



Research Article

Performance Comparison of DenseNet-121 and MobileNetV2 for Cacao Fruit Disease Image Classification

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Received 02 December 2025; Accepted 22 March 2025; Published 31 March 2025

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Abstract:

Introduction: Cacao fruit diseases significantly impact cocoa yield and quality in Indonesia. Early detection is critical, yet traditional methods are often time-consuming and error-prone due to the visual similarity of disease symptoms. This study aims to compare the performance of two Convolutional Neural Network (CNN) architectures—DenseNet-121 and MobileNetV2—for automated image classification of cacao fruit diseases. **Methods:** The dataset comprises 8000 images augmented from 2000 original photos taken in cocoa plantations in Bali, categorized into four classes: fruit rot, fruit-sucking pests, pod borers, and healthy fruits. Both CNN models were trained using the Adam optimizer, a learning rate of 0.001, and a dropout rate of 0.4. The input images were resized to 224×224 pixels. Evaluation metrics included accuracy, precision, recall, and F1-score. **Results:** DenseNet-121 outperformed MobileNetV2 across all metrics. DenseNet-121 achieved an accuracy of 94.50%, precision of 94.75%, recall of 94.25%, and F1-score of 94.50%. In comparison, MobileNetV2 reached an accuracy of 93.88%. Although MobileNetV2 offered faster training time and lower model complexity, DenseNet-121 demonstrated superior feature extraction and stability, supported by its deeper architecture and greater parameter capacity. **Conclusions:** DenseNet-121 is more effective than MobileNetV2 in classifying cacao fruit diseases, providing higher accuracy and robustness. Despite requiring more computational resources, it is better suited for developing a web-based cocoa disease detection tool to assist farmers in timely and accurate disease identification.

Keywords: Convolutional Neural Network, DenseNet-121, Image Classification, Kakao Fruit Disease, MobileNetV2.

1. Introduction

Cacao is one of the most important plantation commodities for the Indonesian economy. The potential of the cacao industry to drive economic growth and income distribution is highly promising, as cacao is a key export commodity that significantly contributes to foreign exchange [1]. According to the latest data from the Central Bureau of Statistics of Bali Province, cacao ranks as the second most important plantation commodity in Bali after coffee, with a production of 4.9 thousand tons in 2023, compared to coffee's 14.6 thousand tons. Cacao plays a strategic role in the regional economy, particularly benefiting farmers in Jembrana, Tabanan, and Buleleng. The increasing global demand for organic and sustainable cacao presents promising export opportunities for Balinese cacao.

In Indonesia, cocoa is cultivated in various regions, one of which is Bali. Cocoa usually starts to bear fruit at the age of 4 years [2]. Despite its economic potential, cacao production is often affected by various plant diseases and pests, leading to yield losses of up to 50–80% [3], [4]. One of the most severe diseases affecting cacao production is cacao pod disease, which directly reduces crop yield [5]. There are three primary diseases that impact cacao pods. The first is fruit rot caused by the *Phytophthora palmivora* fungus. Additionally, fruit-sucking pests

(Helopeltis) and pod borers (*Conopomorpha cramerella*) also pose significant threats, reducing both the quality and quantity of cacao production [6].

Currently, many farmers still rely on conventional observation methods to identify cacao diseases. This manual approach is time-consuming and labor-intensive, with identification results often varying based on the skill level of the observer. Moreover, certain cacao diseases exhibit highly similar symptoms, making differentiation difficult [7], [8]. To address these challenges, artificial intelligence (AI) technology presents a reliable solution. AI-based approaches enable farmers to accurately detect various types of pests and diseases, improving early identification and disease management [9]. The development of an automatic cacao fruit disease identification system requires an effective classification model. The accuracy and efficiency of this classification model are crucial to ensuring reliable disease detection [10], [11]. One of the most widely used methods for image classification is the Convolutional Neural Network (CNN), a deep learning algorithm particularly effective in image processing tasks [12], [13].

While previous studies have explored deep learning models for plant disease classification, research specifically comparing CNN architectures for cacao disease classification remains limited. Most prior studies focus on general plant disease identification without assessing the suitability of different CNN architectures for cacao fruit disease detection. This research aims to fill that gap by comparing the performance of two CNN models, MobileNetV2 and DenseNet-121, in classifying cacao fruit diseases. By analysing these models, this study provides insights into the most suitable architecture for accurately detecting cacao diseases.

This study compares the performance of CNN architectures, MobileNetV2 and DenseNet-121, in cacao fruit disease classification. The dataset consists of 2000 cacao fruit images categorized into four classes: fruit rot (*Phytophthora Palmira*), fruit-sucking pests (*Heliopolis*), pod borers (*Copromorphid camarilla*), and healthy fruit. The objective is to develop a model with high classification accuracy for cacao fruit diseases. The best-performing model from this research will be implemented in a web-based cacao disease detection system to assist farmers in diagnosing and managing cacao diseases effectively.

2. Method:

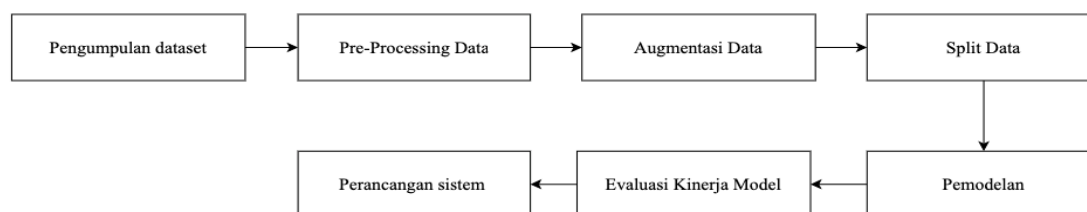


Figure 1. Research flow

Research was conducted in several stages. First, the dataset is collected. Next, the data pre-processing stage aims to improve or prepare the data to be ready for further processing. The flowchart shows the steps that are taken to classify cocoa fruit diseases using a deep learning-based method. Next, data augmentation is performed to increase the amount and variety of training data. Techniques such as random rotation, vertical flip, horizontal flip, and zooming in are used to enhance the image center. After augmentation, the data is divided into data sharing stages, which consist of 80 percent, 10 percent, and 10 percent for training and testing, respectively. Modeling is the next stage where two popular CNN architectures, MobileNetV2 and DenseNet-121, are used to train the model of classification. MobileNetV2 was chosen because it is able to handle devices with limited computing resources, while DenseNet-121 offers more complex inter-layer connections, which allows for deeper feature utilization. Model training was performed using Adam's optimizer to optimize the model weight. After the Model Performance Evaluation stage, the accuracy and reliability of the trained model are evaluated using metrics such as precision, accuracy, recall, and F1-Score. The next step is the comparison of evaluation results, where the results of the MobileNetV2 and DenseNet-121 models are compared based on the metrics of evaluation. A comparison is made to determine which model best performs in classifying cacao fruit diseases. The final step is system design.

Data Selection

The primary data used in this study was collected on cocoa plantations in the Penebel region of Tabanan, Bali. The images were taken using a Redmi 13C mobile phone camera with a resolution of 50MP taken in a portrait position. The images taken were images of ripe and unripe cocoa fruit. Images were taken from various positions, such as from the front, back, and side. in the process of taking pictures directly assisted by cocoa farmers in the garden. The results of the data collected are image data of diseased cocoa fruit and healthy cocoa fruit images, which consist of 2000 original image data and are divided into 4 classes, namely, fruit rot disease (*Phytophthora palmivora*), fruit sucking pest (*Helopeltis*), fruit borer (*Conopomorpha cramerella*), and healthy fruit.



Figure 2. (A) Fruit rot (*Phytophthora palmivora*), (B) pod borer (*Conopomorpha cramerella*), (C) fruit-sucking pest (*Helopeltis*), (D) healthy fruit.

Tools and Technology Used

This research utilizes technologies and tools to train, build, and evaluate models namely:

- a. Program language: Python
- b. Adam optimizer
- c. Deep Learning Framework: TensorFlow and Keras
- d. Trained Models: DenseNet-121 and MobileNetV2
- e. Augmentation Technique: ImageDataGenerator to provide image variability during the training process.
- f. Number of epochs: 25
- g. Batch size: 32
- h. ReLU activation function
- i. Dropout :0.4

Pre-processing Data

Pre-processing is a process used to process the original image data before further image data processing is carried out. The data pre-processing stage aims to prepare the data to fit the needs of the model, reduce noise, align the scale, and ensure dimensional consistency. In this study using data pre-processing by applying resizing techniques. The data is resized to 224×224 pixels, by using the same dimensions, the transfer learning results become more accurate and provide input size consistency, as well as reduce computational load without losing important information.

Data Augmentation

Augmentation is a technique in machine learning that is used to expand the training dataset by creating new variations of existing data [14]. By using augmentation, the model not only learns from the original data but also from the modified data. This helps the model to be more generalist in recognizing patterns so it can perform better when encountering data that is different from the trained data. In addition, augmentation also reduces the possibility of overfitting, which is a condition when the model is over trained on training data so that it performs poorly on new, unfamiliar data [15], [16], [17]. In this research, the augmentation method used is geometric transformation, which provides variations in the position of objects, such as rotation, vertical flip, horizontal flip, and zooming in. This technique provides a variety of object positions in the

dataset so that the model can be better able to handle differences in viewpoint, size, or object orientation in the actual data. From the original data of 2000 images after augmentation to as many as 8000 images.

Model DenseNet-121

DenseNet-121 is a CNN (Convolutional Neural Network) architecture intended to improve feature utilization and make the flow of information easier through different layers of the network [18], [19], [20]. In this architecture, each layer or block uses a feed-forward mechanism to connect with all other layers or blocks. The main elements of each DenseNet layer include batch normalization, the ReLU activation function, and a convolution operation with 3×3 filters. Batch normalization to speed up the training process and allow higher learning rates during model building. Each block receives a matrix representing image pixels as input. This matrix is then processed using batch normalization to reduce the possibility of overfitting during the training process [21], [22], [23].

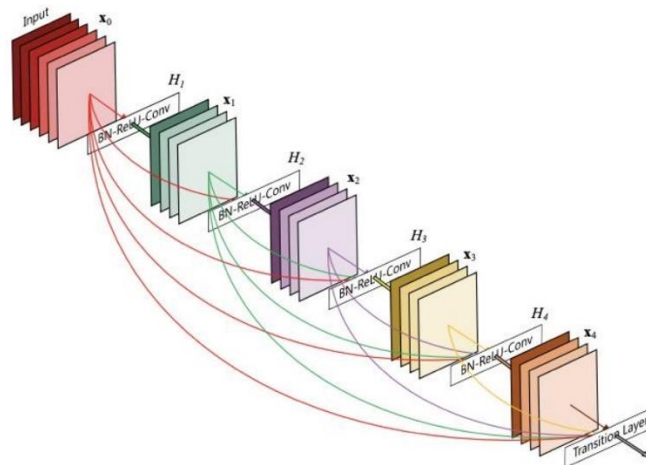


Figure 3. DenseNet-121 Architecture

Model MobileNetV2

MobileNetV2 is a deep neural network architecture called CNN (Convolutional Neural Network) created by Google and intended for devices that have limited computing capacity, such as mobile phones, Internet of Things devices, and real-time systems [24], [25]. This architecture aims to achieve high efficiency in computation usage, memory, and model size while still maintaining optimal accuracy [26]. MobileNetV2 introduces an inverted residual block, where the small input channel dimensions are enlarged using 1×1 convolution, then processed through depthwise convolution on each channel, and finally returned to small dimensions using 1×1 linear convolution. The architecture also uses depthwise separable convolution, which splits the convolution operation into two stages: depth wise convolution to process each channel separately and pointwise convolution (1×1) to combine the information between channels. Finally, MobileNetV2 applies a linear bottleneck (without ReLU activation) to prevent the loss of important information when channels are minimized [27], [28]. With this approach, MobileNetV2 becomes highly computationally and memory efficient, making it ideal for applications on mobile devices or real-time systems such as computer vision [29], [30], [31].

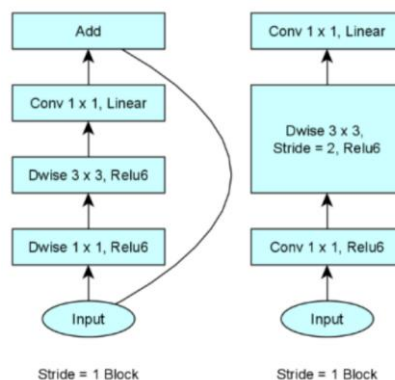


Figure 4. MobileNetV2 Architecture

Data Analysis Method

The evaluation results will compare data using the DenseNet-121 and MobileNetV2 models in cocoa fruit disease classification. Model performance evaluation uses the main metrics, namely precision, accuracy, recall, and F1-score, using the Adam optimizer. In addition to using confusion matrix evaluation, there are several other benchmarks that can be used to determine the weaknesses and strengths of the model, including the loss value to measure the error rate of the model during training and validation. Time: This refers to the time required for the model to perform the training process. Model complexity (number of parameters) Model complexity is seen from the number of parameters that affect efficiency and memory requirements. Size/computation required measures the hardware requirements, such as memory and computing power, to run the model optimally.

System Design

After evaluating the performance of the two models, the model that produces better accuracy will be used to be further developed in the creation of a simple web-based cocoa fruit disease detection system. The system is expected to assist farmers in identifying cocoa fruit diseases quickly so as to enable the implementation of more timely and efficient control measures. With this system, cocoa fruit disease detection can be done automatically and increase productivity and quality of crops

3. Results and Discussion

Results

The following is a table of model evaluation results:

Table 1. Evaluation Results of DenseNet-121 and MobileNetV2 Models

Model	Learning Rate	Optimizer	Accuracy	Precision	Recall	F1-Score
DenseNet-121	0.001	Adam	0.9388	0.9400	0.9375	0.9375
MobileNetV2	0.001	Adam	0.9450	0.9475	0.9425	0.9450

The performance comparison between MobileNetV2 and DenseNet-121 shows that DenseNet-121 has better performance than MobileNetV2. The accuracy of DenseNet-121 (94.50%) is higher than MobileNetV2 (93.88%), indicating that this model makes correct predictions more often. Precision, recall, and F1-score are also higher for DenseNet-121, meaning that the model is better at recognizing each class more equally. MobileNetV2 still performed well, but slightly lower than DenseNet-121.

Benchmark the weaknesses and advantages of each model as follows:

- Loss Value Comparison:** DenseNet-121 has a training loss of 0.1877, while MobileNetV2 has a training loss of 0.2204. This shows that DenseNet-121 is faster at learning from training data than MobileNetV2. The validation loss of DenseNet-121 is more stable than MobileNetV2, which experiences larger fluctuations, which means that DenseNet-121 is better at generalizing to new data.
- Training Time Comparison:** MobileNetV2 requires 895.23 seconds or 14.92 minutes to complete the training process. While DenseNet-121 takes 1016.52 seconds, or 16.94 minutes, longer than MobileNetV2. MobileNetV2 is about 121.29 seconds or 2.02 minutes faster than DenseNet-121, indicating that the MobileNetV2 architecture is more lightweight and computationally efficient.
- Model Complexity Comparison (Number of Parameters):** MobileNetV2 has a total of 2.42 million parameters, while DenseNet-121 has 7.17 million parameters. MobileNetV2 is much lighter, with about 3 times fewer parameters than DenseNet-121.
- Comparison of Model Size or Computation:** MobileNetV2 has a size of 11.1 MB, while DenseNet-121 has a size of 29.62 MB. MobileNetV2 is much lighter, with about 3 times fewer parameters than DenseNet-121. DenseNet-121 is more complex, requiring more memory and computation, but offers better accuracy and stability.

DenseNet-121 performs better because its architecture is more complex and efficient in capturing patterns in cocoa disease images. The main advantage of DenseNet-121 is that the connections between layers are dense, so each layer receives information from all previous layers. This allows the model to reuse learned features, capture patterns better, and maintain learning stability. Its larger number of parameters (7.17 million compared to 2.42

million in MobileNetV2) gives the model a higher capacity to understand image details, although it requires more computing power. In addition, the structure of DenseNet-121 helps maintain gradient stability, reduces overfitting, and results in higher accuracy. With efficient use of features and stability in training, DenseNet-121 is superior in cocoa disease classification, although it requires more resources than MobileNetV2.

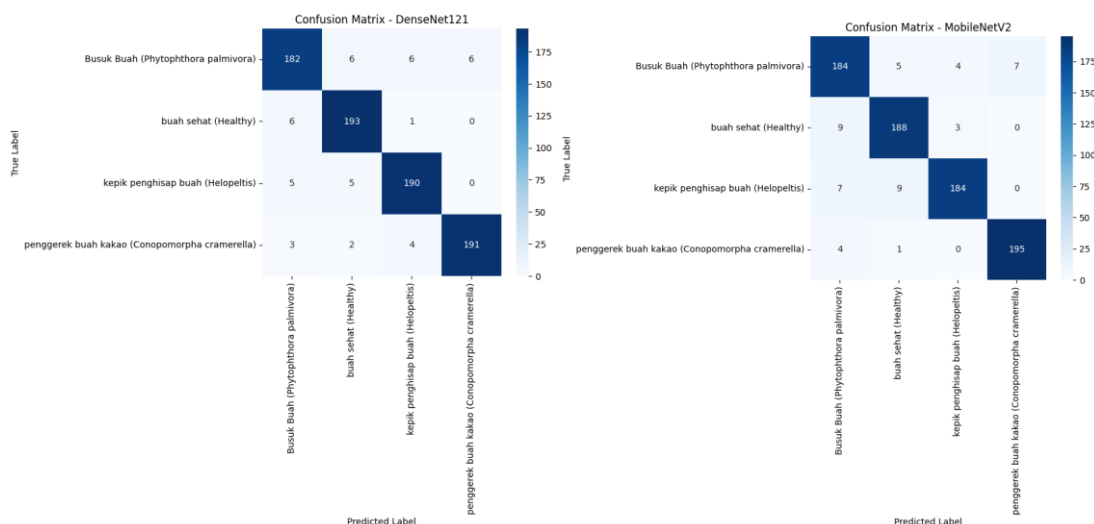


Figure 5. Confusion Matrix DenseNet-121 Without (Left) and MobileNetV2 With (Right)

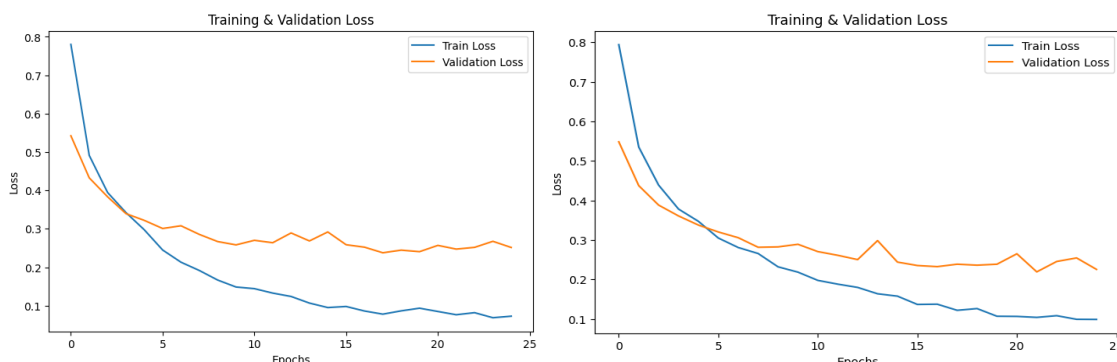


Figure 6. Accuracy and Loss DenseNet-121 Without (Left) and MobileNetV2 With (Right)

Total params: 7,169,220 (27.35 MB)	Total params: 2,422,468 (9.24 MB)
Trainable params: 131,716 (514.52 KB)	Trainable params: 164,484 (642.52 KB)
Non-trainable params: 7,037,504 (26.85 MB)	Non-trainable params: 2,257,984 (8.61 MB)

Figure 7. Number of Parameters DenseNet-121 Without (Left) and MobileNetV2 With (Right)

Discussion

According to the results shown in Table 1, DenseNet-121 achieves a higher accuracy of 94.50% than MobileNetV2, which only achieves 93.88%. DenseNet-121 has a higher precision value than MobileNetV2, with a rating of 94.75 compared to MobileNetV2's 94.00. Finally, the F1-Score value shows that DenseNet-121 is also higher at 94.50 and MobileNetV2 is only 93.75, while the recall value shows that DenseNet-121 is also higher at 94.25 and MobileNet is only 93.75. This demonstrates that MobileNetV2 is not as effective as the DenseNet-121 model.

When the benefits and drawbacks of each model are compared, it is evident that the DenseNet-121 model performs better during training since it has advantages in contrast to a lesser training loss value. Compared to MobileNetV2, which saves time, it has fewer parameters, which reduces computation even though MobileNetV2 has drawbacks in a higher loss value. However, it has drawbacks in a greater number of parameters, a longer training period, and a significant amount of computation.

DenseNet-121 is superior to MobileNetV2 because its more complex architecture allows for more efficient utilization of information. It utilizes tighter inter-layer connections, thus retaining more information from previous data. With a larger number of parameters, DenseNet-121 is able to recognize more complex patterns, resulting in higher accuracy. In addition, its structure also helps reduce overfitting, making the model more stable when tested with new data. In contrast, MobileNetV2 is lighter and faster, but the sacrifice in the number of parameters makes it less accurate than DenseNet-121.

4. Conclusion

This study shows that the CNN architecture DenseNet-121 performs better than MobileNetV2 in classifying cocoa fruit diseases. Using a dataset of 8000 augmented images divided into four classes, both models were tested for performance. The evaluation results show that DenseNet-121 has a testing accuracy of 94.50%, slightly higher than MobileNetV2, which reaches 93.88%. In addition, DenseNet-121 also excels in other evaluation metrics such as precision, recall, and F1 score, which are higher than MobileNetV2. In terms of learning efficiency, DenseNet-121 has a lower training loss value (0.1877) than MobileNetV2 (0.2204), which indicates that the model understands the patterns from the training data faster. However, in terms of training time, MobileNetV2 is faster with 14.92 minutes, while DenseNet-121 takes 16.94 minutes. In terms of model complexity, MobileNetV2 has 2.42 million parameters, much lighter than DenseNet-121, which has 7.17 million parameters. Likewise, in terms of model size, MobileNetV2 is only 11.1 MB, while DenseNet-121 reaches 29.62 MB. Despite being larger and more complex, DenseNet-121 is able to provide more accurate and stable results. Because DenseNet-121 uses information more intelligently than MobileNetV2, it performs better overall. By linking each layer to the one before it, it is able to identify patterns more precisely and in more detail. DenseNet-121 is more accurate in identifying cocoa disease when it has more parameters because it can extract more characteristics from the image.

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