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Research Article

Performance Comparison of MobileNetV2 and NASNetMobile Architectures in Soybean Leaf Disease Classification

I Gede Rian Lanang Oka [1,*], Anak Agung Gede Bagus Ariana [2], Wayan Sauri Peradhayana [3], Ni Luh Wiwik Sri Rahayu Ginantra [4], I Ketut Sutarwiyasa [5]

[1] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, igederianlanangoka21101024@gmail.com
[2] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, gungariana@instiki.ac.id
[3] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, sauri.peradhayana@instiki.ac.id
[4] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, wiwik@instiki.ac.id
[5] Institut Bisnis dan Teknologi Indonesia, Denpasar, Bali 80225, Indonesia, sutardesign@instiki.ac.id

Correspondence should be addressed to I Gede Rian Lanang Oka; igederianlanangoka21101024@gmail.com

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Abstract:

Introduction: Soybeans are a vital food commodity in Indonesia, yet their domestic production remains insufficient to meet national demand. One of the primary causes of crop loss—up to 30%—is leaf disease. Therefore, an accurate and early detection system is crucial to support sustainable agriculture practices. **Methods**: This study compares the performance of two lightweight Convolutional Neural Network (CNN) architectures, MobileNetV2 and NASNetMobile, in classifying soybean leaf diseases. The dataset consists of 6,000 augmented images across five disease categories, collected directly from soybean fields in Klungkung, Bali. The images were preprocessed and split into training, validation, and test sets using an 80:10:10 ratio. Both models were trained using the Adam optimizer with a learning rate of 0.001, alongside dropout and ReduceLROnPlateau techniques to prevent overfitting. **Results**: Experimental results show that MobileNetV2 significantly outperforms NASNetMobile. MobileNetV2 achieved an accuracy of 96.67%, precision of 96.70%, recall of 96.67%, and F1-score of 96.68%. In contrast, NASNetMobile reached only 86.33% accuracy, 86.91% precision, 86.33% recall, and 86.40% F1-score. Additionally, MobileNetV2 demonstrated better training stability and a smaller model size (11.1 MB vs. 20.5 MB), making it more efficient for real-time applications. **Conclusion**: MobileNetV2 is a more suitable model for soybean leaf disease classification due to its superior accuracy and efficiency. These findings support its implementation in mobile-based real-time plant disease detection systems for precision agriculture.

Keywords: Deep Learning, Image Classification, MobileNetV2, NASNetMobile, Soybean Leaf Disease.

1. Introduction

Soybeans are one of the most important food commodities in Indonesia. While demand continues to rise, national production remains insufficient to meet consumption needs. Currently, Indonesia can only produce 30–40% of its total annual requirement, which reaches approximately 2.6 million tons. As a result, imports have become an alternative solution, with recorded soybean imports reaching 2.47 million tons in 2020 [1], [2], [3]. One of the major contributors to this production shortfall is leaf disease, which can cause crop failure of up to 30% [4], [5]. Disease outbreaks not only reduce yield but also negatively impact seed quality and lower the market value of soybeans [6]. Therefore, early detection and intervention are essential to minimize losses.

Several methods have been developed to detect plant diseases, ranging from breeding resistant crop varieties to manual visual inspections by farmers [7], [8]. However, these approaches have limitations, such as being timeconsuming, prone to misidentification, and highly dependent on expert knowledge [9], [10]. With the advancement of technology, deep learning-based solutions—particularly Convolutional Neural Networks (CNNs)—have emerged as promising tools for automatic and accurate leaf image classification [11], [12], [13].

In developing CNN-based leaf disease classification systems, selecting an appropriate model architecture is crucial to achieving optimal performance. Two lightweight CNN architectures widely used in image classification are MobileNetV2 and NASNetMobile. MobileNetV2 is designed for devices with limited computational resources due to its efficiency and speed without sacrificing accuracy [14], while NASNetMobile is the result of a Neural Architecture Search (NAS) process, designed to generate more adaptive structures for various classification tasks [15].

Previous studies have demonstrated that both MobileNetV2 and NASNetMobile are effective in diverse domains, including weld defect classification, non-soybean plant disease identification, everyday object recognition, and medical diagnostics [16]. However, direct comparative studies of MobileNetV2 and NASNetMobile in the specific context of soybean leaf disease classification remain scarce. Most existing works either focus on a single architecture or target different agricultural commodities [17]. Therefore, this study aims to fill that gap by conducting a comparative analysis of these two lightweight CNN models in the context of soybean leaf disease classification.

The dataset used in this research consists of 6,000 augmented soybean leaf images categorized into five classes. Performance evaluation is carried out using accuracy, precision, recall, and F1-score metrics. The findings of this study are expected not only to serve as a reference for selecting efficient and accurate CNN architectures but also to support the development of real-time deep learning-based plant disease classification systems for precision agriculture.

2. Method:

This study aims to compare two Convolutional Neural Network (CNN) architectures—MobileNetV2 and NASNetMobile—for the task of soybean plant disease classification using leaf images. Both models are evaluated based on four performance metrics: Accuracy, Precision, Recall, and F1-Score, in order to determine the most suitable architecture for this classification task.

MobileNetV2 and NASNetMobile were selected because they are lightweight and efficient architectures, making them ideal for deployment on resource-constrained devices such as smartphones or edge computing platforms. These models are designed to deliver high performance with low computational cost, making them suitable for real-time plant disease detection systems in field environments.

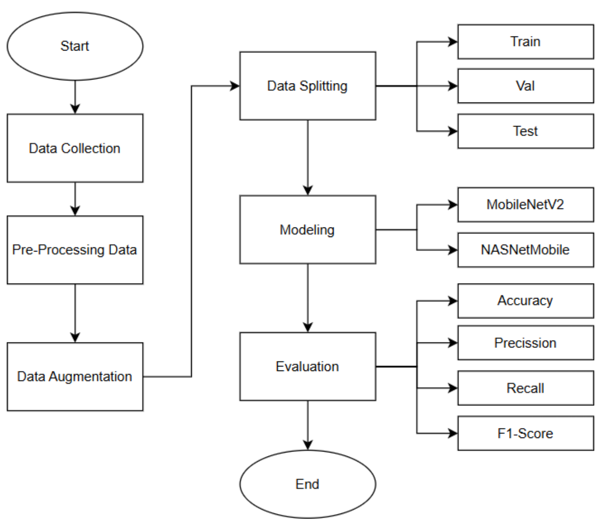

Figure 1. Research process diagram for soybean leaf disease classification

Data Collection

The data were collected through direct field observation in soybean farms located in Klungkung, Bali. The documentation process was conducted using a high-resolution smartphone camera to capture detailed features of the soybean leaves. Image acquisition was carried out on-site at local farms to obtain a diverse set of samples under various plant conditions. The class distribution used in this study is presented in Table 1 below:

Table 1. Distribution of Soybean Leaf Dataset by Class

Class	Number of Images
Bacterial Blight	208
Soybean Rust	226
Target Spot	272
Yellow Mosaic	198
Healthy	234
Total	**1138**

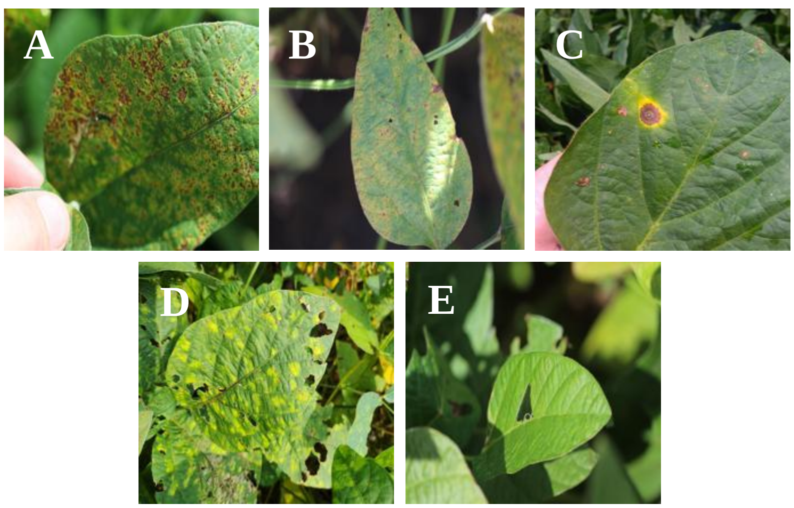

Figure 2. Sample images from the dataset: (A) Bacterial Blight, (B) Soybean Rust, (C) Target Spot, (D) Yellow Mosaic, (E) Healthy.

Tools and Technology Used

The tools and technologies employed in this research cover data processing, model training, and performance evaluation [18].

a. Programming Language: Python, widely used for deep learning development due to its simple syntax and broad library support [19].

b. Deep Learning Frameworks and Libraries: TensorFlow and Keras [20].

c. Data Management and Preprocessing: ImageDataGenerator, NumPy, and Pandas [21].

d. Pretrained Models: MobileNetV2 and NASNetMobile.

e. Optimizer: Adam Optimizer [22].

f. Callbacks: EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint, which enhance training efficiency and stability.

g. Evaluation and Visualization Tools: Scikit-learn, Matplotlib, and Seaborn [23]

Data Collection Process

The data processing workflow includes image standardization, augmentation to increase data diversity, and dataset splitting for training, validation, and testing. Hyperparameter tuning was applied in the final stage to optimize model performance.

a. Pre-processing Data

All images were resized to 224 × 224 pixels to ensure uniform input dimensions for both MobileNetV2 and NASNetMobile models [24].

b. Data Augmentation

Augmentation techniques were applied to increase the quantity and variability of the dataset, helping the model better recognize patterns and reduce overfitting [25]. The augmentation parameters used were:

1 Rotation_range = 30 (random rotation up to 30 degrees) [26].

2 Horizontal_flip = True (horizontal flipping) [27].

3 Vertical_flip = True (vertical flipping).

4 Zoom_range = 0.2 (zoom-in up to 20%) [28].

c. Data Splitting

The dataset was split into 80% for training, 10% for validation, and 10% for testing. This partitioning ensures that the model learns effectively from training data, is evaluated during training using validation data, and is tested on previously unseen data.

d. Hyperparameter Tuning

At the final stage of training, hyperparameter tuning was performed to optimize the model's performance [29].

Table 1. Hyperparameters Used

Hyperparameter	Value
Batch Size	16
Epochs	50
Learning Rate	0.001
Dropout	0.2

Data Analysis Methods

To evaluate the model's performance in classifying soybean leaf images, a confusion matrix was used. The confusion matrix provides a summary of correct and incorrect predictions for each class, which helps in analyzing the model’s error patterns.

The following evaluation metrics were applied:

a. **Accuracy** indicates the proportion of correctly predicted samples out of the total samples tested:

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

b. **Precision** measures the proportion of true positive predictions out of all positive predictions made by the model:

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

c. **Recall** evaluates the model’s ability to identify all actual positive samples:

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

d. **F1-Score** is the harmonic mean of precision and recall, providing a balance between the two:

$$F1 - Score = 2.\frac{Precision.Recall}{Precision+Recall} \tag{4}$$

3. Results and Discussion

Results

The dataset used in this study consists of 6,000 soybean leaf images distributed across five classes. These images were generated through augmentation of 1,138 original images. Prior to training, all images underwent preprocessing to ensure consistent quality and uniform size. Each image was resized to 224 × 224 pixels.

To enhance data variation and improve the model's generalization to different viewing angles and lighting conditions, augmentation techniques such as random rotation, horizontal flipping, vertical flipping, and zooming were applied. These augmentations generated synthetic images that enriched the training data without the need for additional original samples, allowing the model to better recognize visual patterns.

After preprocessing, the dataset was divided into three main subsets using an 80:10:10 ratio—80% for training, 10% for validation, and 10% for testing. This split was designed to allow the model to learn optimally from the training set, be evaluated during training with the validation set, and finally be tested on unseen data.

Table 3. Training Data Evaluation Results

Metric	MobileNetv2	NASNetMobile
Accuracy	96.67%	86,33%
Precision	96,70%	86,91%
Recall	96,67%	86,33%
F1-Score	96,68%	86,40%

The evaluation results indicate that MobileNetV2 outperforms NASNetMobile in classifying soybean leaf diseases. MobileNetV2 achieved an accuracy of 96.67%, higher than NASNetMobile's 86.33%. In terms of precision and recall, MobileNetV2 scored 96.70% and 96.67%, respectively, while NASNetMobile recorded 86.91% and 86.33%. The F1-score of MobileNetV2 was also superior at 96.68%, compared to 86.40% for NASNetMobile.

From a loss perspective, MobileNetV2 demonstrated faster and more stable convergence. The training loss decreased from 0.83 to 0.12, while the validation loss stabilized at 0.12 after dropping from 0.50. In contrast, NASNetMobile's training loss decreased from 1.1 to only 0.30, and its validation loss fluctuated significantly before stabilizing at 0.40. These results suggest that NASNetMobile is more prone to overfitting and less stable than MobileNetV2 during training.

Furthermore, MobileNetV2 has a much smaller model size of only 11.1 MB, compared to NASNetMobile's 20.5 MB. This makes MobileNetV2 more efficient and better suited for deployment on resource-constrained devices.

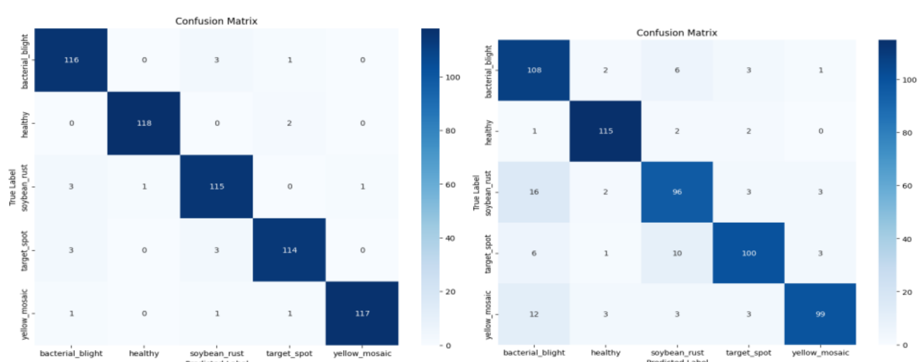

Figure 3. Confusion matrices of the models: MobileNetV2 (left) and NASNetMobile (right)

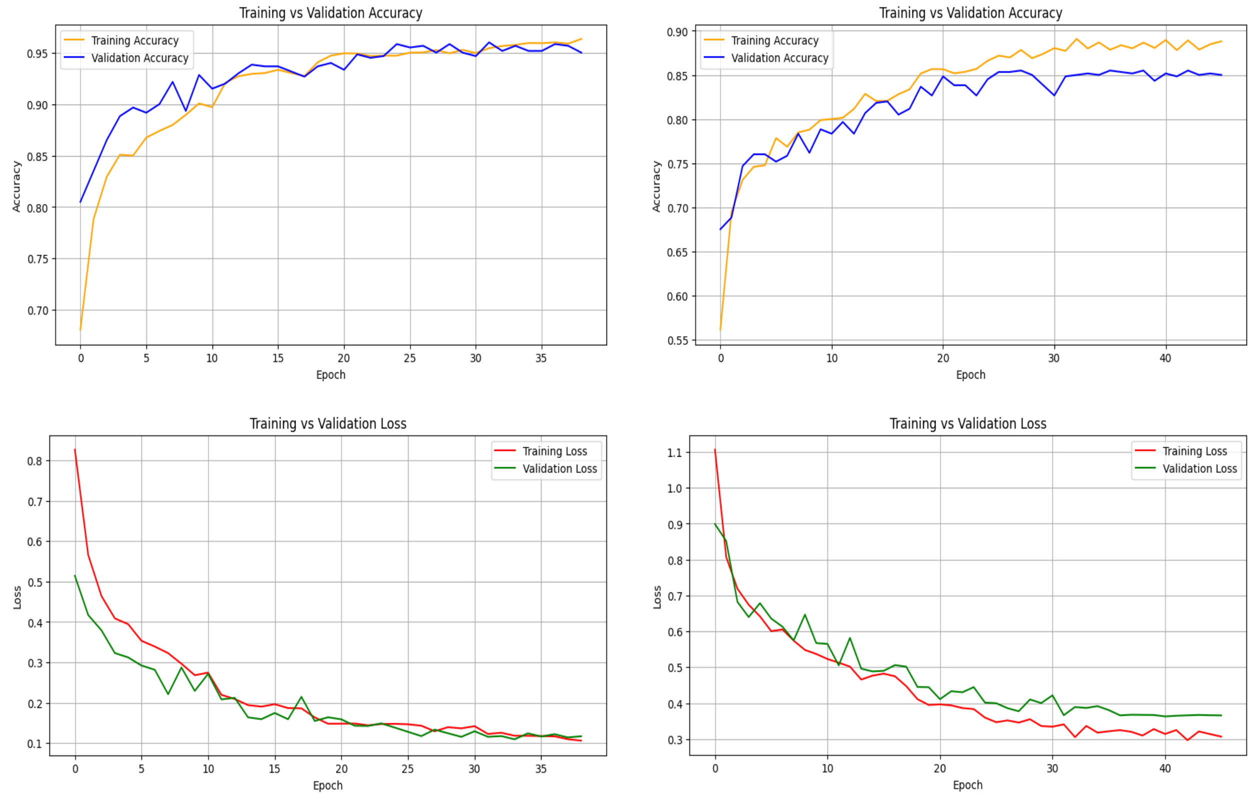

Figure 4. Accuracy and loss curves during training: MobileNetV2 (left) and NASNetMobile (right)

Discussion

This study demonstrates that MobileNetV2 outperforms NASNetMobile in classifying soybean leaf diseases, achieving an accuracy of 96.67% compared to 86.33%. Furthermore, MobileNetV2 achieved higher precision (96.70%), recall (96.67%), and F1-score (96.68%) than NASNetMobile, which obtained 86.91%, 86.33%, and 86.40%, respectively. These results indicate that MobileNetV2 is more accurate and reliable in identifying disease patterns.

This advantage aligns with previous research [30], which compared the performance of the two architectures in tomato leaf disease classification. In that study, MobileNetV2 achieved an accuracy of 93.8%, higher than NASNetMobile's 92.4%. Additionally, MobileNetV2 demonstrated better computational efficiency and superior feature extraction capability, particularly on small-scale datasets.

These findings reinforce the notion that lightweight CNN architectures like MobileNetV2 are not only computationally efficient but also competitive in terms of accuracy, especially in the context of precision agriculture. The lightweight nature of MobileNetV2 also makes it highly suitable for deployment on low-power devices such as smartphones and agricultural drones, supporting the development of real-time, image-based disease detection systems in the field.

However, a limitation of this study is the restricted number of disease classes only five categories were used. Future research should consider expanding the number of disease classes to include more symptoms and leaf types. In addition, exploring other architectures such as EfficientNet or Vision Transformer (ViT) could further improve accuracy and model generalization for real-world agricultural applications.

4. Conclusion

The results of this study indicate that MobileNetV2 performs better than NASNetMobile in classifying soybean leaf diseases, achieving an accuracy of 96.67% compared to 86.33% for NASNetMobile. In addition to accuracy, MobileNetV2 also outperforms NASNetMobile in terms of precision, recall, and F1-score across all classes, demonstrating its superior capability in recognizing leaf patterns and textures.

These findings fulfill the research objective of comparing two lightweight CNN architectures for the automatic and efficient detection of soybean leaf diseases. MobileNetV2 proves to be the more optimal model, not only due to its higher accuracy but also because of its lower misclassification rate. This supports the development of deep learning-based plant disease classification systems that can assist farmers in early disease detection and reduce potential yield losses.

For future research, it is recommended to use a larger and more diverse dataset to improve the model's generalizability. Additionally, exploring other deep learning architectures such as EfficientNet or Vision Transformer (ViT) could help identify even more optimal models. This study can also be extended by designing real-time systems that enable farmers to detect soybean leaf diseases directly via mobile devices or automated monitoring systems in agricultural fields.

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