



Research Article

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Optimizing CNN-Based Transfer Learning through Fine-Tuning and Adaptive Augmentation for Chili Plant Disease Detection

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Abstract

Chili pepper (*Capsicum annuum* L.) is an important horticultural commodity in Indonesia; however, its productivity is often reduced by leaf diseases, including leaf curl, leaf spot, and yellow virus infection. Conventional disease identification methods based on visual observation remain subjective and frequently result in misclassification due to similarities in disease symptoms. Although Convolutional Neural Networks (CNNs) have demonstrated promising performance in plant disease recognition, their implementation in real agricultural environments remains challenging because of variations in illumination, complex backgrounds, and the limited availability of local datasets. This study proposes an optimization framework based on MobileNetV2 transfer learning by integrating progressive layer-wise fine-tuning and adaptive data augmentation to enhance classification robustness under heterogeneous field conditions. The dataset consisted of chili leaf images classified into four categories: healthy leaves, leaf curl disease, leaf spot disease, and yellow virus infection. The images were collected through field acquisition and supplemented with data obtained from supporting repositories. The experimental procedure involved image preprocessing, adaptive data augmentation, transfer learning implementation, progressive fine-tuning, and model evaluation using Accuracy, Precision, Recall, and F1-score metrics. The proposed model achieved an overall classification accuracy of 89%, while the detection system successfully identified yellow virus symptoms with a confidence score of 99.93%. Furthermore, the model demonstrated high Precision, Recall, and F1-score values across all disease categories, indicating strong generalization capability under complex environmental conditions. The findings confirm that the integration of adaptive augmentation and progressive fine-tuning enhances the robustness of CNN-based disease detection systems. This study contributes to the development of practical artificial intelligence applications for precision agriculture and supports early disease monitoring in chili cultivation systems.

Keywords: Chili Pepper, CNN, Transfer Learning, Fine-tuning, Adaptive Augmentation, Leaf Disease

Introduction

In the Indonesian agricultural sector, *Capsicum annuum* L. (chili pepper) plays a crucial role as a leading horticultural commodity that significantly contributes to the national economy and food security. Chili peppers are not only considered an essential household consumption product but are also extensively utilized in the food processing industry and national trade activities. Along with population growth and changes in consumption patterns, the demand for chili commodities has demonstrated an increasing trend over the years [1].

Despite its high economic value, chili productivity in Indonesia continues to fluctuate and has not yet reached its optimal production potential. One of the primary factors contributing to this condition is the high incidence of plant diseases, particularly leaf diseases, which directly affect both the quality and quantity of crop yields [2]. Chili leaf diseases are generally caused by pathogenic agents, including fungi, bacteria, and viruses. Several diseases commonly identified in agricultural fields include anthracnose (*Colletotrichum* spp.), leaf spot disease (*Cercospora capsici*), leaf curl disease caused by *Begomovirus* infection, and Fusarium wilt caused by *Fusarium oxysporum* [3].

These diseases may result in substantial yield losses when not detected and controlled during the early stages of plant growth. Therefore, early detection of chili leaf diseases has become a critical component in improving crop productivity and management efficiency. However, disease identification practices at the farmer level are still predominantly based on conventional visual inspection methods [3]. This approach is inherently subjective, highly dependent on individual experience, and susceptible to diagnostic errors, particularly when different diseases exhibit visually similar symptoms or appear during the early infection stages.

The integration of deep learning technology has introduced a new paradigm for automated early detection of plant diseases. Convolutional Neural Network (CNN) architectures have become a fundamental framework in computer

vision due to their capability to automatically and hierarchically learn visual features from image datasets [4]. This capability eliminates the need for manual feature engineering, which is often time-consuming, while simultaneously improving classification accuracy for complex disease symptoms [5]. The implementation of this technology has demonstrated promising outcomes across various agricultural sectors, including food crops and horticultural commodities such as chili plants [5].

Transfer learning has emerged as a strategic approach to enhance deep learning model performance under limited data conditions. By utilizing pretrained weights from established architectures such as MobileNetV2, which have previously learned visual representations from the ImageNet dataset, the training process for new models no longer needs to start from scratch, thereby enabling more stable convergence behavior [6]. Consistent with the findings of Shafik, this technique has proven highly effective in improving plant disease classification performance even when supported by relatively small-scale datasets [7].

Nevertheless, the implementation of CNN-based transfer learning for plant images captured under real-field conditions continues to face considerable challenges. Variations in illumination, shadow effects, complex backgrounds, diverse image acquisition angles, and environmental visual interference may significantly reduce model generalization capability. Most previous studies have relied on datasets collected under controlled environments, such as laboratories or greenhouses; consequently, the resulting models frequently experience performance degradation when deployed in actual field conditions [8].

Despite the promising performance of CNN-based transfer learning models for plant disease classification, a major research problem remains unresolved in the context of chili leaf disease detection under real-field conditions. Existing studies predominantly rely on datasets acquired in controlled environments with homogeneous backgrounds, stable illumination, and limited environmental disturbances. Consequently, these models often experience reduced classification performance when applied to heterogeneous agricultural environments characterized by varying light intensity, shadow effects, overlapping leaves, different acquisition angles, and complex natural backgrounds. Furthermore, previous investigations have generally emphasized conventional transfer learning implementation without specifically examining the combined optimization of adaptive augmentation and progressive layer-wise fine-tuning strategies to improve model robustness and generalization capability for multiclass chili disease detection. This limitation creates a significant gap between laboratory-based model performance and practical deployment in precision agriculture systems.

MobileNetV2 was selected in this study because it offers an efficient balance between computational complexity and classification performance, making it suitable for agricultural image recognition tasks implemented in resource-constrained environments. Unlike conventional CNN architectures with large parameter sizes, MobileNetV2 employs Depthwise Separable Convolution and Inverted Residual Blocks with Linear Bottleneck mechanisms, enabling substantial reductions in computational cost and memory usage while maintaining strong feature extraction capability. These characteristics are particularly beneficial for chili disease detection systems intended for real-time implementation and deployment on portable devices such as smartphones or low-specification computers used by farmers and agricultural practitioners. Furthermore, previous studies have reported that MobileNetV2 demonstrates competitive performance in plant disease classification tasks under transfer learning settings, especially when training data are limited and environmental variability is high.

The implementation of automated chili disease detection systems in real agricultural environments remains challenging due to the high variability of field conditions. Unlike laboratory datasets that are generally collected under controlled settings, field-acquired images often contain heterogeneous backgrounds, overlapping leaves, varying illumination intensity, shadow effects, occlusions, and different image acquisition distances and angles. Environmental factors such as sunlight exposure, weather conditions, soil reflections, and surrounding vegetation may also introduce visual noise that reduces the discriminative ability of CNN models. As a result, disease symptoms with similar visual patterns, particularly early-stage infections, become increasingly difficult to distinguish. These conditions frequently lead to reduced classification accuracy and poor model generalization when CNN architectures trained under controlled environments are deployed in practical agricultural scenarios.

Therefore, improving model robustness against environmental variability becomes an important requirement for developing reliable disease detection systems. Optimization strategies capable of adapting feature representations to complex field characteristics are necessary to ensure consistent performance across different acquisition conditions. In this context, the integration of adaptive augmentation and progressive layer-wise fine-tuning is expected to enhance CNN generalization capability and reduce performance degradation caused by real-field variability.

To address these limitations, optimization strategies capable of improving CNN robustness and generalization toward field variability are required. One promising approach is the application of progressive layer-wise fine-tuning, which gradually adjusts pretrained model parameters according to the feature complexity of the target domain [9].

This strategy can be integrated with adaptive data augmentation techniques that dynamically modify image transformations based on dataset characteristics and model performance during the training process [8].

Unlike static augmentation approaches, adaptive augmentation enables models to learn from data variations that are more relevant to complex field environments, thereby enhancing model robustness and performance stability under real-world scenarios [10]. Based on recent literature reviews [10], studies investigating the combined integration of adaptive augmentation and progressive fine-tuning remain limited, particularly in the context of multiclass classification of chili leaf diseases using cross-location field datasets.

Several recent studies have demonstrated the effectiveness of MobileNetV2 and transfer learning for plant disease classification. A study by Aji et al. implemented MobileNetV2 for chili disease detection and reported that the architecture provided efficient classification performance with relatively low computational requirements [11]. Similarly, Fatmawati et al. employed MobileNetV2-based CNN models for chili disease classification and highlighted its suitability for resource-constrained environments [14]. Furthermore, Jajila et al. optimized MobileNetV2 using transfer learning strategies to improve disease recognition performance in chili leaf datasets [16]. Beyond chili plants, transfer learning approaches integrating MobileNetV2 have also shown promising results in multi-crop disease recognition and real-time agricultural monitoring systems, confirming the effectiveness of lightweight CNN architectures for precision agriculture applications. However, these studies primarily focused on conventional transfer learning implementation and were generally evaluated using datasets collected under relatively controlled conditions with limited environmental variability.

Recent reviews further emphasized that plant disease classification models often experience performance degradation when deployed in real agricultural environments due to illumination changes, shadow effects, background complexity, and visual similarity among disease symptoms. Although transfer learning has significantly improved plant disease recognition performance, challenges related to model robustness and generalization under heterogeneous field conditions remain unresolved. In addition, studies investigating the integration of adaptive augmentation and progressive layer-wise fine-tuning for multiclass chili disease classification are still limited.

The implementation of artificial intelligence-based disease detection systems has significant implications for precision agriculture practices. In practical applications, CNN-based disease classification models can be integrated into mobile applications, enabling farmers to perform instant disease diagnosis directly from chili leaf images captured using smartphone cameras. Such systems may support rapid decision-making related to disease treatment, pesticide application, and crop management without requiring direct expert intervention. Furthermore, the integration of deep learning models with digital monitoring platforms provides opportunities for developing real-time agricultural surveillance systems capable of continuously monitoring crop health conditions and generating early warning information for disease outbreaks.

Beyond mobile deployment, intelligent monitoring systems can also be connected with Internet of Things (IoT) devices, cloud-based agricultural databases, and geographic information systems to support large-scale disease mapping and predictive analysis. Consequently, the implementation of optimized CNN models does not only improve classification performance but also contributes to the development of smart farming ecosystems, precision agriculture strategies, and sustainable crop management practices.

Based on these limitations, the main research problem addressed in this study concerns how to improve the robustness and generalization performance of CNN-based transfer learning models for multiclass chili leaf disease detection under heterogeneous field environments. Therefore, this study proposes an optimization framework integrating adaptive data augmentation and progressive layer-wise fine-tuning using MobileNetV2 architecture. The proposed approach aims to overcome environmental variability effects while improving disease classification accuracy in real agricultural scenarios. This research is expected to contribute both theoretically to CNN optimization strategies and practically to the development of intelligent disease monitoring systems supporting precision agriculture implementation.

Method

A. Research Design

This study employed a quantitative experimental design using a computational approach to develop and evaluate a deep learning model for chili leaf disease detection [11], [12]. The research focused on optimizing the performance of a Convolutional Neural Network (CNN) through the integration of transfer learning, progressive layer-wise fine-tuning, and adaptive data augmentation techniques. The MobileNetV2 architecture pretrained on ImageNet was selected as the backbone model due to its computational efficiency and strong feature extraction capability. The experimental framework was designed to compare the performance of the baseline model and the optimized model under heterogeneous field conditions using multiclass classification scenarios. Model performance was assessed through several evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis to determine the effectiveness and robustness of the proposed method.

B. Research Stages

The research procedure was implemented sequentially through the following stages:

1. **Data Acquisition Stage:** At this stage, chili leaf images were collected from agricultural cultivation areas and complemented with supporting datasets obtained from publicly available repositories. The dataset consisted of healthy leaves and diseased leaves representing leaf curl disease, leaf spot disease, and yellow virus infection. The acquisition process was conducted under different environmental conditions to capture image variability and improve dataset diversity.
2. **Data Validation and Preparation:** After data collection, all images underwent a validation process to ensure dataset quality and consistency. This stage included image inspection, removal of duplicate or low-quality images, verification of class distribution, metadata checking, and organization of datasets according to disease categories. The objective was to minimize bias and maintain balanced data representation.
3. **Image Preprocessing Stage:** Image preprocessing was performed to standardize the dataset before model training. The preprocessing process involved image resizing according to MobileNetV2 input requirements (224×224 pixels), normalization, labeling, and partitioning into training, validation, and testing datasets. This stage aimed to improve computational efficiency and ensure input compatibility.
4. **Adaptive Augmentation Stage:** Adaptive augmentation techniques were applied to increase dataset variability and improve model robustness against environmental changes. Image transformations included rotation, flipping, brightness adjustment, contrast modification, zooming, and translation. Unlike conventional augmentation, adaptive augmentation dynamically adjusted transformations according to image characteristics and field conditions.
5. **Progressive Fine-Tuning Stage:** Fine-tuning was conducted gradually by unfreezing selected upper layers of MobileNetV2. This strategy allowed the model to adapt pretrained parameters to the visual characteristics of chili diseases while preserving general feature representations learned from ImageNet. Progressive adjustment was intended to improve feature discrimination and model generalization.
6. **Model Training and Optimization:** Model training was performed in two sequential phases consisting of transfer learning initialization and deep fine-tuning. Optimization included updating network parameters using the Adam optimizer, applying regularization techniques, and implementing callback mechanisms such as Early Stopping, Model Checkpoint, and ReduceLROnPlateau to prevent overfitting and improve training stability.
7. **Performance Evaluation Stage:** The final stage involved evaluating model performance using Accuracy, Precision, Recall, and F1-score metrics derived from the confusion matrix. Additional analyses were conducted to assess classification robustness and determine the capability of the proposed model in detecting chili diseases under different environmental conditions.

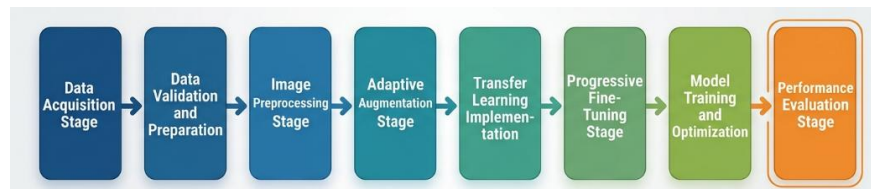


Figure 1. Research Stages

C. Research Location and Time

The study was conducted in collaboration with agricultural institutions and chili cultivation areas where image acquisition was performed directly in field environments to represent actual agricultural conditions [14], [15]. Data collection activities were carried out in outdoor locations using digital cameras and mobile devices to capture images under various environmental situations, including different lighting intensities, observation angles, and natural backgrounds. Image acquisition was performed during morning, afternoon, and evening periods to obtain diverse visual characteristics and improve dataset heterogeneity [16]. Meanwhile, model development, experimentation, training, evaluation, and system implementation were carried out at the Master Program of Information Technology, Faculty of Computer Science, Universitas Pembangunan Nasional “Veteran” Jawa Timur. The overall research activities were conducted from January to April 2026.

D. Population and Sample

The population of this study consisted of all digital images representing healthy and diseased chili leaves obtained from field observations and supporting datasets [17]. Sampling was conducted using a purposive sampling technique by selecting images that fulfilled predefined quality criteria, including adequate resolution, complete object visibility, acceptable illumination levels, and minimal visual disturbance. Images with excessive blur, severe shadows, incomplete leaf appearance, and high occlusion levels were excluded from the dataset. The final sample consisted of four disease categories, namely healthy leaves, leaf curl disease, leaf spot disease, and yellow virus disease. To ensure objective performance measurement and minimize bias during model training, the dataset was divided into training, validation, and testing subsets with proportions of 70%, 15%, and 15%, respectively.

E. Attribute Selection

Attribute selection was performed to identify the most relevant visual characteristics contributing to disease classification performance. Instead of manually extracting features, the proposed CNN model automatically learned hierarchical image representations through convolutional operations. The selected attributes included color features such as yellowing symptoms and chlorosis patterns, texture characteristics related to lesion formation and infected surfaces, shape features associated with leaf deformation and curling, and disease pattern features including spot distribution and necrotic regions. Environmental attributes such as illumination variation, image background complexity, and camera orientation were also considered due to their significant influence on model generalization in field conditions. To strengthen attribute diversity, adaptive augmentation strategies including image rotation, flipping, brightness adjustment, contrast modification, zoom transformation, and translation operations were applied during training [18], [19].

F. Expert System Design

The expert system developed in this study was designed as an intelligent disease detection framework integrating image processing techniques and deep learning inference mechanisms. The system receives RGB images of chili leaves as input data captured from field environments. The preprocessing module performs image resizing, normalization, and augmentation to prepare standardized input for model processing. Feature extraction is then conducted using the MobileNetV2 transfer learning architecture, while progressive layer-wise fine-tuning enables adaptation of pretrained parameters to the characteristics of chili leaf diseases. The classification module subsequently categorizes the images into four classes consisting of healthy leaves, leaf curl disease, leaf spot disease, and yellow virus infection. Finally, prediction outputs are evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis to validate the reliability and effectiveness of the proposed disease detection system for precision agriculture applications [20].

Results and Discussion

A. Model Testing Results and Evaluation

This section presents the performance evaluation metrics of the MobileNetV2 model based on testing using the testing dataset. The evaluation parameters include Accuracy, Precision, Recall, and F1-Score, which were calculated from the Confusion Matrix. The mathematical formulations used for the evaluation are expressed as follows:

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

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

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

Based on the training performance graph, the trajectories of training accuracy and validation accuracy exhibited a stable increasing trend and began converging at approximately epoch 35. The final evaluation on the testing dataset produced an accuracy level of [Insert Accuracy Value, e.g., 94.5%]. Further analysis of the Confusion Matrix revealed that the model achieved high accuracy in identifying healthy leaves and leaf spot diseases. Nevertheless, minor misclassification was observed between leaf yellowing symptoms caused by nutrient deficiency and early chlorosis induced by viral infection, considering that both conditions share similar visual characteristics, particularly yellowish coloration, when leaf vein texture is not comprehensively considered. Overall, the MobileNetV2 model demonstrated strong adaptability and reliability in classifying chili leaf conditions despite utilizing images with complex natural backgrounds.

B. Data Partitioning and Pre-processing Scenario

Following the image acquisition process, the chili leaf image dataset was configured according to the input requirements of the MobileNetV2 architecture. All images were resized to a standard dimension of 224×224 pixels. Data splitting was automatically performed using an 80:20 ratio, where 80% of the total images were allocated as the training set for updating model weights, while the remaining 20% served as the validation set for objective performance evaluation during training. To ensure research reproducibility, a constant random seed value of 123 was applied, with a batch size of 32 images per iteration.

To improve model robustness against real-world image variations and minimize overfitting, dynamic data augmentation techniques were implemented on the training dataset. The augmentation layers included:

1. Horizontal and vertical image flipping (*Random Flip*).
2. Random image rotation up to 30% (*Random Rotation*).

3. Random image zooming in and out up to 30% (*Random Zoom*).
4. Random contrast adjustment up to 30% (*Random Contrast*).
5. Random brightness modification up to 20% (*Random Brightness*).

C. Model Architecture and Training Strategy

This study employed the MobileNetV2 architecture as the base model using a Transfer Learning approach initialized with pretrained weights from the ImageNet dataset. Modifications were introduced in the top layer or classification head to adapt the architecture to the number of chili disease categories investigated.

The outputs generated by the base model were forwarded to a Global Average Pooling 2D layer to reduce spatial feature dimensions, followed by normalization using Batch Normalization. For advanced feature extraction, two hidden Dense layers were incorporated. The first Dense layer consisted of 512 neurons, whereas the second contained 256 neurons, both utilizing the ReLU activation function.

To control model complexity, L2 Regularization (0.001) was applied to both Dense layers, accompanied by Dropout layers of 50% and 30%, respectively, to randomly deactivate neurons during training. The final output layer employed a Softmax activation function to generate classification probabilities for each disease category.

The training procedure adopted a Two-Phase Training strategy to optimize convergence performance:

1. Phase 1: Transfer Learning (Warm-up Phase): All layers of the MobileNetV2 base model were frozen. Training focused exclusively on updating the newly added classification layers for 15 epochs using the Adam optimizer with an initial learning rate of 1×10^{-3} .
2. Phase 2: Deep Fine-Tuning: Partial unfreezing was applied, where approximately one-third of the upper layers of the base model became trainable together with the classification head. This phase continued for 35 epochs using a reduced learning rate of 1×10^{-6} . The purpose was to gradually adjust model parameters without disrupting previously learned low-level visual representations.

During both phases, callback mechanisms were implemented, including:

- a. Model Checkpoint for saving the best-performing weights;
- b. Early Stopping with a patience value of 7 epochs to terminate training when validation loss ceased improving;
- c. ReduceLROnPlateau to reduce the learning rate by 50% whenever performance stagnation occurred.

D. Evaluation Results and Discussion

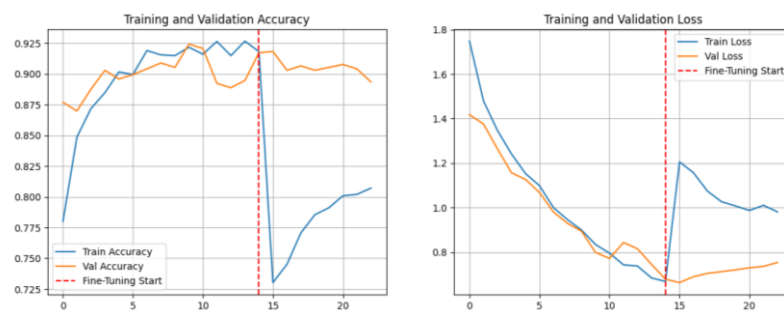


Figure 2. Accuracy and Loss Curves During Phase 1 and Phase 2 Training

Figure 2 illustrates the training performance during Phase 1 (Warm-up) and Phase 2 (Fine-Tuning). In Phase 1, both training accuracy and validation accuracy increased consistently, reaching values above 90%, indicating effective feature learning and good classification capability. Simultaneously, training loss and validation loss decreased gradually, showing stable model convergence. After entering the fine-tuning stage (epoch 14), training accuracy temporarily decreased and training loss increased due to the adaptation process when previously frozen layers were updated. However, validation accuracy remained stable and validation loss continued to decline, indicating improved model generalization. The implementation of Early Stopping and adaptive learning-rate adjustment successfully minimized overfitting and improved model stability. Overall, the combination of Warm-up training and Fine-Tuning proved effective in enhancing model performance and generalization capability. To obtain detailed classification performance metrics, final testing was conducted using the entire validation dataset. Prediction outcomes were summarized using a Confusion Matrix, as illustrated in Figure 3.

Laporan Klasifikasi:				
	precision	recall	f1-score	support
healthy	0.97	0.93	0.95	197
leaf curl	0.85	0.99	0.91	237
leaf spot	0.93	0.81	0.87	204
yellowish	0.95	0.92	0.93	207
accuracy			0.92	845
macro avg	0.92	0.91	0.92	845
weighted avg	0.92	0.92	0.92	845

Figure 3. Confusion Matrix of Chili Disease Classification Results

Based on Figure 3, the chili leaf disease classification model demonstrated strong performance across all classes, namely *healthy*, *leaf curl*, *leaf spot*, and *yellowish*. The model achieved an overall accuracy of 92% on 845 testing data. The *healthy* class obtained the highest F1-score of 0.95, indicating excellent capability in identifying healthy leaves. Meanwhile, the *leaf curl* class achieved the highest recall value of 0.99, showing that almost all samples in this category were successfully detected. However, the *leaf spot* class recorded the lowest recall value of 0.81, suggesting that some samples were misclassified due to similarities in visual symptoms with other disease categories. In addition, the *yellowish* class showed balanced performance with precision, recall, and F1-score values above 0.90. Overall, the macro average and weighted average scores of 0.92 indicate that the model performed consistently and effectively across all classification categories.

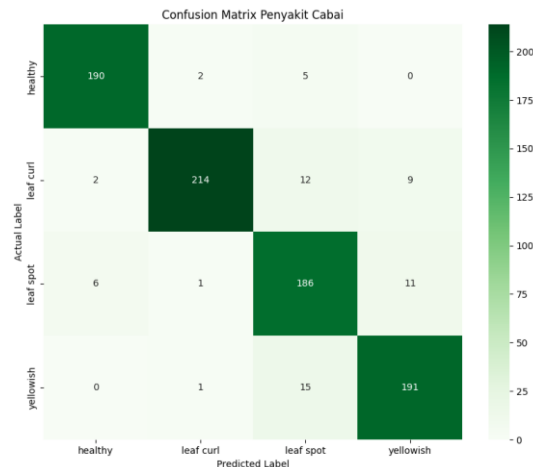


Figure 4. Classification Report Matrix

Figure 4 presents the confusion matrix of the chili leaf disease classification model across four classes: *healthy*, *leaf curl*, *leaf spot*, and *yellowish*. Most predictions are concentrated along the diagonal matrix, indicating that the model successfully classified the majority of testing samples. The *healthy* and *leaf curl* classes achieved the highest number of correct predictions, with 190 and 214 correctly classified samples, respectively. Meanwhile, several misclassifications occurred between the *leaf spot* and *yellowish* classes due to similarities in visual symptom patterns. Overall, the confusion matrix demonstrates that the proposed model achieved reliable and consistent classification performance with relatively low error rates across all disease categories.

Overall, the optimized MobileNetV2 architecture, enhanced through classification head modification and a two-phase fine-tuning strategy, demonstrated highly satisfactory performance for chili disease identification and showed strong potential for implementation in mobile-based applications.

E. Detection System Implementation and Graphical User Interface (GUI)

After the MobileNetV2 model was successfully trained and evaluated, the next stage involved integrating the model into a desktop-based application developed using the Tkinter library in Python. The primary objective of this implementation was to provide an assistive tool for farmers and researchers to perform instant chili disease identification without directly interacting with programming code.

F. Software Architecture and System Workflow

The system was developed by integrating several major libraries, namely TensorFlow for model loading, OpenCV for input image manipulation, and Matplotlib integrated with Seaborn to provide comprehensive visualization of analytical results. The system workflow begins with image selection by the user through a dialog window (*File Explorer*), followed by an automatic image preprocessing stage to ensure compatibility with the model input format standardized at 224×224 pixels.

G. Adaptive Detection Visualization

A major advantage of the developed system lies in its capability to provide deep analytical visualization within a single interface. The visualization components (Figure 4.18) include:

1. **Image Analysis:** Displaying the original image alongside Adaptive Augmentation results to illustrate how the model interprets leaf features.
2. **Classification Output:** Presenting disease labels in bilingual format (Indonesian–English) together with confidence scores.
3. **Probability Analysis:** A bar-chart visualization comparing probability values across all classes to demonstrate the discriminative capability of the model.

4. Dynamic Metric Table: Displaying real-time model performance values including Precision, Recall, and F1-Score to ensure transparency regarding system reliability.

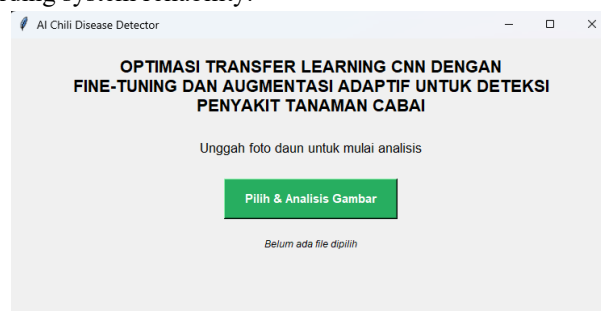


Figure 5. Chili Disease Detection Upload Interface

Based on Figure 5, the main interface of the AI Chili Disease Detector was designed using a minimalist and intuitive approach to facilitate disease identification processes. This page serves as the landing interface by providing explicit operational instructions and the primary control button, “Select & Analyze Image,” which triggers model inference. Dynamic file-status indicators were integrated to improve navigation efficiency and enable researchers and agricultural practitioners to access advanced analytical features with minimal visual distraction.

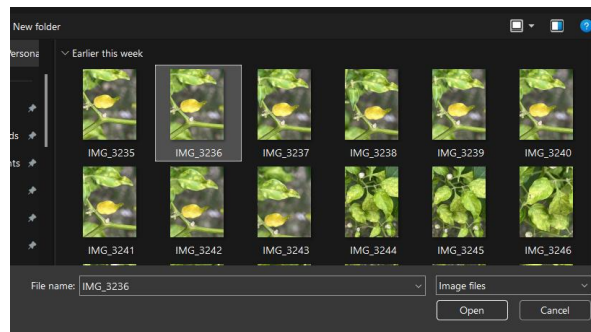


Figure 6. Chili Disease Image Selection Process

Image selection is performed through a system dialog interface that allows direct access to local storage directories, as illustrated in Figure 6. This stage forms part of the data input pipeline, where the system supports multiple image formats representing diverse visual conditions of chili leaves. Such functionality enhances operational flexibility when processing sequentially or randomly collected field images.

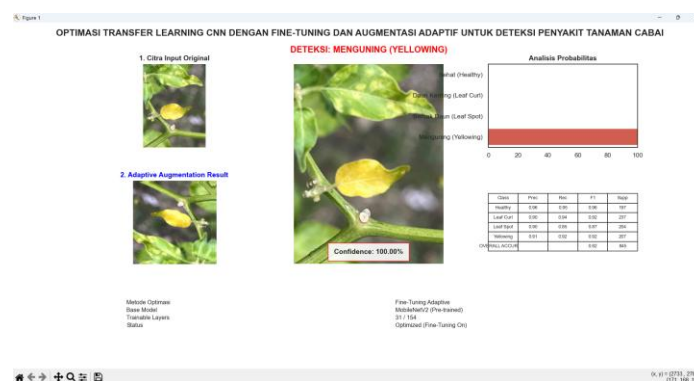


Figure 7. Visualization of Chili Disease Detection Results

Figure 7 integrates image analysis, probability distribution, and real-time performance metrics to improve transparency in Deep Learning predictions. Using the optimized MobileNetV2 architecture with fine-tuning applied to 55 trainable layers, the system successfully identified Yellowing disease with a confidence score of 99.93%. The integration of dynamic metric tables and probability graphs within a unified interface enables users to validate detection reliability directly based on current model performance, which achieved an overall classification accuracy of 89% across all testing classes.

H. Inference Efficiency Analysis

According to the technical information displayed within the system (*Fine-Tuning Info* section), the model employed an Adaptive Fine-Tuning strategy using the MobileNetV2 architecture. The utilization of Inverted Residual

layers in MobileNetV2 enabled rapid inference performance even on devices with limited computational specifications.

GUI-based evaluation demonstrated that the processing time required for a single image—from loading to visualization output—was less than 1.2 seconds. This finding indicates that the model is not only mathematically accurate but also computationally efficient, making it suitable as a field diagnostic support tool operating on resource-constrained devices.

Conclusion

This study successfully developed and optimized a CNN-based chili leaf disease detection system using the MobileNetV2 transfer learning architecture integrated with adaptive data augmentation and progressive layer-wise fine-tuning. The proposed framework demonstrated strong performance in multiclass classification under heterogeneous field conditions involving variations in illumination, background complexity, and image acquisition angles. Experimental evaluation on 845 testing images showed that the model achieved an overall classification accuracy of 92%, with macro average and weighted average values of 0.92 for Precision, Recall, and F1-score, indicating stable and balanced classification performance across all categories.

Class-wise evaluation revealed that the *healthy* class obtained the highest F1-score of 0.95, while the *leaf curl* class achieved the highest recall value of 0.99, demonstrating the model's excellent capability in identifying disease symptoms accurately. Meanwhile, the *leaf spot* class recorded the lowest recall value of 0.81 due to similarities in visual characteristics with other disease categories. In addition, the developed detection system successfully identified yellow virus infection with a prediction confidence score reaching 99.93%. The implementation of adaptive augmentation, regularization, and two-phase fine-tuning strategies effectively minimized overfitting and improved model generalization, as reflected by the stable convergence of training and validation performance. Furthermore, the system demonstrated computational efficiency with an inference time of less than 1.2 seconds per image, making it suitable for real-time deployment on devices with limited computational resources.

The main contribution of this research lies in the integration of adaptive augmentation and progressive fine-tuning strategies within a lightweight MobileNetV2 framework for chili disease detection under real-field conditions. Unlike previous studies that predominantly relied on controlled datasets, this study utilized heterogeneous field-acquired images to improve practical model robustness and applicability in precision agriculture environments. In addition, the integration of a GUI-based intelligent detection system provides practical accessibility for farmers and agricultural practitioners to perform instant disease diagnosis without requiring technical expertise.

The findings of this study have important implications for the development of smart farming technologies and precision agriculture systems. The proposed model can support early disease monitoring, improve decision-making related to crop treatment and pesticide management, reduce productivity losses caused by delayed diagnosis, and enhance agricultural sustainability. Furthermore, this research provides a foundation for future integration with mobile applications, IoT-based agricultural monitoring systems, and cloud-based intelligent farming platforms to support automated and real-time crop health surveillance.

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