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Deep Learning-Based Soybean Leaf Disease Classification Using DenseNet121, Xception, and MobileNetV2

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Abstract

This study is driven by the challenge of soybean leaf diseases, which significantly reduce agricultural productivity and pose a threat to food security. To address this issue, we developed a deep learning–based classification model for soybean leaf disease detection, employing three prominent architectures: DenseNet121, Xception, and MobileNetV2. The dataset comprised 770 images representing six disease categories and one healthy category, which was expanded to 5,880 images using data augmentation techniques. The dataset was evaluated under three experimental scenarios with splits of 70% training, 10% validation, and 20% testing. Experimental results demonstrated that the DenseNet121 model, optimized with AdamW, achieved the highest accuracy at 90.14%, outperforming MobileNetV2 (85.48%) and Xception (65.37%). Moreover, DenseNet121 exhibited the most consistent performance in classifying the diverse categories of soybean leaf diseases.

Keywords: data augmentation; DenseNet121; MobileNetV2; Xception; soybean leaf disease classification

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1. Introduction

Soybeans are a strategic agricultural commodity and serve as a primary source of vegetable protein for both human consumption and animal feed [1]. In Indonesia, soybean productivity frequently encounters challenges, particularly leaf diseases. Common diseases such as Bacterial Pustule, Frogeye Leaf Spot, Rust, Sudden Death Syndrome, Target Leaf Spot, and Yellow Mosaic can substantially reduce both the quality and quantity of crop yields. Therefore, early detection and accurate classification of these diseases are essential to minimize economic losses and to enhance the effectiveness of mitigation strategies.

Currently, the identification of soybean leaf diseases is predominantly performed manually by farmers or agricultural experts. This conventional approach is labor-intensive, time-consuming, and highly dependent on expert availability, often leading to inconsistencies in diagnosis, particularly at large production scales. Hence, the development of an automated, efficient, and accurate diagnostic method is imperative to enable rapid and reliable disease identification.

Advancements in artificial intelligence and deep learning have created significant opportunities to automate plant disease classification through leaf image analysis. Several state-of-the-art deep learning architectures, including DenseNet121, Xception, and MobileNetV2, have demonstrated strong performance in image classification tasks [2]. DenseNet121 is recognized for its parameter efficiency and ability to support very deep networks, Xception leverages depthwise separable convolutions to enhance computational efficiency, and MobileNetV2 is optimized for resource-constrained devices while maintaining competitive performance in large-scale data processing [3].

A study by R. Pan [4] introduced a two-stage feature aggregation network for the identification of various soybean leaf disease categories. This approach improves classification accuracy through multi-stage

feature fusion and was evaluated using a soybean leaf disease dataset. The results demonstrated notable improvements in both accuracy and F1-score, particularly for disease categories that are difficult to differentiate. Nevertheless, the proposed models are characterized by high complexity and require large-scale datasets to achieve optimal performance.

Research conducted by F. Salim [5] explored the application of deep learning techniques for automating fruit classification across various use cases. The findings indicated that all models achieved nearly 99% accuracy or higher on the Fruits-360 dataset and approximately 98% on the Fruit Recognition dataset, with DenseNet-201 and Xception emerging as the best-performing models.

The strength of this research lies in its achievement of very high accuracy, demonstrating the effectiveness of deep learning models in classifying fruit images. Furthermore, the use of two distinct datasets enhances the validity and generalizability of the findings. However, a notable limitation is the substantial requirement for computational resources, which may hinder large-scale implementation, particularly in regions with limited hardware capacity.

Research conducted by F. Huang [6] integrated machine learning with spectral data to predict soybean yields based on the leaf area index. By combining spectral data with machine learning techniques, the study improved prediction accuracy. Validation against real field data demonstrated increased R-squared values and reduced RMSE. However, reliance on precise spectral data remains a major challenge, highlighting the need for more adaptive methods applicable to other crops or the incorporation of additional data features. In a related study, [7] applied the ResNet model for soybean leaf disease classification, achieving an accuracy of up to 94.29%. Nevertheless, this approach encountered difficulties due to image quality variations under different environmental conditions. The findings emphasize the importance of diversifying datasets and enhancing image preprocessing techniques to improve the robustness of plant disease detection models[8].

Building upon these prior works, the present study aims to develop a deep learning–based classification model for soybean leaf diseases, focusing on the DenseNet121, Xception, and MobileNetV2 architectures. The performance of each architecture will be evaluated in classifying soybean leaves into diseased and healthy categories. The proposed approach is expected to enable rapid and accurate identification of soybean leaf diseases, thereby supporting early mitigation efforts to minimize yield losses in both quality and quantity.

This deep learning–based approach also contributes to advancements in precision agriculture, particularly through the use of image analysis to automate plant disease classification [9]. MobileNetV2 was selected for its efficiency in computational resource usage, while DenseNet121 and Xception were employed for comparative evaluation to determine the most suitable model for soybean leaf disease classification [10]. Overall, this research is expected to represent a significant step toward artificial intelligence–driven innovation in the agricultural sector, especially in soybean cultivation.

2. Methods

The research methodology employed in this study is illustrated in Figure 1.

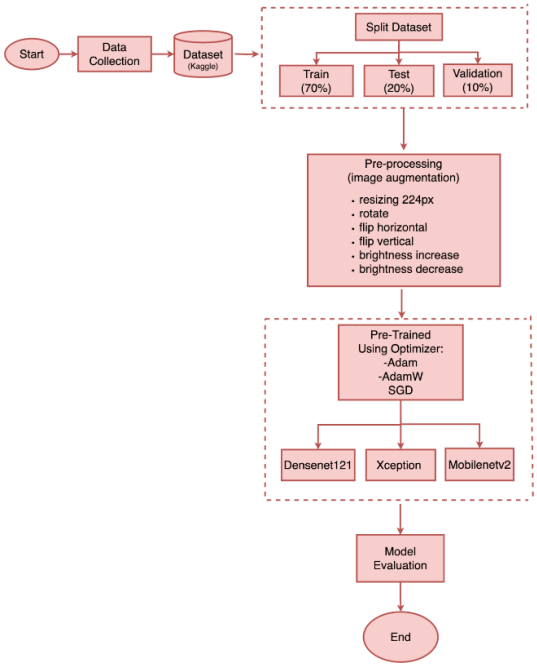


Figure 1. Research Method

The research methodology comprises several stages designed to achieve the objective of developing a soybean leaf disease classification model. The detailed steps of the process are outlined as follows:

2.1 Data Collection

In the initial stage, data were collected in the form of soybean leaf images representing various diseases as well as a healthy category [11]. The dataset comprised 770 images, with each sample belonging to one of seven categories: Bacterial Pustule, Freckle Leaf Spot, Rust, Sudden Death Syndrome, Target Leaf Spot, Yellow Mosaic, and Healthy, with 110 images per category.

The data collection process involved acquiring images from relevant sources, categorizing them according to disease type, and carefully verifying image quality to ensure that all samples were representative and suitable for classification.

2.2 Preprocessing

In the preprocessing stage, the collected data underwent several steps to prepare the soybean leaf images for deep learning model training. A key component of this stage was data augmentation, which aimed to increase both the quantity and variability of training data. Augmentation was performed using random techniques, thereby introducing greater diversity into the dataset and enhancing the model's robustness in handling different image conditions.

Moreover, data augmentation was applied to mitigate the risk of overfitting by enabling the model to learn from more diverse patterns. This random augmentation strategy follows the principle of data exploration, providing the model with richer training inputs to improve generalization. It also simulates natural variations in real-world data, such as differences in viewpoint, lighting, or distortions during image capture [7].

2.3. *Architecture Implementation*

At the architecture implementation stage, experiments were conducted using three deep learning architectures: DenseNet121, Xception, and MobileNetV2. These architectures were selected due to their respective strengths in addressing challenges associated with image classification. DenseNet121, with its deep network structure and dense layer connections, enables more efficient utilization of feature information [5]. Xception, designed for computational efficiency, applies depthwise separable convolutions to accelerate processing while reducing the number of parameters [12]. MobileNetV2, characterized by its lightweight design optimized for resource-constrained devices, is particularly well suited for mobile or edge computing applications [7].

All three models were trained and tested to evaluate their performance in soybean leaf disease classification, with the objective of identifying the most optimal architecture. Each architecture employed the AdamW optimizer, and the implementation workflows of DenseNet121, Xception, and MobileNetV2 are illustrated in Figures 2–4.

Figure 2 presents the DenseNet121 architecture, which employs dense connections to facilitate efficient feature sharing across layers [13]. Figure 3 depicts the Xception architecture, which applies depthwise separable convolutions—dividing convolution operations into depthwise and pointwise steps—thereby improving processing efficiency and reducing parameter counts [14]. Figure 4 illustrates the MobileNetV2 architecture, which employs a bottleneck design combined with depthwise separable convolutions to reduce computational complexity, thereby achieving high efficiency for applications on resource-constrained devices [15], [16].

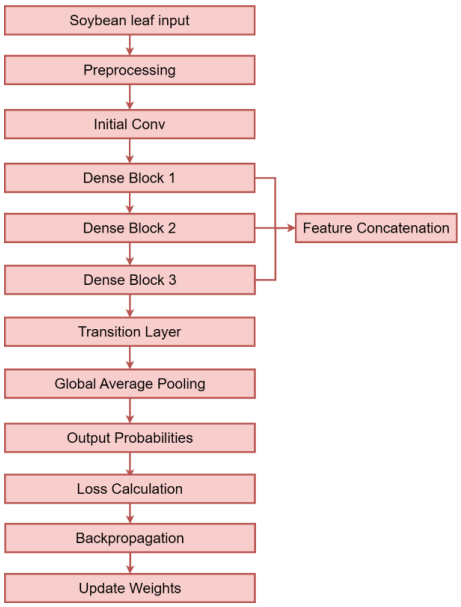


Figure 2. DenseNet121

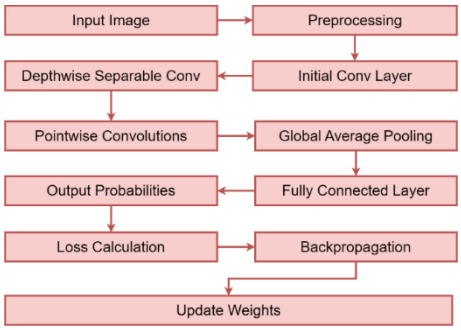


Figure 3. Xception

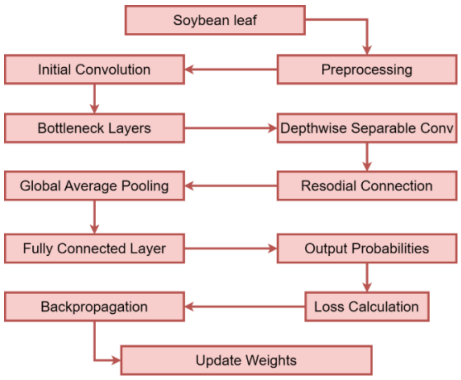


Figure 4. MobileNetV2

2.4. *Model Training*

At the model training stage, the preprocessed data were used to train the implemented deep learning architectures. A critical aspect of this stage was the selection of an appropriate learning rate, as it directly influences both the convergence speed and the accuracy of the model. To optimize this process, a learning rate scheduling strategy was applied, allowing the learning rate to adapt dynamically during training and enabling

the model to adjust effectively to parameter updates. The dataset was divided into three subsets: training, validation, and testing. The training set was used to fit the model, the validation set served to monitor performance during training and mitigate overfitting, and the test set was employed to evaluate the final accuracy and generalization capability of the model in classifying soybean leaf images.

2.5. *Model Evaluation*

Following model training, the next stage was evaluation to assess performance. This evaluation was conducted using test data that had not been included in the training process. Model performance was measured primarily using accuracy, which quantifies the proportion of correct predictions relative to the total predictions made [6]. The evaluation results of DenseNet121, Xception, and MobileNetV2 were then compared to identify the model that achieved the highest performance in classifying soybean leaf diseases. In addition to predictive accuracy, computational efficiency was also taken into consideration. The formula for accuracy is presented in Equation 1.

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

Accuracy, as defined in Equation 1, is used to evaluate the performance of the classification model by comparing the number of correct predictions with the total number of tested samples. In this context, TP (True Positive) refers to the number of positive samples correctly predicted as positive by the model, while TN (True Negative) denotes the number of negative samples correctly predicted as negative. Conversely, FP (False Positive) represents the number of negative samples incorrectly predicted as positive, and FN (False Negative) corresponds to the number of positive samples incorrectly predicted as negative [17].

3. Results and Discussions

The following section presents the results and discussion of the experiments conducted in this study to classify soybean leaf diseases using three deep learning architectures: DenseNet121, Xception, and MobileNetV2.

3.1 Data Collection

In this study, the dataset was obtained from Kaggle and consists of a collection of soybean leaf images used to identify various diseases affecting soybean plants. The dataset details are presented in Figure 5. It comprises seven categories, including six disease types and one healthy category, with each category containing 110 images for a total of 770 images. Image resolution varies according to the source. The categories of Bacterial Pustule, Frogeye Leaf Spot, Sudden Death Syndrome, and Yellow Mosaic have a resolution of 3456 × 4608 pixels, while the Rust and Healthy categories are 3120 × 4160 pixels. The Target Leaf Spot category has the highest resolution, 6000 × 8000 pixels, providing greater visual detail for analysis. These variations in resolution highlight the practical challenges of image data processing for soybean leaf disease classification, as the models must be robust in handling differences in scale, detail, and overall image quality.



Bacterial Pustule 3456 x 4608 | Fregeve Leaf Spot 3456 x 4608 | Rust 3120 x 4160 | Sudden Death Syndrome 3456 x 4608 | Target Leaf Spot 6000 x 800 | Yellow Mosaic 3456 x 4608 | Healthy 3120 x 4160

Figure 5. Dataset

3.2 Preprocessing

The data augmentation techniques applied in this study were designed to increase the diversity of the training data by expanding both the number and variety of images without the need for additional data collection. Several augmentation methods were implemented, including spatial transformations, brightness adjustments, and color modifications [18]. Specifically, 90-degree rotations were applied to alter image orientation, while horizontal and vertical flips were used to mirror images along respective axes. Brightness adjustments were performed by increasing or decreasing light intensity, and zoom operations were applied to magnify specific regions of the image. Noise addition was introduced to simulate suboptimal imaging conditions, while exposure adjustments were used to control overall light intensity. Finally, saturation enhancement was applied to intensify colors and create more vivid image representations. The results of these augmentation techniques are illustrated in Figure 6. Figure 6 presents the original dataset alongside the augmented results, illustrating the application of various techniques to increase training data diversity. Image (a) represents the original soybean leaf image. Image (b) shows a rotated version, producing a different orientation and enabling the model to learn patterns from multiple viewpoints, thereby improving adaptability to positional variations in real-world data.

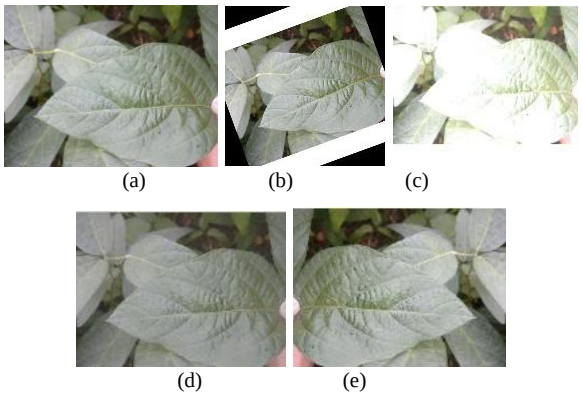


Figure 6. Original (a), Rotasi acak (b), Noise (c), Brightness Adjustment (d), Flip Horizontal (e)

Image (c) demonstrates the addition of noise to simulate suboptimal imaging conditions, such as low-quality images or distortions. Image (d) depicts brightness adjustment, reflecting variations in lighting conditions that may occur in practice. Finally, Image (e) illustrates a horizontally flipped version of the original image, providing further variation in object positioning. After augmentation, the dataset expanded to a total of 5,880 images, which were divided into three subsets: 70% for training, 20% for validation, and 10% for testing. This division ensured that the model could be effectively trained, validated to monitor performance during the training process, and tested to evaluate its accuracy on previously unseen data.

3.3 Training Model

The model training stage presents the results of training three deep learning architectures: DenseNet121, Xception, and MobileNetV2. Each model was evaluated using three key metrics: accuracy, training time, and learning rate [19] - [21]. The outcomes of the initial training process are summarized in Table 1, while the results obtained through fine-tuning are presented in Table 2.

Table 1. Training Model Initial

Model	Optimizer	Accuracy			
		P1	P2	P3	AVG
Xception	Adam	0.5408	0.5330	0.52688	0.53356
	AdamW	0.5221	0.5221	0.5314	0.5252
	SGD	0.4284	0.374	0.409	0.4038
MobilenetV2	Adam	0.8533	0.8357	0.7400	0.8097
	AdamW	0.8543	0.8614	0.8357	0.8505
	SGD	0.7643	0.7686	0.6200	0.7176
Densenet121	Adam	0.8629	0.8730	0.8486	0.8615
	AdamW	0.8743	0.8870	0.8614	0.8742
	SGD	0.7690	0.8257	0.7871	0.7939

Table 2. Training Model Fine-Tuning

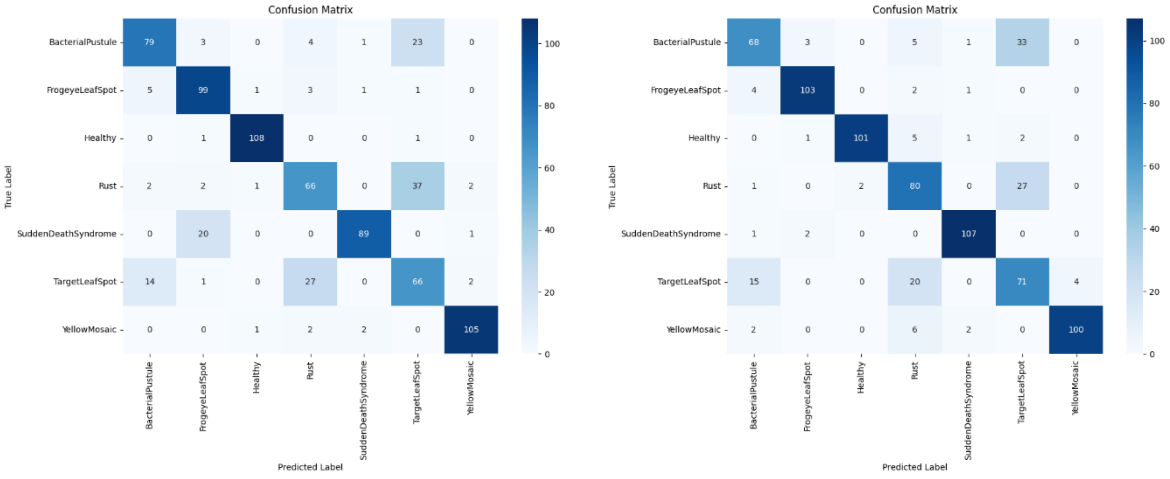
Model	Optimizer	Accuracy			
		P1	P2	P3	AVG
Xception	Adam	0.64967	0.6703	0.6411	0.6537
	AdamW	0.6368	0.6389	0.656	0.6439
	SGD	0.4563	0.32	0.405	0.3938
MobilenetV2	Adam	0.8571	0.842857	0.8571	0.8524
	AdamW	0.8730	0.8414	0.8500	0.8548
	SGD	0.8157	0.8090	0.8043	0.8097
Densenet121	Adam	0.896	0.9029	0.877	0.8920
	AdamW	0.9	0.9014	0.9029	0.9014
	SGD	0.6643	0.8271	0.8286	0.7733

In this study, we evaluated the effectiveness of several deep learning models on a soybean leaf dataset using different optimizers and fine-tuning strategies. In the initial phase, three architectures Xception, MobileNetV2, and DenseNet121 were trained with two optimizers, AdamW and SGD. Each model was trained with a learning rate of 0.001 and employed ModelCheckpoint and ReduceLROnPlateau callbacks to enhance training performance. The results indicated that DenseNet121 combined with the AdamW optimizer achieved the best performance, with an average accuracy of 87.42%. Specifically, the accuracy values for DenseNet121 in scenarios P1, P2, and P3 were 87.43%, 88.70%, and 86.14%, respectively. By contrast, Xception demonstrated considerably lower accuracy, averaging 53.36%, confirming the superiority of DenseNet121 in managing data complexity in this experiment. In the fine-tuning phase, the same models were re-evaluated to examine potential improvements. Using the AdamW optimizer, DenseNet121 again achieved the best results, with an average accuracy of 90.14%, reflecting a substantial improvement through fine-tuning. MobileNetV2 and Xception also demonstrated performance gains, with MobileNetV2 achieving a maximum accuracy of 89.20%. These findings highlight the effectiveness of parameter adjustments in improving model capability. Overall, DenseNet121 with the AdamW optimizer consistently

delivered the best results across both phases, underscoring the importance of selecting appropriate architectures and training techniques to achieve optimal accuracy on complex datasets. Several related studies provide further context for these findings. J. Liu and X. Wang [22] proposed MobileNetV2-YOLOv3 for tomato leaf disease detection, achieving an F1-score of 94.13% and a detection speed of up to 246 frames/s on GPU. Their work demonstrates the efficiency of MobileNetV2 in resource-limited environments, supporting our conclusion that MobileNetV2 is an effective lightweight model, even if its accuracy is lower than DenseNet121 and Xception in our study. Similarly, S. A. Albelwi [23] reported that models trained from scratch achieved 91.3% accuracy, while those initialized with ImageNet pre-trained weights reached 95.7%. This aligns with our findings, as fine-tuning significantly improved accuracy in our experiments. However, while their work emphasized weight initialization strategies, our results underscore the role of the AdamW optimizer in boosting model performance. Another study by S. Roopashree and J. Anitha [24] introduced DeepHerb, an ANN-optimized Xception-based model, which achieved an average accuracy of 97.5% on a specialized dataset. This performance surpasses the 90.14% accuracy achieved by our Xception model. Nonetheless, their results reinforce that Xception remains a reliable architecture for plant disease classification tasks. Finally, research by F. Salim et al. [5] demonstrated that DenseNet-201 and Xception achieved accuracies of 99.87% and 98.94%, respectively, on the Fruits-360 dataset. They also noted that larger input image sizes improved accuracy, albeit at the cost of longer training times. This supports our conclusion that DenseNet and Xception are highly effective architectures for classification tasks. However, the higher accuracy reported in their study likely reflects the use of a more structured and information-rich dataset compared with the more limited dataset employed in our research.

3.4 Model Evaluation

Model evaluation is a critical step in the development and analysis of machine learning models, as it assesses the ability of a model to generalize to previously unseen data [25]. Figure 6 presents two confusion matrices generated from the best training runs for soybean leaf disease classification. In matrix (a), the Healthy category achieved perfect accuracy with 108 correct predictions, demonstrating the model's strong capability in identifying healthy plants. The Frogeye Leaf Spot category also performed well, with 99 correct predictions, although some misclassifications into other categories were observed. By contrast, the Sudden Death Syndrome category performed poorly, with all 20 predictions misclassified, indicating substantial difficulty in recognizing this condition. Misclassification was also observed in the Rust category, where 66 correct predictions were accompanied by errors in other categories. In matrix (b), a clear improvement in performance is observed. Frogeye Leaf Spot achieved 103 correct predictions, while the Healthy category maintained strong results with 101 correct predictions. The Rust category also demonstrated fewer errors, with 80 correct predictions. Notably, the Sudden Death Syndrome category showed marked improvement, with 107 correct predictions, reflecting the model's enhanced ability to recognize this condition compared to matrix (a). Overall, matrix (b) indicates a significant improvement in classification performance, particularly in reducing errors in categories that were previously problematic. The accuracy of the evaluation results was calculated using Equation (1), and the overall outcomes are summarized in Figure 7.



(a) (b)

Figure 7. (a) Initial, (b) Fine Tuning

4. Conclusions

This study successfully developed a deep learning–based classification model to detect soybean leaf diseases using three main architectures: DenseNet121, Xception, and MobileNetV2. Experimental results demonstrated that DenseNet121 and Xception achieved the highest accuracy of 90.14% after fine-tuning with the AdamW optimizer. MobileNetV2 followed with an accuracy of 85.48%, showing that despite being designed for computational efficiency on resource-limited devices, it remains competitive in terms of accuracy. By contrast, Xception, although improving to 65.37% after fine-tuning, still underperformed relative to the other two models.

Overall, the evaluation indicates that DenseNet121 and Xception provide the best balance between accuracy and efficiency, making them strong candidates for plant disease classification tasks, particularly when working with limited datasets. Nevertheless, this research is constrained by the relatively small dataset of 770 images across seven categories, which may not fully capture the diversity of soybean leaf diseases under varying environmental conditions. Furthermore, the models were trained and tested under controlled conditions, without considering real-world factors such as image noise, inconsistent lighting, or variations in camera quality, all of which may affect generalization.

Future work should prioritize expanding the dataset with larger and more diverse image collections, investigating alternative deep learning architectures or hybrid approaches (e.g., combining convolutional neural networks with attention mechanisms), and incorporating domain adaptation techniques to improve robustness and generalizability in real-world applications.

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