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Performance Comparison of Adam and SGD Optimizers in Transfer Learning Based CNN for Banana Leaf Disease Classification

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Abstract

Banana leaf diseases significantly reduce crop productivity, yet automated detection systems based on deep learning often rely on limited datasets, where training stability and generalization become critical challenges. Although Convolutional Neural Networks (CNNs) have been widely applied for plant disease classification, systematic comparisons of optimization algorithms under small dataset conditions remain limited, particularly for banana leaf disease identification. This study addresses this gap by comparing the performance of Adaptive Moment Estimation (Adam) and Stochastic Gradient Descent (SGD) optimizers within a transfer learning–based CNN framework. Six pre-trained architectures VGG16, VGG19, ResNet50, DenseNet121, MobileNet, and NASNetMobile were evaluated using 1,652 annotated banana leaf images classified into Sigatoka, Cordana, Pestalotiopsis, and healthy leaves. Both optimizers were trained under identical experimental settings to ensure a fair comparison. Experimental results show that VGG19 achieved the highest accuracy, reaching 85% with Adam and 83% with SGD, while lightweight architecture exhibited lower performance due to underfitting. The findings demonstrate that optimizer selection plays a crucial role in improving CNN performance for banana leaf disease classification, especially when data availability is limited.

Keywords: Banana leaf disease; convolutional neural network; transfer learning; Adam optimizer; SGD optimizer

1. Introduction

Bananas (Musa spp.) are among the world's most important horticultural crops, cultivated in more than 130 countries and contributing significantly to global fruit production. Indonesia plays a major role in banana cultivation, both economically and in terms of food security [1]-[4]. However, banana production is highly vulnerable to fungal leaf diseases, which can reduce photosynthetic capacity and cause yield losses of up to 50%. Major fungal diseases affecting banana leaves include Sigatoka, particularly Black Sigatoka caused by Mycosphaerella fijiensis, Cordana leaf spot caused by Cordana musae, and Pestalotiopsis leaf blight [24]-[27]. These diseases are characterized by expanding dark lesions that merge and lead to leaf necrosis and defoliation, especially under warm and humid conditions. Limited farmer awareness and delayed detection further exacerbate productivity losses in banana cultivation. Recent studies have demonstrated the effectiveness of computer vision and deep learning techniques, particularly Convolutional Neural Networks (CNNs), for automated plant disease detection [6],[8]. Transfer learning has further improved banana leaf disease classification performance under limited data conditions [11], [12]. Nevertheless, most existing works focus on single CNN architectures or specific disease types, limiting their generalizability. Comparative evaluations of optimization methods such as Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam) for banana leaf disease classification remain scarce [13]-[15].

To address this gap, this study conducts a controlled comparative evaluation of Adam and SGD optimizers applied to six CNN architectures within a transfer learning framework. The objective is to analyze how optimizer selection influences classification performance and convergence behavior in banana leaf disease detection. The contributions of this work include providing empirical evidence on optimizer effectiveness across different CNN architectures and offering practical guidance for automated banana disease monitoring systems.

2. Research Methods

In recent years, SGD has been regarded as an effective deep-learning optimization method [18], an additional optimization method called Adaptive Moment Estimation (Adam), which is believed to improve the performance of SGD in many tasks [16],[17]. This study compares the performance of two optimization

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methods—Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam)—in classifying banana leaf diseases using Convolutional Neural Networks (CNNs). Figure 1 presents the overall workflow of the proposed approach, which consists of four main steps: (i) dataset preparation and preprocessing, (ii) model selection, (iii) training with SGD and Adam optimizers, and (iv) performance evaluation and analysis. The figure emphasizing that data augmentation is applied only to the training set, followed by resizing, normalization, and model training. This separation ensures methodological validity and prevents data leakage between training and evaluation phases.

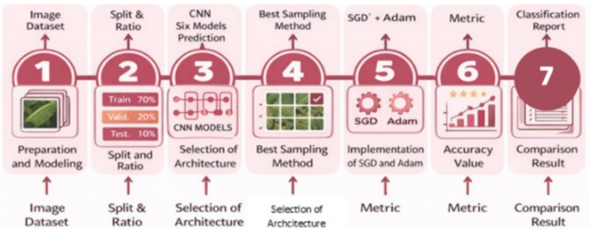


Figure 1. A workflow illustration of the suggested approach

Several CNN architectures have been presented in the last ten years [22, 23]. Architectural patterns are crucial to improving the performance of various applications. From 1989 to the present, CNN's architecture has undergone some changes. Structural reformulation, regularization, and parameter optimization are some of the changes that fall into this category. Instead, it should be noted that the reorganization of the processing unit and the development of new blocks contributed to a significant improvement in CNN performance. The use of network depth is the latest innovation in CNN design. Here is the most popular CNN architecture, used in this study with input size 224x224x3.

Table 1. A synopsis of CNN architecture

Architectures	Main finding	Depth and Dataset	Year
Visual Geometry Group (VGG)	Increased depth, small filter size	16, 19 ImageNet	2014
Residual network (ResNet50)	Based on symmetry mapping that causes overfitting	107 ImageNet	2016
Dense convolutional network (DenseNet121)	blocks made up of layers; layers attached to one another	242 CIFAR-10 and 100, ImageNet	2017
MobileNet	Inverted residual structure	55 ImageNet	2018
NASNetMobile	Exactly three inputs channels	389 ImageNet	2018

Selecting the appropriate architecture for a given goal task, then researchers should study architectural attributes such as input size, depth, and resistance. In the field of agriculture, suitable architecture can function as automation. Cheap sensors have driven farming automation. In recent days, better data acquisition methods and better analytical algorithms have driven the growth of this sector [2]. In a recent study, transfer learning was used to solve the problem of identifying musa diseases with limited data [28], highlighting the possibility of using in-depth learning to identify plant diseases and emphasizing the need for larger and more diverse data [29]. For control and management actions to be implemented, early detection of plant diseases is essential. One of the most common methods to detect plant disease is by visual detection. However, the process of visual detection takes a lot of labor and is less accurate. One alternative method to detect plant diseases is to carry out analysis in a lab. This approach takes time and extensive technical knowledge, and a laboratory that is not available to many farmers in developing countries [30]. In recent decades, AI has also been utilized to diagnose illnesses in plants. [31]. However, Convolutional Neural Networks (CNN) has helped automatic object recognition and image classification in recent years. Using various machine learning techniques, musa crops and their main diseases can be identified through aerial imaging.

2.1. Dataset

The dataset consists of 1,652 annotated images across four classes: Sigatoka, Cordana, Pestalotiopsis, and healthy banana leaves [6],[19],[20]. Data augmentation techniques, including random rotations, flips, and zooming, were applied to increase dataset diversity and balance class distribution. Each class was expanded to 413 images. An 80:20 split was applied to divide the dataset into training and validation sets.

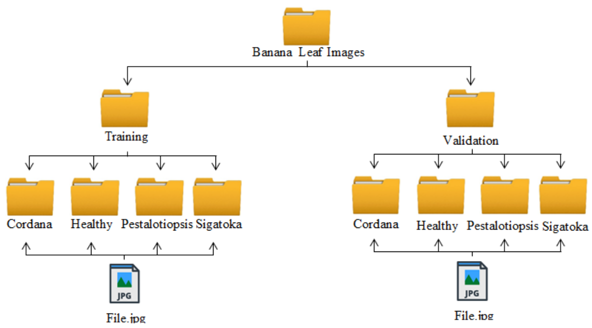


Figure 2. Dataset directory structure

2.2. Preprocessing.

Data preprocessing is a process aimed at preparing raw data to be better and ready for processing. Data sets collected from previous research have undergone a preprocessing process that includes image size adjustment and cropping. As a result, there are only two folders, a training picture and a test picture. The image cropping process cuts the non-essential part of the image, leaving the important part to be identified, while resizing the image is the process of processing the image by changing the original resolution of the picture to the desired resolution [5]. A data flow diagram before processing can be found in the image below. categories: training data and validation data. The distribution ratio is 80% training and 20% validation. Images were cropped to remove non-relevant background regions and resized to a fixed resolution to ensure compatibility with CNN input layers [7],[11]. Pixel values were normalized to accelerate convergence during training.

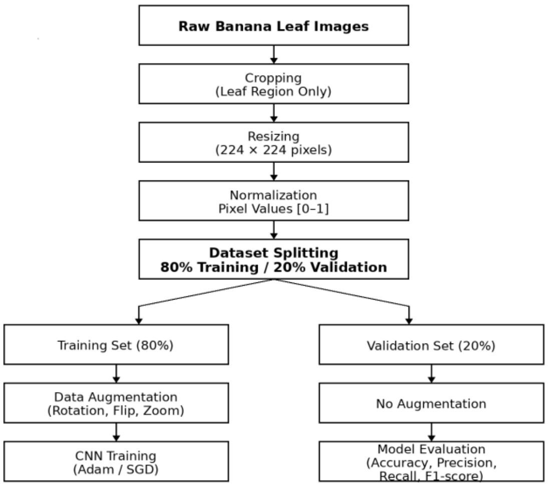


Figure 3. Flowchart data preprocessing

All experiments were conducted using a batch size of 32. For the Adam optimizer, the learning rate was set to 0.0001, with $\beta_1 = 0.9$ and $\beta_2 = 0.999$, which are commonly adopted values for stable convergence in deep CNN training. For the SGD optimizer, a learning rate of 0.01 and a momentum value of 0.9 were used to improve gradient stability and convergence speed.

2.3. CNN Architectures.

Six CNN models were evaluated: VGG16, VGG19, ResNet50, DenseNet121, MobileNet, and NasNetMobile. Each architecture was initialized with pre-trained ImageNet weights through transfer learning [8],[13],[15]. To ensure stable training and prevent overfitting, partial fine-tuning was employed. Specifically, the convolutional base layers of each pre-trained model were frozen, while the fully connected (classification) layers were fine-tuned during training. This approach allows the models to retain general visual feature representations learned from ImageNet while adapting the high-level features to the specific characteristics of banana leaf diseases. Fine-tuning all layers was not performed to avoid overfitting and excessive computational cost, which are common risks when training deep CNNs on relatively small datasets.

2.4. Optimization Methods

SGD and Adam optimizers were applied to train each architecture. To ensure a fair and controlled comparison between Adam and SGD, both optimizers were trained using the same number of epochs, set to 15 epochs for all CNN architectures. Hyperparameters such as learning rate, batch size, and momentum/β values were tuned based on prior studies and preliminary experiments [17],[18]. The comparison indicates that Adam is more suitable for deeper CNN architectures under limited data conditions**,** offering faster convergence and higher accuracy, whereas SGD remains competitive in terms of generalization but may require careful tuning and longer training durations.

2.5. Evaluation Metrics

Model performance was assessed using accuracy (ACCU)**,** precision (PREC)**,** recall (RECA)**,** and F1-score (F1-S)**,** calculated from the confusion matrix of test predictions [20],[21]. These metrics provide complementary insights into the model's behavior:

- Accuracy measures the proportion of correct predictions.
- Precision reflects the correctness of positive predictions.
- Recall indicates the model's ability to identify all relevant samples.
- F1-score provides a harmonic balance between precision and recall.

The formulas are expressed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where *TP*, *TN*, *FP*, and *FN* denote true positives, true negatives, false positives, and false negatives, respectively. All models were trained and validated using the same data partition and evaluated on the identical test set for fair comparison.

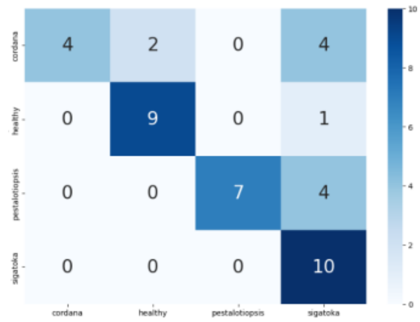
3. Results and Discussions

In addition to the 80:20 training–validation split, a small independent test set consisting of 10–11 images per class was used in the final identification stage to observe model behavior. Identification was performed using independent test images comprising 10 samples from each class (Cordana, Healthy, Sigatoka, and 11 from Pestalotiopsis). Model performance was evaluated using a confusion matrix, as shown in Figure 4 for Adam, and summarized in Figure 5 for SGD. Across the six architectures, VGG19 consistently demonstrated the highest classification accuracy, achieving 85% with Adam and 83% with SGD. VGG16 and ResNet50 also showed competitive performance, whereas DenseNet121, MobileNet, and

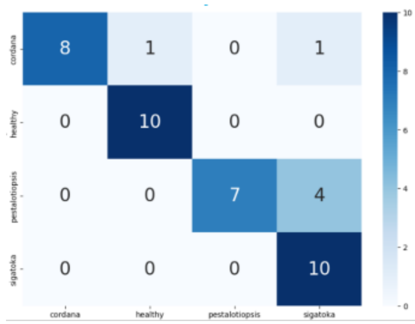
NasNetMobile performed poorly, particularly with accuracies below 50%.

These results suggest that deeper architectures such as VGG19 are more effective in capturing relevant features of Musa leaf diseases compared to lightweight models like MobileNet and NasNetMobile, which may suffer from underfitting given the relatively small dataset [6],[13],[15],[20].

In terms of optimization methods, Adam generally yielded higher accuracy for VGG-based and ResNet architecture, while SGD showed comparable performance in certain cases. This indicates that Adam's adaptive learning rate provides better convergence in complex architectures, whereas SGD remains stable in simpler models [16],[17]. Similar findings were also reported in recent plant disease classification tasks, where Adam outperformed SGD in terms of generalization [18]. Compared to MusaSqueezeNet, which achieved an accuracy of 84% [1], the present study demonstrates that transfer learning using VGG19 with Adam can surpass this benchmark. This highlights the importance of optimizer selection and architecture depth in improving classification outcomes. From a practical perspective, the ability of VGG19 with Adam to achieve reliable accuracy contributes to earlier and more accurate detection of leaf diseases. This can reduce yield losses and support better disease control strategies, ultimately enhancing yield quality and harvest efficiency in banana cultivation[19],[20].

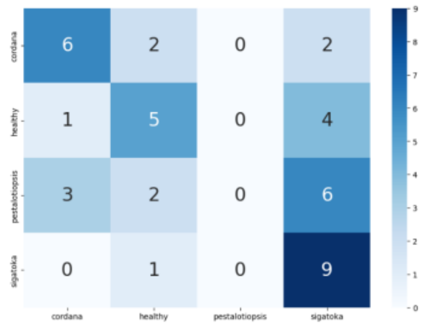


VGG 16



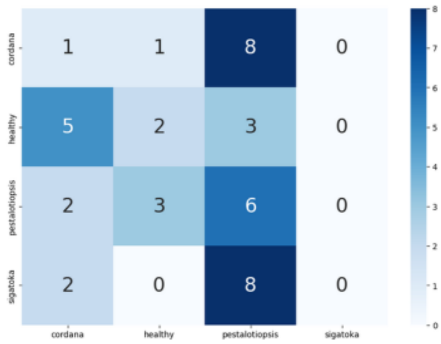
VGG 19

ResNet50



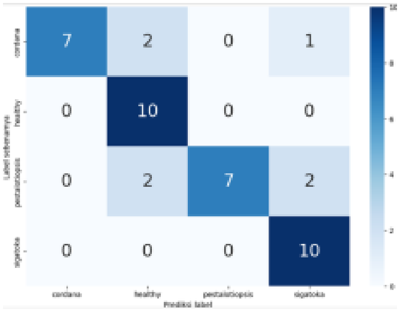
DenseNet121

MobileNet



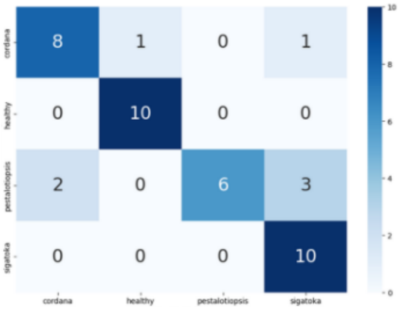
NASNetMobile

Figure 4. Confusion matrix results Adam

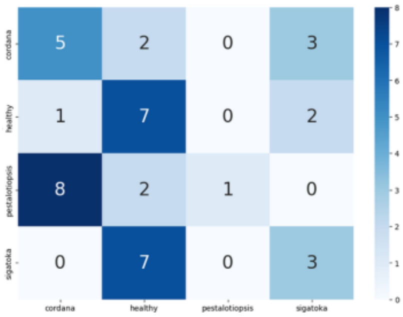


VGG 16

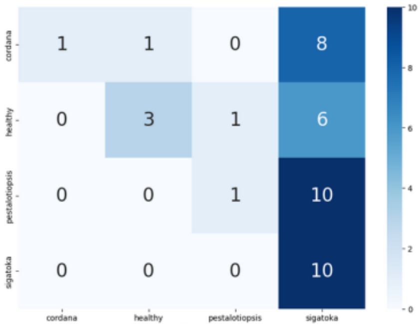
VGG 19



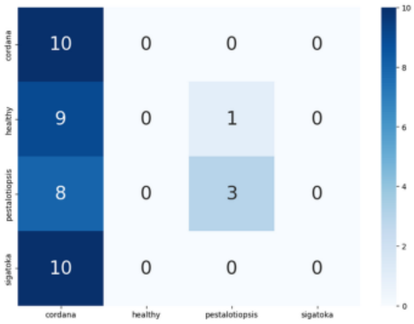
ResNet50



DenseNet121



MobileNet



NASNetMobile

Figure 5. Confusion matrix results SGD

At the end of training and validation, the performance of each CNN model optimized with Adam and SGD is summarized below. For VGG16, Adam achieved 73% accuracy, with the highest precision (100%) for Cordana and Pestalotiopsis, while the best recall was obtained for Sigatoka (100%). The F1-score was highest for the Healthy class (86%). Using SGD, accuracy improved to 83%, with precision again reaching 100% for Cordana and Pestalotiopsis, and recall of 100% for Sigatoka. Overall, SGD slightly outperformed Adam for this model.

Table 2. Evaluation of model effectiveness Classification (C) VGG16

C	VGG 16							
	ACCU		PREC		RECA		F1-S	
	Adam	SGD	Adam	SGD	Adam	SGD	Adam	SGD
1	0,73	0,8	1	1	0,4	0,6	0,57	0,75
2	0,73	0,8	0,82	0,82	0,9	0,9	0,86	0,86
3	0,73	0,8	1	1	0,64	0,73	0,78	0,84
4	0,73	0,8	0,53	0,62	1	1	0,69	0,77

For VGG19, Adam obtained the best overall results, with 85% accuracy and perfect recall (100%) for both Healthy and Sigatoka classes, and an F1-score of 95% in the Healthy class. In contrast, SGD achieved 80% accuracy, with some metrics remaining equal but slightly lower F1-scores.

Table 3. Evaluation of model effectiveness Classification (C) VGG19

C	VGG 19							
	ACCU		PREC		ACCU		F1-S	
	Adam	SGD	Adam	SGD	Adam	SGD	Adam	SGD
1	0,85	1	0,85	1	0,85	1	0,85	1
2	0,85	2	0,85	2	0,85	2	0,85	2
3	0,85	3	0,85	3	0,85	3	0,85	3
4	0,85	4	0,85	4	0,85	4	0,85	4

For ResNet50, Adam achieved 83% accuracy with perfect precision for Pestalotiopsis and perfect recall for Healthy and Sigatoka. Interestingly, SGD produced identical results across all parameters, showing no significant differences between the two optimizers.

Table 4. Evaluation of model effectiveness Classification (C) ResNet50

C	ResNet50							
	ACCU		PREC		ACCU		F1-S	
	Adam	SGD	Adam	SGD	Adam	SGD	Adam	SGD
1	0,83	1	0,83	1	0,83	1	0,83	1
2	0,83	2	0,83	2	0,83	2	0,83	2
3	0,83	3	0,83	3	0,83	3	0,83	3
4	0,83	4	0,83	4	0,83	4	0,83	4

For DenseNet121, Adam reached only 49% accuracy, while SGD performed even worse at 39%. Adam achieved the highest precision (60%) in the Cordana class, while SGD produced its best recall (70%) in Pestalotiopsis. These results indicate that DenseNet121 is unsuitable for this dataset.

Table 5. Evaluation of model effectiveness Classification (C) DenseNet121

C	DenseNet121							
	ACCU		PREC		ACCU		F1-S	
	Adam	SGD	Adam	SGD	Adam	SGD	Adam	SGD
1	0,49	1	0,49	1	0,49	1	0,49	1
2	0,49	2	0,49	2	0,49	2	0,49	2
3	0,49	3	0,49	3	0,49	3	0,49	3
4	0,49	4	0,49	4	0,49	4	0,49	4

For MobileNet, Adam achieved 46% accuracy, with its highest recall (80%) for Sigatoka, while SGD obtained 37% accuracy with perfect recall (100%) for Sigatoka but very low F1-scores (45%). These findings suggest that MobileNet tends to underfit the data due to its lightweight architecture [8].

Table 6. Evaluation of model effectiveness Classification (C) MobileNet

C	MobileNet							
	ACCU		PREC		ACCU		F1-S	
	Adam	SGD	Adam	SGD	Adam	SGD	Adam	SGD
1	0,46	1	0,46	1	0,46	1	0,46	1
2	0,46	2	0,46	2	0,46	2	0,46	2
3	0,46	3	0,46	3	0,46	3	0,46	3
4	0,46	4	0,46	4	0,46	4	0,46	4

For NasNetMobile, performance was the lowest among all tested models. Adam achieved only 22% accuracy, while SGD performed slightly better with 32%. Precision and recall values varied greatly, showing instability and poor generalization.

Table 7. Evaluation of model effectiveness Classification (C) NASNetMobile

C	NASNetMobile							
	ACCU		PREC		ACCU		F1-S	
	Adam	SGD	Adam	SGD	Adam	SGD	Adam	SGD
1	0,22	1	0,22	1	0,22	1	0,22	1
2	0,22	2	0,22	2	0,22	2	0,22	2
3	0,22	3	0,22	3	0,22	3	0,22	3
4	0,22	4	0,22	4	0,22	4	0,22	4

Figure 6 visualizes the comparative accuracy of all CNN architectures under Adam and SGD optimization. Consistent with previous studies [19],[20],[21] deeper architectures such as VGG19 outperform lightweight architectures, confirming the importance of optimizer choice and model depth in disease classification tasks. The following is a graphical visualization based on the accuracy of CNN

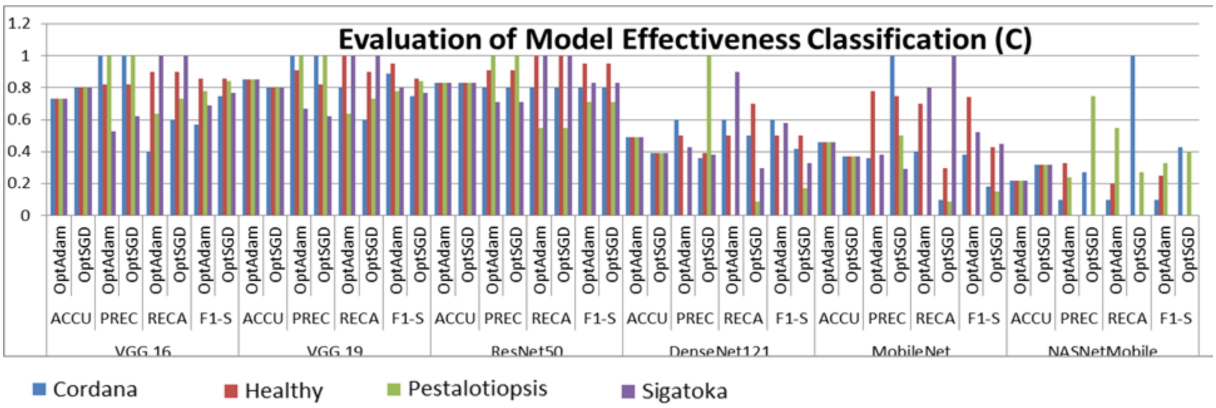


Figure 6. Evaluation of model effectiveness Classification (C)

models using VGG16, VGG19, ResNet50, DenseNet121, MobileNet, and NASNetMobile architectures, using Adam and SGD optimization. An explicit analysis of learning curves further supports this statement, as lightweight models exhibited early convergence with limited accuracy improvement, whereas deeper architecture continued to benefit from extended training, indicating higher representational capacity.

4. Conclusion

This study employed a dataset of 1,652 images with an 80:20 train-test split to evaluate six CNN architectures optimized with Adam and SGD. Among the tested models, NasNetMobile showed the lowest performance, with 22% precision using Adam and 32% accuracy using SGD. In contrast, VGG19 achieved the best results, with 85% accuracy under Adam and 83% with SGD, confirming its effectiveness in banana leaf disease classification. This study addressed two research questions: the impact of optimizer selection on CNN performance for banana leaf disease classification under limited data conditions and the identification of the most effective CNN–optimizer combination. The results show that optimizer choice significantly influences convergence and accuracy, with VGG19 optimized using Adam achieving the best performance, indicating that deeper architectures benefit from adaptive optimization on small datasets. In contrast, lightweight models such as MobileNet and NASNetMobile consistently underperformed, suggesting that limited model capacity restricts their ability to capture fine-grained disease features. It should be noted that the final identification stage employed a relatively small number of test samples (10–11 images per class), which may limit the statistical reliability of the reported class-wise metrics. These results should therefore be interpreted as indicative rather than definitive.

The future work of this study will focus on extending the dataset to include additional banana leaf disease categories, applying k-fold cross-validation and cross-dataset evaluation to improve statistical robustness, exploring different input image resolutions and training iterations, and investigating deployment-oriented optimizations for real-world agricultural monitoring systems.

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