Journal of Computer Networks, Architecture and High Performance Computing
Volume 08, Number 1, Januari 2026
https://doi.org/10.47709/cnapc.v8i1.7501

Submitted: 2025-12-14
Accepted: 2025-12-28
Published: 2026-01-19

Effects of Adam and SGD on ResNet50 Transfer Learning for Palm Leaf Disease Classification

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ABSTRACT

Plants from the palm tree family (Arecaceae), such as coconut, oil palm, and date palm, have an important role in the economy and food security,especially in Indonesia.However, leaf diseases such as leaf spot disease pose a serious threat that can reduce productivity.Manual disease identification is time-consuming and prone to errors, necessitating an image-based automatic classification system.This study aims to apply the ResNet50 Convolutional Neural Network (CNN) architecture for palm tree leaf disease classification and compare two popular optimization algorithms, Adam and Stochastic Gradient Descent (SGD),in terms of model training accuracy and efficiency.The dataset used is public, covering five classes of leaf images: Healthy, White Scale, Brown Spot, Leaf Smut, and Bacterial Leaf Blight.The research process includes data collection and preprocessing (resizing, normalization, and augmentation), dividing the dataset into three parts, namely training, validation, and testing data using the train/validation/test split approach.This approach provides a fairly representative evaluation of model performance while being computationally efficient.Model training was performed using transfer learning with ResNet50, and performance evaluation was performed using a confusion matrix to obtain accuracy, precision, recall, and F1-score values. The results of the two optimizers were compared to determine their effect on model performance. The experimental results show that the ResNet50 model optimized with Adam achieved a higher test accuracy of 99.57% compared to SGD with 99.15%,along with consistently strong precision, recall, and F1-score across all classes.This performance advantage is attributed to Adam's adaptive learning rate and moment estimation mechanism, which enable faster convergence and more effective optimization during training.

Keywords: *Adam; CNN; Palm Tree; ResNet50; SGD;*

INTRODUCTION

Plants from the Palm Tree family (*Arecaceae*), such as coconut (*Cocos nucifera*), oil palm (*Elaeis guineensis*), and date palm (*Phoenix dactylifera*), have a strategic role in the economic sector and food security of tropical countries. Coconut itself is a multifunctional commodity, with almost all parts of the plant being used for food, cosmetics, renewable energy, and handicrafts. Asian and Pacific countries are the world's largest coconut producers, with Indonesia producing a total of 17.19 million tons in 2022 (Punzalan & Rosentrater, 2024). In addition to being an important export commodity, coconuts also serve as the primary source of livelihood for millions of small farmers in various regions of Indonesia (Vaulina et al., 2024).

One of the main problems in palm cultivation is leaf diseases such as leaf spot diseases, which can threaten the health of trees and cause significant crop losses. The symptoms of leaf diseases often have visual similarities between species, making them difficult to distinguish manually using conventional methods. Early detection plays a crucial role in effective disease management, as timely identification and classification can help stakeholders take targeted interventions to minimize negative impacts on ecosystems and human livelihoods (Soujanya & Aravind, 2024). The process of identifying plant diseases is generally carried out through manual inspection in the field. This method requires a lot of time, energy, and skill, but it still has limitations because it is prone to human error and is inefficient when applied to large-scale agricultural land. These limitations emphasize the need for an automated detection system that is faster, more accurate, and more consistent. One widely used approach is digital image analysis to identify disease symptoms through color, texture, and leaf shape characteristics. Among various techniques, Convolutional Neural Networks (CNN) stand out as they are capable of learning patterns directly from image data without the need for manual feature extraction (González-Briones et al., 2025).

In developing a leaf image-based plant disease classification system, selecting the right CNN model architecture is an important factor in determining the accuracy and efficiency of the training process. One of the most widely used architectures is the Residual Network (ResNet), specifically ResNet50. The use of ResNet50 has also been proven effective in the context of leaf image-based plant disease classification. The results of model evaluation in a study

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conducted by (Jayashree & Sumalatha, 2024) show that the ResNet50 model for leaf image-based plant disease classification is capable of achieving an accuracy of 95.1%, precision of 96.5%, and recall of 95.7%. In addition, research conducted by (Kulsum & Cherid, 2023) shows that using the ResNet50 model for apple leaf disease classification can achieve an accuracy value of 91%.

Although various studies such as (Magsi et al., 2020) and (Ahmed & Ahmed, 2023) have already discussed the use of Convolutional Neural Networks (CNN) for automatic leaf image-based plant disease classification with high accuracy, most of these studies focus on model architecture without considering the impact of optimization algorithm selection on model performance. Most existing works evaluate model architectures, yet do not isolate the role of optimizer choice in convergence stability and generalization,this study fills that gap. This limitation represents a clear research problem, as the lack of optimizer-centered analysis hinders a comprehensive understanding of model convergence behavior and generalization performance in palm tree leaf disease classification. Research by (Choi et al., 2020) shows that the selection of an optimizer has a significant impact on deep learning model performance, particularly in terms of convergence rate, training stability, and generalization ability. They found that although Adam often produces faster convergence at the beginning of training, SGD can sometimes achieve higher final accuracy and a more stable model on new data. To date, there has been minimal research that explicitly compares the performance of various optimizers such as Adam and SGD in the context of palm tree leaf disease classification using the ResNet50 architecture.

Based on these issues, this study focuses on examining how the choice of optimizer (Adam and SGD) affects the classification performance of a ResNet50-based model for palm tree leaf disease detection. This comparison is expected to provide insights into the impact of optimization algorithm selection on model accuracy and training efficiency, as well as support the development of a more effective deep learning-based plant disease detection system. Accordingly, the main research question addressed in this study is: How does the choice of optimization algorithm Adam and SGD affect the classification performance of a ResNet50-based model for palm tree leaf disease detection?.

LITERATURE REVIEW

Previous studies have shown that Deep Learning, particularly Convolutional Neural Networks (CNN), has been widely used in the classification of diseases in oil palm trees. CNN has been proven capable of recognizing complex patterns in leaf images, making it effective for the identification and analysis of plant diseases. Various studies show that CNN can provide high classification performance for coconut, oil palm, and date palm plants, which are taxonomically classified as palm trees.

(Abimanyu et al., 2025) developed a Sequential architecture-based CNN model to identify oil palm leaf diseases and achieved an accuracy of 91.25% with the Adam optimizer. This study confirms that the choice of optimizer affects the quality of training, although the study did not directly compare several optimizers. Another study conducted by (Mandiri et al., 2025) using AlexNet on a palm oil leaf dataset showed that data augmentation can increase pattern variation and aid the model generalization process, although the test accuracy was still in the range of 79%.

In other types of palm trees, several studies also show the effectiveness of CNN in detecting leaf diseases. (Abu-zanona et al., 2022) demonstrated that simple CNN, VGG16, and MobileNet were able to identify four major diseases of date palms with an accuracy of over 99%, especially when using high-resolution image datasets and optimal preprocessing. Meanwhile, (Alaa et al., 2020) utilized CNN and SVM to detect Leaf Spot and Blight Spots diseases in date palms as well as the Red Palm Weevil (RPW) pest, showing that a combination of methods can produce high accuracy for various types of leaf anomalies.

The performance of the ResNet architecture has also been extensively tested in the context of plant disease detection. (Jayashree & Sumalatha, 2024) applied ResNet50 for plant leaf disease classification and achieved an accuracy of over 95%. A similar study was conducted by (Ahmed & Ahmed, 2023), who compared ResNet, Inception-ResNet, and the modified variant MResNet. The results showed that MResNet provided the highest accuracy, namely 99.62% on the original dataset and 100% on the augmented dataset. Across these studies, ResNet50 consistently outperforms shallow architectures due to its residual skip connections, which facilitate deeper feature learning and mitigate vanishing gradient problems. Research by (Sun, 2020) provides a comprehensive theoretical analysis of deep learning optimization, explaining how learning rate scheduling, momentum accumulation, and weight decay regularization critically influence convergence speed, training stability, and generalization performance. The study highlights that adaptive optimizers such as Adam dynamically adjust learning rates using first- and second-order moment estimates, whereas SGD relies on carefully designed learning rate schedules and momentum to achieve stable optimization and improved generalization. Despite the well-established theoretical importance of these mechanisms, optimizer choice remains underexplored in palm tree leaf disease classification studies using ResNet50.

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In addition to the classical CNN-based approach, other studies utilize additional algorithms such as ensemble learning, YOLOv10, and Random Forest Group to detect oil palm leaf diseases from UAV images and field images. (Lestandy & Nugraha, 2025) showed that DenseNet and ensemble CNN were able to achieve validation accuracy above 88%, while (Kurniawan & Nurcahyo, 2025) used YOLOv10 for object detection and obtained a mAP@0.5 of 75.3%. However, these methods focus more on object detection than on detailed leaf disease classification.

Based on related studies, it can be concluded that CNN and its architectural variants have provided excellent results in detecting plant leaf diseases, including plants from the palm tree family. However, most studies have focused more on model architectural variations and have not given full attention to systematic comparisons between optimizers, particularly Adam and SGD, in the context of the ResNet50 architecture. Therefore, this study attempts to fill this gap by comparing the two optimizers to gain a more complete understanding of their influence on accuracy, model stability, and training efficiency in palm tree leaf disease classification.

METHOD

This research was conducted in several stages, starting from dataset collection, preprocessing of palm tree leaf images, dataset division, design of a ResNet50-based model architecture, implementation of two training scenarios using Adam and SGD optimizers, to model evaluation based on various performance metrics. All stages were designed to obtain an optimal palm tree leaf disease classification model and enable comparative analysis of the two optimizers used. The research process is systematically divided into several stages as shown in Figure 1 :

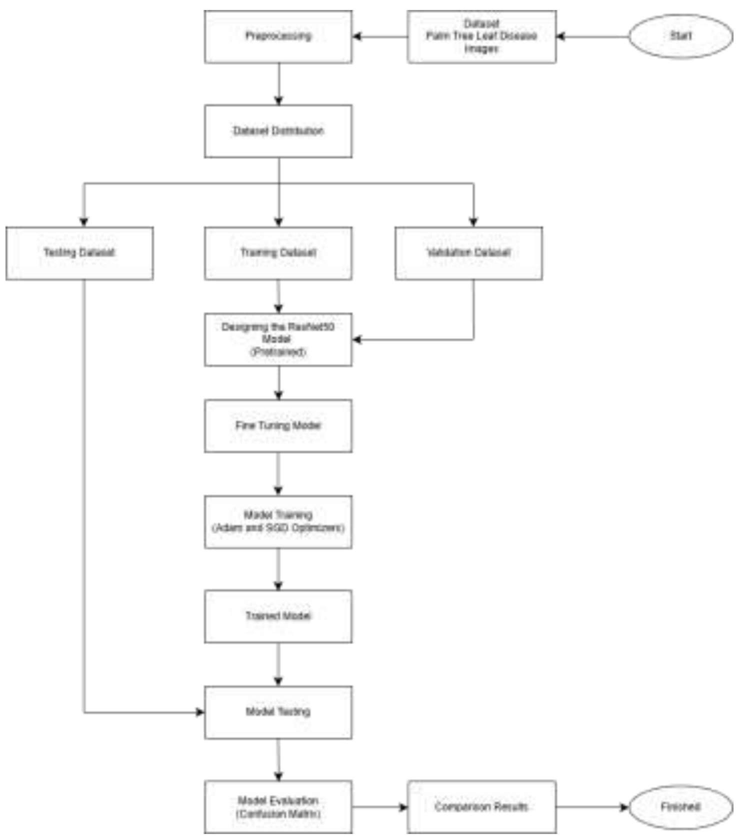

Fig. 1 Research Stages

A. Data Collection

The dataset used in this study consisted of five classes of palm tree leaf images, namely Healthy, White Scale, Brown Spot, Leaf Smut, and Bacterial Leaf Blight. Each class contains 470 images, bringing the total data to 2,350 images. The dataset was obtained from two public datasets on the Kaggle platform, namely Date Palm made by (Hamaidi, 2018) and Leaf_Disease_3 made by (Research27, 2019), both of which provide palm tree leaf images with varying lighting conditions, shooting angles, and disease severity levels. All images are in color and have varying resolutions, providing a rich visual representation for model training.

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These datasets were selected because they provide leaf disease categories that are relevant and consistent with the research objective, which is to classify five main classes of palm tree leaves. The balanced distribution of images in each class (470 images) is an additional advantage, as it helps reduce potential bias during the model training process. This dataset also provides sufficient visual variation to support the model generalization process in recognizing leaf damage patterns in various real conditions.

B. Data Preprocessing

The preprocessing stage was carried out to prepare the images to suit the needs of the ResNet50 architecture. All images were resized to 224 × 224 pixels to match the ResNet50 input requirements and were normalized using the ImageNet preprocessing function. To improve generalization and mitigate overfitting, data augmentation was applied exclusively to the training set with controlled intensity. The augmentation strategy included random rotations up to ±20 degrees, horizontal shifts and vertical shifts up to 15%, shear transformations up to 15%, zoom variations within a 15% range, horizontal flipping, and brightness adjustments within the range of 0.9 to 1.1. Vertical flipping was not applied to preserve the natural orientation of leaf structures. These augmentation parameters were selected to introduce realistic visual variability while maintaining disease-related patterns.

C. Data Splitting

Dataset splitting was performed using a fixed random seed with a value of 42 to ensure consistent data partitions across experimental runs. This fixed seed guarantees that variations in model performance are attributable to optimizer behavior rather than random data allocation.Then the dataset was divided explicitly into three subsets using an 80/10/10 ratio, corresponding to training, validation, and test sets, respectively. The training set was used for model learning, the validation set for monitoring performance and tuning hyperparameters, and the test set for final evaluation. This explicit split prevents information leakage and enables an objective assessment of generalization performance.

D. Modeling (ResNet50 with Transfer Learning)

In the modeling stage, the ResNet50 model pretrained on the ImageNet dataset was employed as the backbone network using a transfer learning approach. During the initial feature extraction phase, all layers of the ResNet50 backbone were frozen to retain generic visual representations. The classification head consisted of a Global Average Pooling layer, Batch Normalization, a fully connected layer with 256 neurons using ReLU activation and L2 regularization, a Dropout layer with a rate of 0.3, and a Softmax output layer corresponding to the five disease classes. Training was conducted in two stages: feature extraction and fine-tuning. In the fine-tuning stage, the top 40 layers of the ResNet50 backbone were unfrozen, while Batch Normalization layers remained frozen to maintain training stability.

E. Implementation

The model implementation was carried out in two separate scenarios, using the Adam and SGD optimizers. Both scenarios used the same training parameters for a more objective comparison. The implementation parameters are as shown in Table 1:

Table 1
Model Parameter

Parameter	Configuration
Input Image Size	224 x 224
Dense	256
Batch Size	32
Epoch	200
Seed	42
Early Stop, Patience	Yes, 15
Optimizer	Adam, SGD
Learning Rate (Adam and SGD)	0.001
Activation Function	ReLU + Softmax

These parameters are taken directly from the research design in the Final Project document and adjusted to common practices in transfer learning-based deep learning model training. The use of two optimizers allows for a

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more comprehensive performance analysis based on training stability, convergence speed, and model generalization quality.

RESULT

This section presents the results of testing the performance of the ResNet50 model trained using two optimizers, namely Adam and Stochastic Gradient Descent (SGD), on a dataset of palm tree leaf diseases consisting of five classes. The evaluation was carried out using test data to assess the model's generalization ability, as well as validation data to support the training stability analysis. The evaluation metrics used include accuracy, loss, precision, recall, and F1-score.

A. Performance of ResNet50 with Adam Optimizer

Testing results on the test data show that the ResNet50 model trained using the Adam optimizer achieved a test accuracy of 99.57% with a test loss of 0.4033. This value indicates that the model is capable of classifying palm tree leaf diseases with a good level of accuracy on data that was never seen during the training process. Meanwhile, on the validation data, the model obtained a validation accuracy of 99.99% with a validation loss of 0.4017, which indicates high training performance but potentially shows a difference between the validation performance and the test data. A visualization of the confusion matrix for the model testing results with the Adam optimizer is shown in Figure 2 to provide an overview of the distribution of correct and incorrect predictions for each leaf disease class. In addition, a graph comparing the accuracy values during the testing process is shown in Figure 3 to support the model performance analysis.

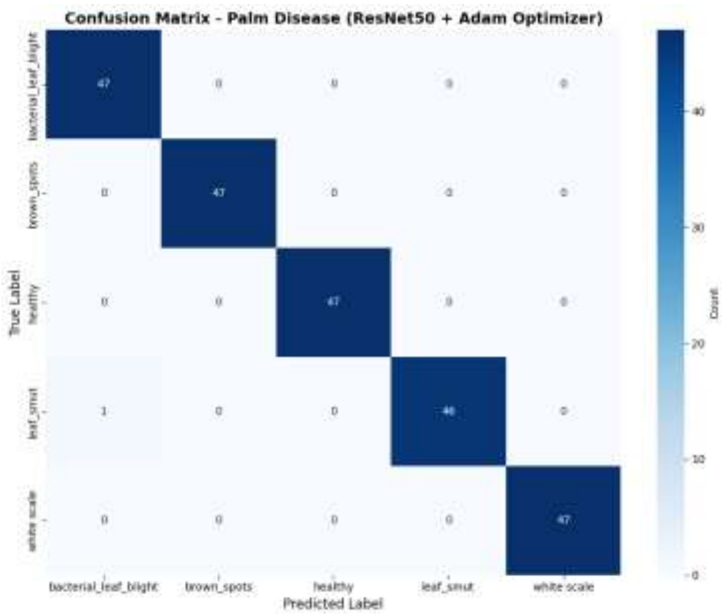

Fig. 2 Confusion Matrix Model With Adam

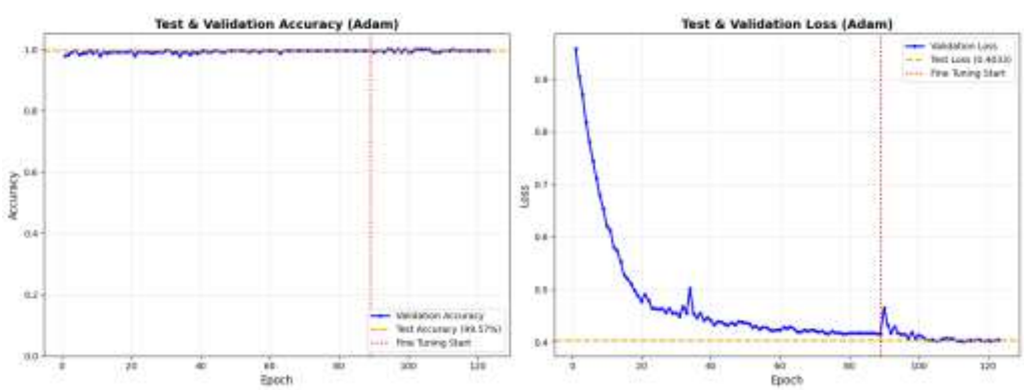

Fig. 3 Test and Validation Accuracy/Loss Adam

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Based on the classification report, the Adam model showed excellent performance in the brown spots, healthy, and white scale classes, with high precision and recall values. The white scale class achieved perfect precision, recall, and F1-score values, indicating that the model was able to recognize the visual patterns of this class very consistently. However, in the bacterial leaf blight and leaf smut classes, the model's performance was relatively lower than in other classes. This was reflected in smaller recall and F1-score values, indicating that the model had a little difficulty distinguishing disease patterns in these two classes. The precision, recall, and F1-score values for each class in the Adam optimizer scenario are summarized in Table 2 to provide a more structured comparison of performance between classes.

Table 2
Precision, Recall, and F1-Score of Adam Optimizer

Class	Precision	Recall	F1-score
bacterial_leaf_blight	0.98	1.00	0.99
brown_spots	1.00	1.00	1.00
healthy	1.00	1.00	1.00
leaf_smut	1.00	0.98	0.99
white scale	1.00	1.00	1.00

B. Performance of ResNet50 with SGD Optimizer

In the training scenario using the SGD optimizer, the ResNet50 model achieved a test accuracy of 99.15% with a test loss of 0.9154. Although the test accuracy value is slightly lower than that of the Adam optimizer and the loss values relatively high, the model's performance remains competitive. On the validation data, the model achieved a validation accuracy of 98.72% with a validation loss of 0.9197, which shows consistency between the validation performance and the test data. The confusion matrix of the model testing results using the SGD optimizer is presented in Figure 4 to show the classification error patterns in each class. The test and validation accuracy graph for the SGD optimizer is also displayed on Fig 5 to support the model performance evaluation.

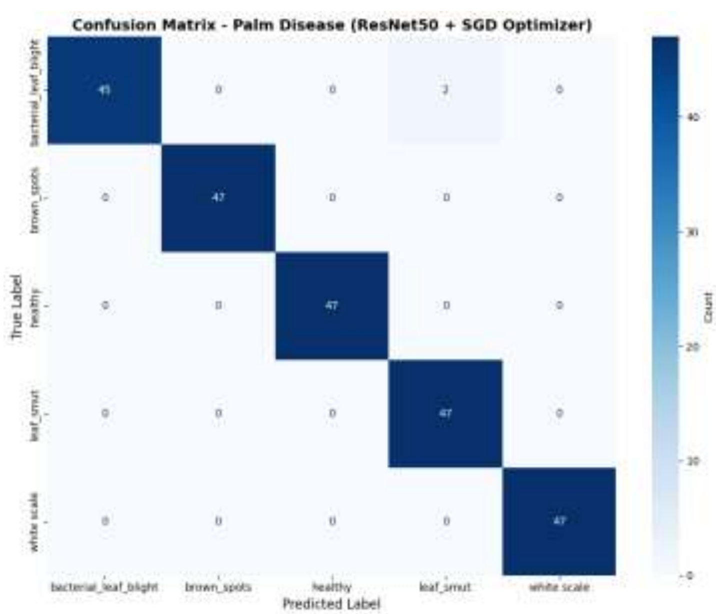

Fig. 5 Confusion Matrix Model With SGD

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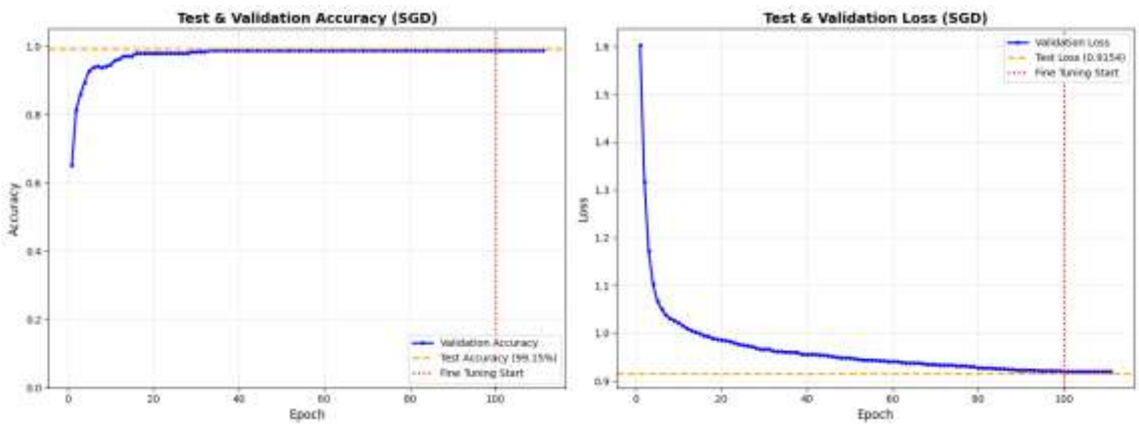

Fig. 6 Test and Validation Accuracy/Loss SGD

The classification report results indicate that the ResNet50 model optimized with SGD achieves consistently high performance across all classes. The brown spots, healthy, and white scale classes demonstrate perfect precision and recall values, indicating that the model is able to recognize these classes without misclassification. The bacterial leaf blight class also shows strong performance with high precision and recall values, suggesting that the model effectively captures the distinguishing features of this disease. Similarly, the leaf smut class achieves high precision and perfect recall, indicating robust and reliable classification. Overall, the performance distribution across all classes using the SGD optimizer is highly balanced, reflecting the model's strong generalization capability despite a slightly lower overall accuracy compared to the Adam optimizer. The precision, recall, and F1-score values for each class in the SGD optimizer scenario are summarized in Table 3 to provide a more structured comparison of performance between classes.

Table 3
Precision, Recall, and F1-Score of SGD Optimizer

Class	Precision	Recall	F1-score
bacterial_leaf_blight	1.00	0.96	0.98
brown_spots	1.00	1.00	1.00
healthy	1.00	1.00	1.00
leaf_smut	0.96	1.00	0.98
white scale	1.00	1.00	1.00

C. Comparison of Adam and SGD Results

Based on the test results, the Adam optimizer produced a higher test accuracy value than SGD, while SGD showed a smaller difference between validation accuracy and test accuracy. This difference indicates that Adam is superior in achieving high training performance, while SGD provides more consistent stability between the training and testing processes. These results form the basis for further discussion of the characteristics of each optimizer in the Discussion section.

DISCUSSIONS

This section discusses and interprets the research results obtained from the training and testing process of the ResNet50 model using two different optimizers, namely Adam and SGD. The discussion focuses on the meaning behind the model's performance, the factors that affect generalization quality, and how these findings relate to previous research in the field of plant leaf disease classification. Additionally, this section reviews potential biases in the dataset and methodological limitations that may affect the consistency of results and provides direction for further research development.

A. Comparison with Related Deep Learning Models

Several previous studies on leaf disease detection in plants, particularly plants from the palm family, have shown that deep learning methods such as CNNs are capable of delivering high performance. For example, a study by (Abu-zanona et al., 2022),used CNN and VGG16 models to identify four major diseases in date palm leaves and achieved very high accuracy. Their findings show that CNN-based architectures with transfer learning are very effective in handling the visual variation and complexity of diverse leaf disease patterns. In addition, research by (Magsi et al.,

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2020) using CNN to detect Sudden Decline Syndrome (SDS) disease in date palm leaves also showed good results, confirming that deep learning methods consistently provide competitive performance in the palm tree domain.

When compared to that study, the results of this study show that ResNet50 is also capable of providing strong performance in palm tree leaf disease classification. The differences that arise mainly lie in the use of optimizers. The faster convergence observed when using the Adam optimizer in this study is consistent with findings reported by (Selvakumari & Durairaj, 2025), who describe Adam as achieving fast convergence by combining momentum and adaptive learning rates. In contrast, the same study describes SGD as a basic optimizer that is simple and computationally efficient, yet highly dependent on the selection of an appropriate learning rate, which constitutes a major performance bottleneck. These complementary characteristics explain why Adam converges rapidly during early training stages, whereas SGD tends to exhibit slower but more stable convergence behavior. Thus, this study reinforces the literature that the choice of optimizer can affect the stability and performance of models in the plant image domain, especially in datasets with complex disease patterns such as Brown Spot or Bacterial Leaf Blight.

B. Dataset Challenges and Generalization Bias

This study uses a dataset from a single combined source, namely two Kaggle datasets that have relatively homogeneous image characteristics in terms of background, shooting angle, and lighting conditions. This has the potential to create visual bias, because the model may learn to recognize certain patterns associated with specific shooting styles or environmental conditions, rather than purely leaf disease patterns. In addition, all disease classes have the same number of images (470 images per class), so the dataset appears quantitatively balanced but does not necessarily reflect natural visual variation in the field.

This bias can affect the model's generalization ability when faced with images of palm tree leaves from different locations, camera devices, or lighting conditions. For example, Brown Spot or Leaf Smut diseases may exhibit a wider range of colors in outdoor environments that are not covered in the dataset. This potential bias indicates that although the model performs well on internal test data, its performance in real-world environments or on more diverse image populations may differ. Therefore, further research should consider using multi-source datasets from various geographical conditions and photographic environments to improve model generalization.

C. Limitations of the Optimization Approach

Several limitations of this study should be noted. First, although the dataset size was balanced for the five leaf disease classes, the overall dataset size (2,350 images) is still relatively small for a deep learning architecture such as ResNet50. A relatively small dataset increases the risk of overfitting, especially with the Adam model, which tends to be more sensitive to variations in training data. Although image augmentation has been applied to enrich visual variation, the limited amount of real data remains a factor that needs to be considered.

The second limitation is the use of two training stages, namely feature extraction and fine tuning, each with a different number of epochs. Although this approach provides greater flexibility in the learning process, it can also make the model sensitive to the selection of learning rates and other training parameters. Furthermore, the comparison between Adam and SGD was only conducted on one model architecture, namely ResNet50. Optimization algorithms may show different performance when used on other architectures such as EfficientNet, MobileNet, or DenseNet.

Although the SGD-optimized ResNet50 model achieved very high accuracy on both validation and test datasets, the corresponding loss values remain relatively high. Additionally, early stopping and learning rate constraints during the fine-tuning phase may have limited further loss minimization. This suggests that accuracy alone may not fully represent the confidence calibration of the model, and future work should consider loss optimization strategies or calibration techniques to improve prediction reliability.

For further research, several directions that can be taken include the use of larger and more varied datasets, cross-architecture evaluation to see the consistency of optimizer performance, and the integration of interpretability methods to improve model transparency. This approach is expected to produce a palm tree leaf disease classification system that is more accurate, stable, and applicable in real field conditions.

CONCLUSION

This study shows that the ResNet50 architecture based on Convolutional Neural Network can be effectively applied to classify palm tree leaf diseases into five classes, namely Healthy, White Scale, Brown Spot, Leaf Smut, and Bacterial Leaf Blight. Through a transfer learning approach combined with preprocessing and data augmentation, the model achieved a test accuracy of 99.57% using the Adam optimizer and 99.15% using the Stochastic Gradient Descent (SGD) optimizer. These results indicate that both optimizers provide competitive performance in palm tree leaf disease classification, with Adam demonstrating superior overall performance in this study.

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Furthermore, a comparison of the two optimizers reveals differences in learning characteristics that affect model performance. The Adam optimizer consistently produces higher accuracy and more effective loss minimization, while SGD exhibits more stable validation and test behavior. These results highlight that optimizer choice is not merely a training parameter, but a design decision shaping convergence stability and generalization. Therefore, when the primary objective is to achieve maximum classification accuracy and lower loss, Adam is a more suitable optimization choice for this task.

Although the results obtained are quite promising, this study still has several limitations, such as the relatively limited dataset size and the use of a single deep learning architecture. Therefore, further research is recommended to use larger and more diverse datasets, explore various architectures and other optimization strategies, and integrate model interpretability methods so that the palm tree leaf disease classification system can be more reliable and applicable in real-world conditions in the field.

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