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Early Detection System For Shallot Diseases Using Deep Learning With Mobilenet V2 Architecture

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ABSTRACT

This study investigates the application of Artificial Intelligence, specifically Convolutional Neural Networks (CNN), to support early detection of shallot leaf diseases, namely Moler and Purple Spot, which are commonly identified through manual visual inspection and are prone to subjectivity. The MobileNetV2 architecture is employed using a transfer learning approach on a publicly available shallot leaf image dataset. The research stages include data preprocessing, image augmentation, model training with a fine-tuning strategy, and implementation within a web-based system. Experimental results on the test dataset indicate that the proposed model achieved an accuracy of 99.07%. In particular, the model demonstrated high recall in detecting Moler disease and high precision in identifying Purple Spot disease. These findings suggest that lightweight architectures such as MobileNetV2 are suitable for efficient and accurate plant disease detection with relatively low computational requirements.

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1. INTRODUCTION

Shallots (Allium ascalonicum L.) are a strategic horticultural commodity in Indonesia, yet their productivity is severely threatened by Purple Blotch (Alternaria porri) and Moler (Fusarium oxysporum). These diseases can cause rapid yield losses of up to 50% [1]. Despite the urgency, farmers still rely on manual inspection, which is subjective and prone to misdiagnosis, especially when distinguishing between early-stage symptoms of different pathogens.

The current research landscape in deep learning for shallot diseases shows a significant gap between model performance and field applicability. For instance, Zaki et al. [2] achieved high accuracy in Purple Blotch detection, but their model relies on a dense DCNN architecture that demands substantial computational power, making it impractical for low-end mobile devices [3]. Similarly, Gbadebo et al. [4] utilized a hybrid feature extraction approach; however, such methods often suffer from high latency during real-time inference and lack robustness when faced with the non-uniform lighting and complex backgrounds inherent in Indonesian shallot fields. Most existing studies focus on high-performance server-side models, leaving a void for lightweight solutions that can operate on hardware with limited RAM and processing speed [5].

To bridge this gap, this study proposes an early detection system utilizing the MobileNetV2 architecture[6]. MobileNetV2 is strategically selected over newer or heavier models because of its mature optimization for Android-based "low-end" smartphones typically owned by local farmers[7]. Its use of Inverted Residuals and Linear Bottlenecks significantly reduces the parameter count and memory footprint without a proportional loss in accuracy.

The novelty of this research lies in the optimization of a transfer learning strategy specifically tuned for multi-class classification (Moler and Purple Blotch) under uncontrolled field conditions. Unlike previous works that use idealized datasets, this study emphasizes computational efficiency for real-time field deployment on resource-constrained devices, ensuring that the diagnostic tool is not only accurate but also accessible and responsive in the hands of the farmers.

2. METHOD

The research methodology employs a transfer learning approach utilizing the MobileNetV2 architecture as the foundational model [8], [9]. The systematic workflow of this study is illustrated in Figure 1, depicting the primary stages in developing the deep learning-based detection system for shallot leaf diseases.

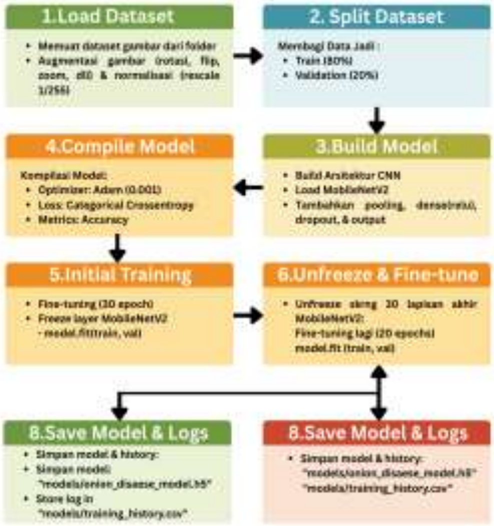

Figure 1. Research Workflow

The process initiates with the acquisition of a shallot leaf image dataset from a public repository. This is followed by data preprocessing and augmentation techniques to enhance image diversity and improve model robustness. The dataset is subsequently partitioned into training and validation sets to ensure an objective evaluation of the model's performance.

In the subsequent phase, the model is constructed using the MobileNetV2 architecture, initialized with weights pre-trained on the ImageNet dataset [10]. The classification layers of the base model are customized to meet the specific requirements of this study. The training process is executed in two distinct phases:

2.1. MobileNetV2 Architecture

This research implements the MobileNetV2 architecture, which centers on the use of Depthwise Separable Convolution a technique originally introduced in the first MobileNet iteration to enhance efficiency [7]. MobileNetV2 further advances this concept by introducing Inverted Residuals and Linear Bottlenecks, enabling efficient image processing on resource-constrained devices without significantly compromising accuracy [6][10].

In the depthwise convolution stage, each input channel is processed independently using a single filter[11]. Subsequently, a pointwise convolution employs a 1 x 1 convolution to combine information across channels. This approach substantially reduces the number of parameters and total computational cost compared to standard convolution.

Mathematically, the efficiency of depthwise separable convolution is demonstrated by comparing its computational cost against standard convolution. Let H and W represent the height and width of the feature map, C_{in} the number of input channels, C_{out} the number of output channels, and K the kernel size. The computational cost for standard convolution (C_{std}) is defined in Equation (1), while the cost for depthwise separable convolution (C_{dws}) is shown in Equation (2):

$$C_{std} = H \times W \times C_{in} \times C_{out} \times K^2 \tag{1}$$

$$C_{dws} = H \times W \times C_{in} \times (K^2 + C_{out}) \tag{2}$$

The significant reduction in computational cost as shown in Equation (2) allows the model to operate with low latency on end-user devices, such as those used by farmers, without requiring high-capacity server-side GPUs.

2.2. Experimental Setup

Experimental Environment and Tools: The model development and training were conducted in a cloud-based environment using Google Colab . The system was implemented using the TensorFlow framework with Keras as the high-level API for model construction and fine-tuning. For data manipulation and visualization, the OpenCV, NumPy, and Matplotlib libraries were utilized. The hardware configuration consisted of an NVIDIA Tesla T4 GPU with 16GB GDDR6 memory to accelerate the deep learning computations.

Input Specifications: All images from the shallot leaf dataset were standardly preprocessed to an input resolution of 224 × 224 pixels with three color channels (RGB). This specific input size was chosen to align with the default requirements of the MobileNetV2 architecture, ensuring that the spatial hierarchy of features like lesion textures and color gradients is preserved while maintaining computational efficiency.

2.3. Dataset Preparation and Preprocessing

The dataset utilized in this study comprises shallot leaf images categorized into two disease classes: Moler and Purple Blotch. These images were sourced from the Kaggle public repository, featuring various visual conditions of shallot leaves. Prior to training, the data underwent a rigorous preparation and preprocessing pipeline to ensure quality and input consistency. It is important to note that since the dataset originates from a public repository with relatively controlled conditions, further evaluation using field-acquired data is essential to validate the model's generalization capabilities.

The preprocessing stage consists of three primary steps:

1. Dataset Partitioning: The dataset was divided into three subsets: a training set (70%), a validation set (20%), and a testing set (10%). The testing set was isolated from the outset and excluded from both the training and augmentation processes. This ensures an objective evaluation of the model's performance on entirely unseen data.
2. Data Augmentation: To enhance visual diversity and mitigate the risk of overfitting, augmentation techniques were applied exclusively to the training set. These techniques included basic transformations such as rotation, width/height shifts, and horizontal flips, designed to simulate the varied conditions of image capture in real agricultural environments.
3. Image Normalization: Pixel values were rescaled to a specific range compatible with the MobileNetV2 architecture requirements. This normalization process is crucial for stabilizing the gradient flow and accelerating model convergence during training.

The entire preprocessing pipeline was engineered to ensure that the data consistently represents the visual characteristics of shallot leaf diseases, thereby facilitating an effective and robust model training process.

2.4. Model Training Strategy

The training strategy in this study employs a transfer learning approach [12], leveraging pre-trained weights from the ImageNet dataset, which has been proven effective in accelerating model convergence [13]. Specifically, this research implements a parameter-based transfer learning approach using a parameter-sharing mechanism, where the majority of the source model's network parameters are frozen to transfer visual feature extraction knowledge [14]. This fine-tuning approach was selected for its capability to adapt models to specific plant disease datasets [15]. The default classification head of the base model was replaced with a Global Average Pooling layer, a Dropout layer for regularization, and a Dense layer with a Softmax activation function, configured to match the number of target classes for shallot leaf diseases.

The model training was executed in two primary phases:

1. Initial Training Phase: All base layers of MobileNetV2 were frozen, and the model was trained for 30 epochs. This phase aimed to utilize the general visual features learned from ImageNet while preventing aggressive weight updates at the early stage of training. The Adam optimizer was employed with a learning rate of 0.001, utilizing Categorical Cross-Entropy as the loss function.
2. Fine-tuning Phase: The last 30 layers of the base model were unfrozen to allow for the adjustment of high-level features specific to the texture and lesion patterns of shallot diseases. Training continued for an additional 20 epochs to align these representations without compromising overall model stability.

This dual-phase strategy was engineered to achieve an optimal balance between training stability and the model's adaptability to the specific domain of plant pathology imagery.

2.5. System Design

The system design in this research aims to support the implementation and testing of the shallot leaf disease detection model through a web-based prototype application. The system was designed using a layered Data Flow Diagram (DFD) approach to structurally represent the process flow, ranging from user interaction to the storage and management of prediction results.

The system architecture comprises several core modules: user management, image processing, and diagnostic result presentation. Users can upload shallot leaf images to be processed by the deep learning model. Subsequently, the system displays the classification results, including the detected disease type, the confidence score, and relevant supporting information regarding the prediction.

Furthermore, the database was designed to ensure data persistence for critical information generated during system operation. The stored data includes user credentials, uploaded images, and a comprehensive diagnostic history—encompassing disease categories and their respective confidence values. This historical logging is intended to facilitate audit trails for testing results and support continuous system performance evaluation. Through this approach, the system serves not only as an inference interface for the model but also as a structured platform for managing plant disease detection data.

3. RESULTS AND DISCUSSION

This section presents the performance evaluation of the deep learning model based on the MobileNetV2 architecture, trained using transfer learning and fine-tuning approaches. The evaluation assesses the model's capability to classify shallot leaf diseases—specifically Moler and Purple Blotch—based on leaf imagery.

In accordance with the research methodology, the analysis focuses on two primary aspects: the model's convergence behavior during the training process and its classification performance on the testing dataset. The performance on the test set was evaluated using standard classification metrics to provide an objective overview of the model's ability to recognize each disease category. These evaluation results serve as the foundation for discussing accuracy levels, training stability, and the practical potential for deploying the model within a plant disease detection system.

3.1. Training Process and Model Convergence Analysis

The performance evaluation obtained during the training of the MobileNetV2 architecture, utilizing transfer learning and fine-tuning strategies, is detailed in this section. The progression of accuracy and loss values for both training and validation sets is illustrated in Figure 2. This graph provides a comprehensive overview of the model's learning dynamics across each epoch.

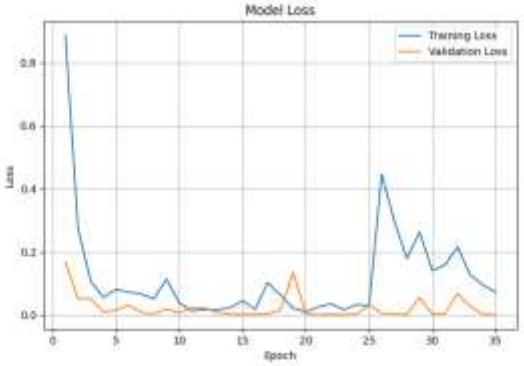

Figure 2. Model Loss

A detailed analysis of the data in Figure 3 indicates that the model achieved a perfect training accuracy of 100% by epoch 11 and maintained this performance through subsequent iterations. Notably, the validation accuracy remained at 1.0000 from the very first epoch. This suggests that the visual features distinguishing Moler from Purple Blotch possess exceptionally high discriminative power within the current dataset, allowing the model to effectively separate the two classes even with minimal parameter updates.

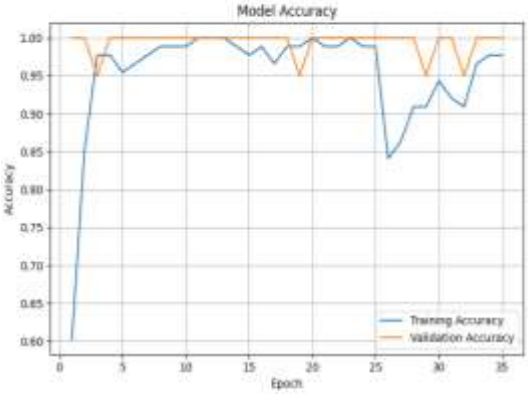

Figure 3. Model Accuracy

3.2. Fine-Tuning Dynamics and Performance Fluctuations

During the fine-tuning phase, where specific high-level layers were unfrozen and the learning rate was reduced, a notable shift in training performance occurred at epoch 26. At this stage, the training accuracy decreased from 0.9886 to 0.8409, while the loss value increased from 0.0293 to 0.4467. This transition coincided with the learning rate adjustment from 0.001 to 0.00001.

This phenomenon reflects the weight re-adaptation process within the high-level layers following the parameter adjustments. At this stage, the model recalibrates its feature representations to align more closely with the specific visual characteristics of shallot leaf diseases. Consequently, temporary fluctuations in training performance are expected as the model navigates the updated loss landscape.

Despite the temporary decline in training accuracy, the validation metrics remained stable. This stability indicates that the performance fluctuations did not impair the model's generalization capabilities on data excluded from the weight update process. In subsequent epochs, training performance recovered and stabilized until the completion of the training process.

Based on these observations, the fluctuations during the fine-tuning phase are interpreted as an inherent part of the model's adaptation to a specific data domain, rather than an indication of overall performance degradation.

3.3. Test Data Evaluation

3.3.1. Overall Performance Metrics

The overall performance of the model was evaluated using a testing dataset based on key classification metrics: Accuracy, Precision, Recall, and F1-score. All metrics were calculated using the Macro Average approach to provide a balanced performance overview across each disease class. This method ensures that the evaluation is not biased by any specific class, considering the relatively balanced distribution of samples.

The summary of the overall performance is presented in Table 1. The model achieved an accuracy of 0.9907, indicating that nearly all test data were correctly classified. A Macro Precision of 0.9909 demonstrates high precision in disease labeling, effectively minimizing false positives.

Furthermore, a Macro Recall of 0.9907 signifies the model's ability to identify almost all disease cases within the test set. This balance between precision and completeness is reflected in the Macro F1-score of 0.9907, confirming stable and consistent performance across all tested categories. These results validate that utilizing a pre-trained network as a feature extractor, combined with fine-tuning, successfully adapts general domain features (ImageNet) to the specific plant pathology domain [14].

Table 1. Performance Metrics Summary

Metric	Value	Description
Accuracy	9,907	Indicates that approximately 99% of the test data were correctly classified.
Precision (Macro)	9,909	Measures the exactness of the model in labeling diseases, minimizing false positives.
Recall (Macro)	9,907	Indicates the model's ability to retrieve all actual disease cases in the test set.
F1 (Macro)	9,907	The harmonic mean of Precision and Recall, showing balanced model performance.

3.3.2. Per-Class Performance

Per-class evaluation was conducted to analyze the model's consistency in identifying Purple Blotch and Moler individually. This analysis aims to detect any performance imbalances or specific error patterns between the two classes.

As shown in Table 2, the model demonstrates high predictive accuracy for both categories. Specifically, for the Purple Blotch class, the model achieved a precision of 1.00, meaning every image predicted as Purple Blotch was indeed correct. Conversely, the Moler class achieved a recall of 1.00, indicating that the model successfully identified every single Moler sample present in the test set.

Table 2. Per-Class Performance Metrics

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Purple Blotch	1,000	981	991	54
Moler	982	1,000	991	54

3.3.3. Confusion Matrix

The Confusion Matrix provides a detailed distribution of the model's predictions against the actual labels. Table 3 illustrates the specific misclassifications that occurred during the testing phase.

Out of the 108 total test samples, the model committed only one misclassification. One "Purple Blotch" sample was incorrectly predicted as "Moler." Meanwhile, all "Moler" samples were correctly identified. This minimal error rate suggests that the model does not suffer from systematic bias and maintains high consistency across the target domain.

Table 3. Confusion Matrix

	Predicted: Purple Blotch	**Predicted: Moler**
Actual: Purple Blotch	53	1
Actual: Moler	0	54

4. CONCLUSION

This study evaluated the application of Deep Learning using the MobileNetV2 architecture to support the early detection of shallot leaf diseases, specifically Moler and Purple Blotch. The transfer learning approach, combined with a fine-tuning strategy, yielded a high-performance classification model, as evidenced by a testing accuracy of 99.07% and a minimal misclassification rate. These results demonstrate that MobileNetV2 effectively leverages visual features to distinguish between the two investigated diseases.

Throughout the training process, the model exhibited relatively stable learning dynamics. Although performance fluctuations occurred during the fine-tuning phase due to learning rate adjustments, the model successfully regained consistency in subsequent epochs. This indicates that the MobileNetV2 architecture—utilizing depthwise separable convolutions—enables efficient extraction of plant disease features with a significantly lower computational load.

Beyond algorithmic evaluation, this research produced a web-based prototype system as a platform for model implementation and testing. The system facilitates image management and structured diagnostic logging, providing a technical foundation for integrating deep learning models into practical agricultural support applications.

Despite these promising results, this study is constrained by its reliance on a public repository dataset with limited visual variation. Consequently, further evaluation using field-acquired data under diverse lighting and environmental conditions is essential to validate the model's generalization capabilities before operational deployment. This research is expected to serve as a baseline for developing more robust and applicable image-based plant disease detection systems.

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