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COMPARISON OF MOBILENETV2 AND RESNET50 PERFORMANCE IN CLASSIFICATION OF SHALLOT PLANT DISEASES

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Abstract

Red onions (Allium ascalonicum L.) are a high-value agricultural commodity in Indonesia, but their productivity is often compromised by plant diseases, particularly yellow spot and leaf blight. Visual identification in the field is subjective, prone to error, and time-consuming. Using artificial intelligence, this problem is addressed with a Convolutional Neural Network (CNN) trained to identify disease types from images. For this purpose, this study applies transfer learning to two CNN architectures, MobileNetV2 and ResNet50, to classify red onion leaf diseases into three classes yellow spot, leaf curl, and healthy leaves. A dataset of 1,752 field-captured, pre-labeled images sourced from a public Roboflow repository was split into 70% for training, 20% for validation, and 10% for testing. Both models were trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. Evaluation was conducted using accuracy, precision, recall, and F1-score metrics based on the confusion matrix. The results show that ResNet50 achieved a test accuracy of 93.33% and an average F1-score of 0.93, outperforming MobileNetV2, which achieved 90.26% accuracy and an average F1-score of 0.90. MobileNetV2 excels in computational efficiency, achieving faster training times in field implementation than ResNet50, which required longer training times for the 20 epoch run. However, in general, ResNet50 demonstrates better generalization, with a stable training curve, and outperforms MobileNetV2 in terms of accuracy, precision, recall, and F1-score for the classification of onion diseases based on leaf images.

Keywords: Red Onion Disease; MobileNetV2; ResNet50; Transfer Learning; Classification

Abstrak

Bawang merah (Allium ascalonicum L.) merupakan komoditas pertanian bernilai ekonomi tinggi di Indonesia yang produktivitasnya kerap terganggu oleh penyakit tanaman, khususnya bercak kuning dan daun moler. Identifikasi secara visual di lapangan bersifat subjektif, rentan kesalahan, dan memakan waktu. Dengan bantuan kecerdasan buatan, masalah tersebut diatasi dengan menggunakan model Convolution Neural Network (CNN) yang dilatih untuk mengidentifikasi jenis penyakit berbasiskan citra. Untuk tujuan tersebut, penelitian ini menerapkan transfer learning terhadap dua model arsitektur CNN, yaitu MobileNetV2 dan ResNet50 untuk klasifikasi penyakit daun bawang merah ke dalam tiga kelas: bercak kuning, daun moler, dan daun sehat. Dataset sebanyak 1.752 citra bersumber dari Roboflow, dibagi menjadi 70% data latih, 20% validasi, dan 10% data uji. Kedua model dilatih menggunakan optimizer Adam dengan learning rate 0,001, batch size 32. Evaluasi dilakukan menggunakan metrik akurasi, precision, recall, dan F1-score berdasarkan confusion matrix. Hasil menunjukkan ResNet50 mencapai akurasi pengujian 93,33% dengan rata-rata F1-score 0,93, melampaui MobileNetV2 yang memperoleh akurasi 90,26% dan F1-score 0,90. MobileNetV2 unggul dalam efisiensi komputasi dengan waktu pelatihan yang relatif lebih cepat untuk implementasi di lapangan dibandingkan ResNet50 yang membutuhkan waktu yang lebih lama pada pelatihan 20 epoch yang dilakukan. Namun, secara umum ResNet50 menunjukkan kemampuan generalisasi yang lebih baik dengan kurva pelatihan yang stabil dan lebih unggul dalam hal akurasi, precision, recall dan F1-score dibanding MobileNetV2 dalam klasifikasi penyakit pada bawang merah berdasarkan citra daun.

Kata kunci: Penyakit Bawang Merah; MobileNetV2; ResNet50; Transfer Learning; Klasifikasi

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INTRODUCTION

The red onion plant *(Allium ascalonicum L.)* is a high value bulb vegetable commodity in Indonesia (Zalvadila, Darwis, & Syafie, 2023). In 2023, total national red onion production reached 1.98 million tons, with six major producing provinces contributing 90.22% of national output (Pertanian, 2024). However, this productivity is frequently hampered by plant disease outbreaks. In 2022, a production decline of 301,418 tons was recorded due to pest and disease damage (Roidah, Syah, Prasekti, & Putri, 2025). The two most prevalent diseases are Leaf Curl (Daun Moler) and Purple Blotch. Losses caused by Leaf Curl disease can reach up to 50% and may even result in total crop failure, while attacks of *Alternaria porri*, the causal agent of purple blotch, can suppress production by up to 57% depending on the severity of the infection (Jusriadi, Mutmainah, Balosi, & Nensi, 2023). Accurate early detection is key to timely and effective management. The current process of disease identification in the field still relies on manual visual observation, which is subjective, dependent on the observer's expertise, and prone to error, especially when symptoms of different diseases share visual similarities (Pratiwi & Wahyudi, 2026). Delayed or incorrect diagnosis can lead to improper treatment and financial losses for farmers. Deep learning approaches based on Convolutional Neural Networks (CNN) have proven effective for classifying plant disease images (Rijal, Yani, & Rahman, 2024). A Convolutional Neural Network (CNN) is a deep learning method specifically designed for image data processing, inspired by the biological visual neural system of humans and developed from artificial neural networks (ANN) (Putra, Rusbandi, & Alamsyah, 2023). CNN architectures generally consist of *convolution layer, pooling layer,* and *fully connected* layers that work hierarchically to extract features and perform classification (Asrafil, Paliwang, Septian, Cahyanti, & Swedia, 2020). One efficient strategy for limited data is transfer learning, which leverages pre-trained weights from large datasets such as ImageNet as a feature extraction basis, enabling the model to achieve high performance without requiring a large volume of training data (Salim, Abdullah, & Utami, 2024).

A number of previous studies have applied this approach to various classification tasks. In the context of red onion classification, (Zalvadila et al., 2023) combined CNN and SVM with GLCM feature extraction using 320 images across two classes, achieving a CNN accuracy of 100% and SVM accuracy of 75%. However, the dataset used was very limited and covered only two disease classes. (Pratiwi & Wahyudi, 2026) classified banana leaf diseases using transfer learning-based MobileNetV2 with 2,537 images across four classes and achieved an accuracy of 81%, (Gunawan et al., 2025) implemented MobileNetV2 for potato leaf disease detection on 4,072 images across three classes, achieving an accuracy of 95.31%. Both of these studies used only a single architecture without comparative analysis. (Putra et al., 2023) compared various optimizers on the ResNet50 architecture for corn leaf disease classification using 4,225 images and obtained the highest accuracy of 98.4%, while (Anshari, Mahalisa, & Muflih, 2025) implemented ResNet50 for apple leaf disease classification and achieved an accuracy of 91%. Among studies that directly compare two architectures, (Santosa, Sasikirana, Ramadhan, Putra, & Satria, 2025) compared MobileNetV2 and ResNet50 for tomato ripeness classification using 1,200 images, obtaining MobileNetV2 accuracy of 98.33% and ResNet50 accuracy of 93.33%, without applying epoch variation. (Hermanto, Aziz, & Sudianto, 2024) also compared MobileNetV2 and ResNet50 based on transfer learning for the classification of three date fruit varieties with epoch variations of 20, 40, and 60, where MobileNetV2 achieved the best accuracy of 95% while ResNet reached only 85%, but with a very limited dataset of only 300 images. (Puspita & Sabri, 2024) compared the transfer learning performance of MobileNetV2 and DenseNet121 for spice plant classification using 638 images across five classes with epoch variations of 5, 10, 20, and 30. The results showed that DenseNet121 outperformed in terms of accuracy, precision, and F1-score at epoch 30, while MobileNetV2 was faster in training time but tended to overfit. This study is relevant as a reference for the transfer learning concept on pre-trained CNNs, particularly MobileNetV2, which is used in the present research.

The studies reviewed above indicate that most of them used only a single architecture, and none has specifically compared MobileNetV2 with ResNet50 on a red onion leaf disease dataset.

Based on a review of previous studies, CNNs and transfer learning have proven effective in classifying plant diseases. However, a direct comparison between MobileNetV2 and ResNet50 specifically for shallot diseases has not been conducted. This study addresses this gap by analyzing the performance of both architectures based on accuracy, precision, recall, and F1-score. This comparison is important because MobileNetV2

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and ResNet50 represent two contrasting design philosophies in CNN architecture: lightweight, computationally efficient networks versus deeper, higher-capacity networks. Identifying which tradeoff is more suitable for shallot disease classification provides practical guidance for real-world applications. Shallots were chosen as the object of this study because of its two main diseases, yellow spot and leaf moler. The symptoms of these two diseases are visually very similar in shallots, especially in the early stages. Therefore, if farmers only rely on their eyes and experience, misidentification can occur. This is where the idea of utilizing technology, specifically deep learning, to make disease identification more objective and accurate arose. These characteristics make the classification of shallot leaf diseases a quite challenging case to evaluate and compare the discriminatory capabilities of the two architectures. The findings of this study are expected to serve as a practical reference for selecting the right architecture in developing a transfer learning-based shallot disease detection system in the agricultural sector.

RESEARCH METHODS

The research workflow comprises several main stages: dataset collection, preprocessing, model architecture design, model training, and model performance evaluation. This is illustrated in Figure 1.

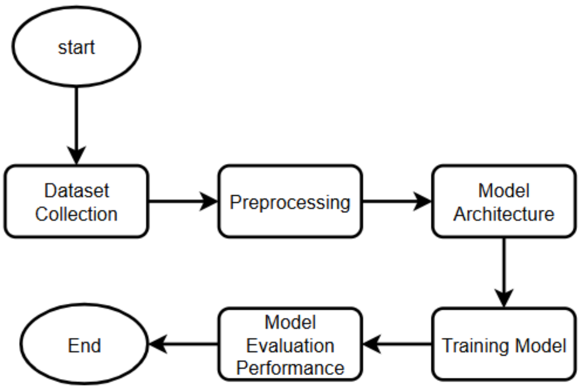

Figure 1. Research Stages

Dataset Collection

This study utilizes a public dataset from *Roboflow* (https://universe.roboflow.com/arfan-g6v0w/skripsi-2-tk3dx) consisting of 1,752 red onion leaf images with three classes: yellow spot, leaf curl, and healthy leaves. The dataset is pre-divided into three subsets: 70% training data (444 images per class), 20% validation data (75 images per class), and 10% test data (65 images per class). This dataset was selected because it is a publicly available, pre-labeled resource compiled specifically for red onion leaf disease classification, allowing this study to focus on comparing the two architectures rather than on primary data collection. Preliminary visual inspection of the dataset confirmed that the images were captured under natural field conditions representative of real-world red onion cultivation, with variation in lighting, leaf orientation, and disease severity across samples. To preserve the authentic color and texture characteristics of the disease symptoms, this study intentionally did not apply data augmentation (e.g., color jittering, rotation, or flipping), as such transformations risk distorting the subtle color and textural cues used to distinguish yellow spot and leaf curl symptoms; the dataset size was considered adequate for this purpose given the use of transfer learning, which reduces the need for large volumes of training data. Sample images for each class can be seen in Figure 2.

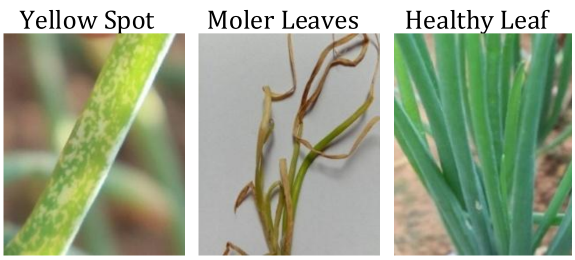

Figure 2. Red Onion Leaf Images

Preprocessing

The preprocessing stage is performed to prepare the data prior to the training process. Next, images are resized to ensure a pixel resolution of 224×224×3. This dimension was selected because it is the standard input size required by the pre-trained MobileNetV2 and ResNet50 architectures on ImageNet, allowing both models to fully utilize their pre-trained weights while maintaining a practical balance between computational cost and the preservation of disease-relevant visual detail on the leaf surface. This resizing ensures that all data have uniform dimensions so they can be processed in a batch size of 32 for efficiency and improved performance (Hermanto et al., 2024). Subsequently, the rescaling process is applied so

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that the value range falls within 0–1 for each image; pixel value normalization is performed to ensure stability during testing (Putra et al., 2023).

Model Architecture

MobileNetV2 employs a depthwise separable convolution and linear bottleneck and inverted residuals, which makes it lightweight yet accurate (Ceren, 2026).

ResNet50 is a 50-layer model that uses skip connections to allow gradients to flow more effectively during training, thereby mitigating the vanishing gradient problem (Babu, Maravarman, & Pitchai, 2022).

The models employed in this study adopt a transfer learning approach, with MobileNetV2 and ResNet50 serving as *feature extractors*. The extracted features are then processed through Global *Average Pooling*, *Batch Normalization*, and a *Dense* layer for classification. Dropout is applied to reduce *overfitting*, while the output layer uses *softmax* to classify the three shallot leaf disease categories. The entire model training process was executed using Google Colaboratory with a T4 GPU (Kulsum & Cherid, 2023). See Table 1, table 2, and Figure 3.

Table 1. hardware

No	Hardware	Specifications
1	Procesor	Intel(R) Core(TM) i5-1035G1 CPU @ 1.00GHz (1.20 GHz)
2	RAM	8.00 GB
3	Operating System	64-bit Operating System
4	Storage	477 GB

Table 2. Software

No	Software	Specifications
1	Operating System	Microsoft Windows 11
2	Programming Language	Python
3	Framework	TensorFlow + Keras
4	Dataset Storage	Google Drive
5	Training Platform	Google Colaboratory
6	Tools	MS word 2021

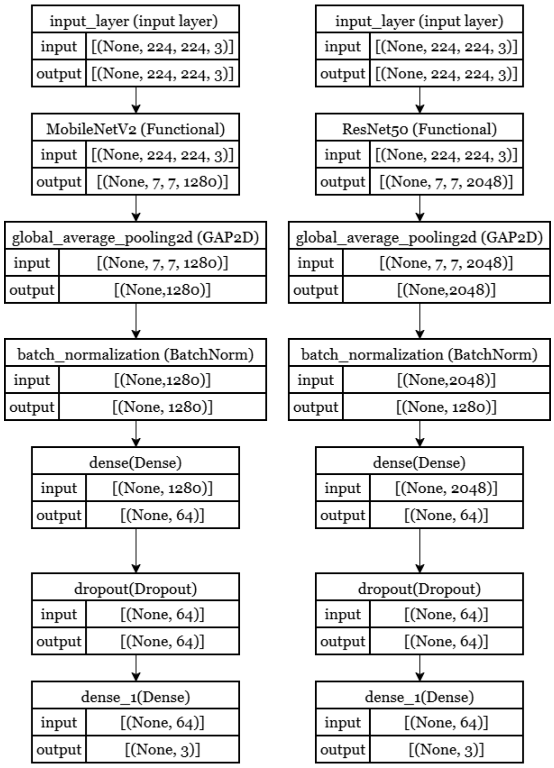

Figure 3. Model Architecture

Testing was conducted to evaluate the performance of each model. The testing parameters are summarized in Table 3.

Table 3. Testing Scenario

Parameter	Description
Data Split	Train 70%, Validation 20%, Test 10%
Class	Yellow spot, Moler Leaves, healthy leaves
Image Size	224 × 224 pixels
Batch size	32
Epoch	20
Optimizer	Adam (lr = 0,001)

Model Evaluation

Evaluation was conducted on the test data using *accuracy*, *precision, recall,* and *F1-score* metrics obtained from the *classification report.* A more detailed analysis was performed using the *confusion matrix* to identify misclassification patterns for each class.

Accuracy is used to measure the overall correctness of the model by comparing the number of correct classifications against the total number of

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tested data. The accuracy value encompasses all classification outcomes, including both true positive and true negative categories (Pratama, Gustriansyah, & Purnamasari, 2024).

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision is used to measure how accurately the model classifies a specific class. The precision value reflects the ratio of correct classifications to all incorrect classifications produced by the model. This metric is important for assessing the rate of false positive errors (Nurfahrudin & Akbar, 2026).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall is used to measure the model's ability to identify all data that truly belong to a particular class. The recall value indicates how many actual positive instances were successfully detected by the model compared to all true positive instances (Hermanto et al., 2024).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

The F1-score is the harmonic mean of precision and recall, used to provide a balance between the two metrics. The F1-score is particularly useful when there is a class imbalance in the data, as it offers a fairer evaluation than relying on accuracy alone (Hakim, Sobri, Sunardi, & Nurdiansyah, 2025).

$$F1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Description:

TP adalah *(True Positive)* when the obtained result is correct and the system classifies it as positive.

TN adalah *(True Negative)* when the obtained result is correct and the system classifies it as negative

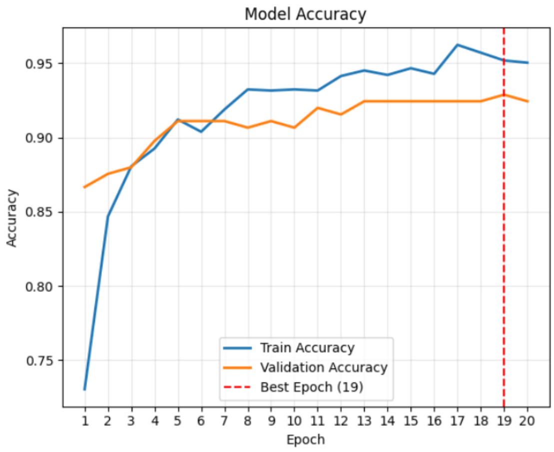
FP adalah *(False Positive)* when the predicted result is incorrect and the system classifies it as positive.

FN adalah *(False Negative)* when the obtained result is incorrect and the system classifies it as negative.

RESULTS AND DISCUSSION

MobileNetV2 Model Training Results

In the MobileNetV2 training shown in Figure 4, training accuracy consistently improved from 0.7305 at epoch 1 to 0.9505 at epoch 20 with slight fluctuations. The validation accuracy followed a similar pattern but with greater variation, increasing from 0.8667 to approximately 0.9244, close to the training accuracy. Both training loss and validation loss declined sharply in the early epochs before stabilizing toward the final epochs. However, a slight gap of 0.0261 between training and validation accuracy indicates mild overfitting, with the best epoch occurring at epoch 19.



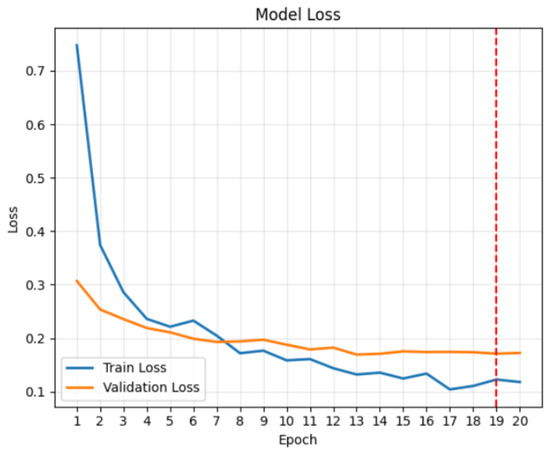


Figure 4. *Accuracy* and *Loss MobileNetV2*

ResNet50 Model Training Results

In the ResNet50 training shown in Figure 5, validation accuracy was initially higher than training accuracy in the early epochs, after which both converged and rose together until epoch 20. Training loss and validation loss declined

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consistently and were closely aligned by the final epochs. This model showed no signs of overfitting, as the gap between training and validation accuracy was only −0.0017, with the best epoch at epoch 20.

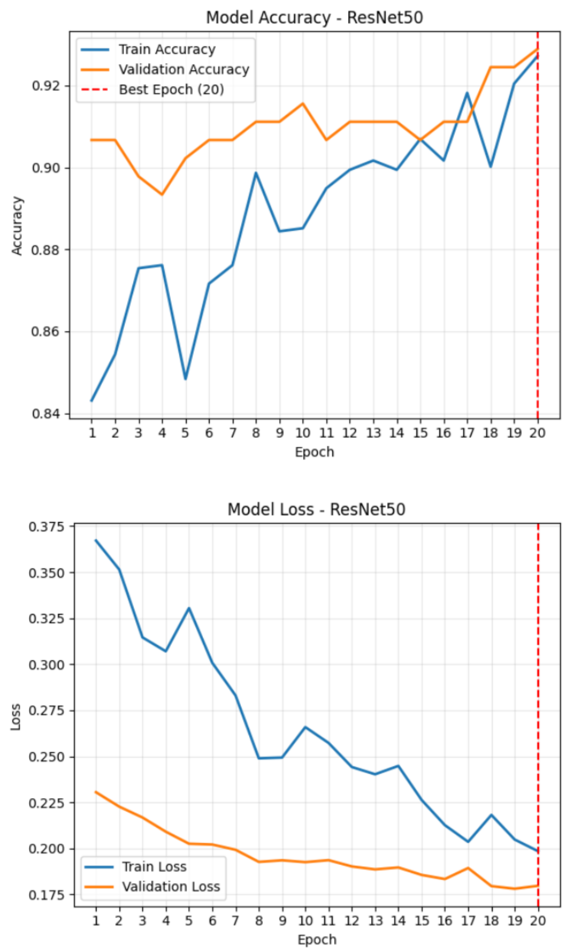

Figure 5. *Accuracy* and *Loss ResNet50*

Summary of Transfer Learning Results

Table 4 presents the transfer learning results of both architectures along with the difference in training time. MobileNetV2 completed training in a shorter time with a training accuracy of 0.95 and validation accuracy of 0.92, while ResNet50 required more time with a training accuracy of 0.93 and validation accuracy of 0.93.

Table 4. Transfer Learning Results

Model	**Train**		**Validation**		
	Accuracy	Loss	Accuracy	Loss	Time minute
MobileNetV2	0,95	0,12	0,92	0,17	33 minute
ResNet50	0,93	0,19	0,93	0,18	51 minute

The test accuracy results of each model are presented in Table 5.

Table 5. Test Accuracy

Model	**Test Accuracy**
MobileNetV2	90,26%
ResNet50	93,33%

Model Evaluation

The following presents the evaluation results of each model based on the confusion matrix (accuracy, *precision, recall, F1-score)* and classification report on the test data.

MobileNetV2 Model Evaluation

In the MobileNetV2 evaluation on the test data, the yellow spot class correctly classified 57 images, with eight yellow spot images misclassified as healthy leaves. The leaf curl class correctly classified 62 images, with two images misclassified as yellow spot and one image as a healthy leaf. The healthy leaf class correctly classified 57 images; however, 6 images were misclassified as yellow spot and two as leaf curl. A total of 19 misclassifications out of 195 images yielded a test accuracy of 90.26% (Figure 6).

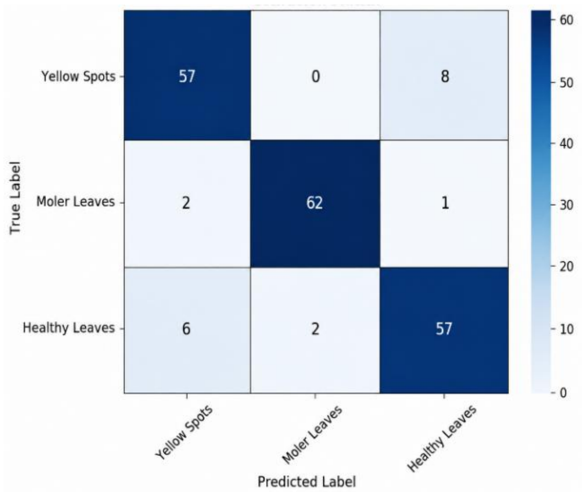

Figure 6. Confusion Matrix MobileNetV2

Table 6. Classification Report MobileNetV2

Class	**Precision**	**Recall**	**F1-score**
Yellow Spots	0,88	0,88	0,88

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Moler Leaves	0,97	0,95	0,96
Healthy Leaf	0,86	0,88	0,87
Average	0,90	0,90	0,90

ResNet50 Model Evaluation

The ResNet50 evaluation demonstrated better performance compared to MobileNetV2. On the test data, the yellow spot class correctly classified 62 images, with three images misclassified as healthy leaves. The leaf curl class correctly classified 64 images, with only one image misclassified as yellow spot. The healthy leaf class correctly classified 56 images, with 6 images misclassified as yellow spot and three as leaf curl. A total of only 13 misclassifications out of 195 images yielded a test accuracy of 93.33%. The confusion matrix results can be seen in (Figure 7).

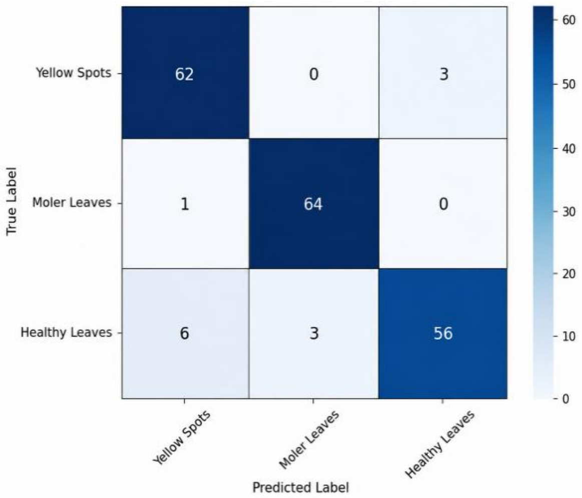

Figure 7. Confusion Matrix ResNet50

Table 7. Classification Report ResNet50

Class	Precision	Recall	F1-score
Yellow Spots	0,90	0,95	0,93
Moler Leaves	0,96	0,98	0,97
Healthy Leaf	0,95	0,86	0,90
Average	0,93	0,93	0,93

Comparative Analysis

Overall, ResNet50 demonstrated more stable classification performance than MobileNetV2 in the testing scenarios conducted. The largest misclassification errors in both models consistently occurred in the yellow spot and healthy leaf classes. This is attributed to the similarity in color and leaf texture characteristics between the two classes, which makes it difficult for the model to optimally distinguish their visual features. Conversely, the leaf curl class achieved high accuracy in both models due to its more distinctive visual characteristics. Under the best-case scenario for each architecture, ResNet50 achieved a test accuracy of 93.33% with an average F1-score of 0.93, while MobileNetV2 achieved a test accuracy of 90.26% with an average F1-score of 0.90.

Based on the confusion matrix, ResNet50 exhibited a lower number of classification errors (13 errors) compared to MobileNetV2 (19 errors). These results indicate that ResNet50 possesses superior feature extraction capability in recognizing patterns in shallot leaf images. Conversely, the gradual decline in MobileNetV2 performance from Train (0.95) to Val (0.92) to Test (90.26%) indicates mild overfitting, which is consistent with the findings of Puspita & Sabri (2024), who showed that MobileNetV2 tends to overfit at higher epochs.

From a computational efficiency standpoint, MobileNetV2 was able to complete the training process faster than ResNet50. This difference is attributable to MobileNetV2's use of depthwise separable convolution, which results in lower computational complexity compared to the standard convolution used in ResNet50. MobileNetV2 has approximately 3.4 million parameters, while ResNet50 has approximately 25.6 million parameters (Puspita & Sabri, 2024).

Although ResNet50 achieves higher accuracy, this performance improvement comes at the cost of increased computational requirements and training time. Therefore, MobileNetV2 is the preferred choice from a computational efficiency standpoint for field deployment, while ResNet50 is superior in classification performance in this study, particularly across the *accuracy, precision, recall,* and *F1-score* metrics for classifying disease types in red onion plants.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This study conducted a comparison of *transfer learning* for MobileNetV2 and ResNet50 models in classifying red onion disease types based on leaf images across three classes: yellow spot, leaf curl, and healthy leaves. Based on the performance

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evaluation of both models, *transfer learning* the ResNet50 model took longer to train than MobileNetV2. ResNet50 achieved an accuracy of 93.33% and an F1-score of 0.93, while MobileNetV2 obtained an accuracy of 90.26% with an average F1-score of 0.90. During the training process, MobileNetV2 experienced rapid accuracy gains in the early epochs but showed indications of *overfitting* mild overfitting, whereas ResNet50 exhibited a more stable training curve with no symptoms of *overfitting*. In general, MobileNetV2 is the optimal choice in terms of computational efficiency for implementation in mobile applications for farmers in the field, while ResNet50 outperforms MobileNetV2 in terms of accuracy, *precision, recall* and *F1-score* in classifying diseases in red onions using leaf images.

Suggestion

Based on the findings of this study, several recommendations for future development are as follows. First, future research is advised to use a larger dataset with greater variety to improve the performance of models that face high visual similarity challenges. Second, other CNN architectures such as EfficientNet or DenseNet may be explored to determine whether more optimal models exist. Third, the application of gradual fine-tuning strategies on selected layers can be further investigated to improve accuracy without the risk of excessive overfitting. Fourth, the developed model should be implemented into a web- or mobile-based application so that it can be utilized directly by farmers in the field.

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