95% F1-score.

These findings indicate that the ResNet architecture has better generalization capability in detecting and classifying watermelon leaf diseases. This supports the research hypothesis that different CNN architectures produce varying performance results and that selecting the appropriate architecture significantly influences model accuracy in image classification tasks.

When compared with a previous study by Muhammad Yusuf et al. (2024), which used the VGG16 architecture and achieved 98% precision, recall, and F1-score, this study shows that although ResNet's performance is slightly lower, the difference is not substantial. Moreover, the advantage of this study lies in comparing two distinct architectures rather than one, demonstrating that ResNet remains a competitive alternative even against VGG16.

A study by Pratama et al., (2022), which employed CNN with transfer learning for banana leaf disease classification, reported an accuracy of 92% and an F1-score of 91%. These results are lower than those achieved by

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both ResNet and MobileNet in this study. The difference may be attributed to variations in datasets, class numbers, image quality, and the specific CNN architectures applied.

Therefore, this study reinforces the importance of selecting the right CNN architecture in plant disease classification tasks. ResNet has proven to outperform MobileNet for the watermelon leaf dataset used, further supporting the recommendation by Muhammad Yusuf et al. (2024) that exploring various CNN architectures is essential to achieve an optimal classification model.

4. CONCLUSION

In this study, a comparison was conducted between MobileNet and ResNet for classifying watermelon leaf diseases using a preprocessed dataset. The evaluation results indicate that ResNet outperformed MobileNet, achieving an accuracy of 97%, recall of 97%, and F1-score of 97%, while MobileNet obtained an accuracy of 95%, recall of 94%, and F1-score of 95%. Both models achieved the same precision of 96%, indicating a balanced level of accuracy in predicting each class. However, when tested on sample images, MobileNet correctly classified all images, whereas ResNet made one misclassification on a Mosaic Virus image. Despite this, ResNet still demonstrated higher overall accuracy, suggesting its superior ability to capture complex feature patterns. Therefore, ResNet is a better choice when overall accuracy is the main priority, while MobileNet is preferable for applications that value prediction stability and computational efficiency.

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TIN: Terapan Informatika Nusantara
Vol 6, No 1, June 2025, page 45-54
ISSN 2722-7987 (Media Online)
Website https://ejurnal.seminar-id.com/index.php/tin
DOI 10.47065/tin.v6i1.7543

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