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Optimizer Evaluation for Maize Leaf Disease Using Transfer Learning with MobileNetV3-Small

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Abstract

Manual identification of maize leaf disease presents significant challenges, including time-consuming processes, dependence on expert availability, and a high risk of misdiagnosis due to similar symptoms among different diseases. These limitations often lead to delays in disease management, unstable crop yields, and economic losses for farmers. This study aims to address these issues by evaluating the performance of different optimizers in classifying maize leaf disease using transfer learning with the MobileNetV3-Small architecture. A total of 2,850 images of maize leaf disease were used and divided into training, validation, and testing sets. Model evaluation involved systematically comparing the Adam, RMSprop, and SGD optimizers by training each configuration under identical conditions and assessing the resulting model performance. The results show that the RMSprop optimizer provides the best performance with 92.98% accuracy, 93.08% precision, 92.98% recall, and 92.98% F1-score. Based on the evaluation, selecting an appropriate optimizer is essential to improve accuracy and reliability of transfer learning models in maize leaf disease classification. These findings highlight the potential to advance smart agricultural systems by enabling more accurate disease detection, which can reduce crop failure risks and enhance disease management in maize production.

Keywords: Maize Leaf Disease, CNN, Transfer Learning, MobileNetV3-Small, Optimizer

1. INTRODUCTION

Maize (Zea mays L.) plays a crucial role as a major agricultural commodity and a staple food after rice. It has significant economic value due to its diverse uses, including food, industrial raw materials, and animal feed [1]. Data from Badan Pusat Statistik (BPS) reveals an unstable trend in maize production over the last three years. Production reached 16.53 million tons in 2022 but decreased to 14.77 million tons in 2023. Production increased again in 2024 to 15.14 million tons but remained below the 2022 level. This data indicates fluctuations that reflect low maize productivity due to various factors.

Climate change is one of the main factors influencing the plant life cycle [2]. Unpredictable weather causes variations in temperature and humidity that make plants more vulnerable to disease attacks. These diseases are often caused by pests

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and microorganisms such as fungi, bacteria, and viruses that attack plant organs and ultimately cause plant death [3]. Currently, plant disease identification is mostly done manually by visual inspection. This approach is limited by time constraints, costs, physical accessibility, and the availability of resources [4]. Additionally, manual diagnosis is prone to errors, especially when diseases have similar symptoms. If untreated, this can affect maize quality, reduce production stability, and cause economic losses.

Advances in artificial intelligence and image processing have provided a robust solution for automated leaf disease identification by enabling recognition of complex visual patterns. One of the most effective deep learning methods for image classification is Convolutional Neural Network (CNN) [5], which extracts features at multiple scales and achieves high accuracy [6]. Furthermore, CNN accelerates model development by utilizing GPU power to efficiently manage repetitive computations [7], leading to faster convergence and improved training performance. Architectures like VGG16 [8], ResNet50 [9], and DenseNet201 [10] have excelled in plant disease classification. Nonetheless, these advanced models often require substantial computation, increased memory usage, or lack portability [11]. Among the available architectures, MobileNetV3 stands out as a lightweight alternative that overcomes such constraints while offering impressive accuracy and efficiency for image classification tasks [12]. The MobileNetV3- Small variant has demonstrated reliable performance across a range of similar tasks according to recent studies [5], [13], and [14], proving highly adaptable for deployment on low-performance mobile devices as well as embedded systems.

Despite the proven advantages of MobileNetV3-Small in plant disease image classification, there remains a distinct gap in evaluating how different optimizers influence model performance when integrated with transfer learning. Previous research has only compared model architectures, overlooking training strategies such as optimizer selection that may affect overall model performance. Detailed assessment of optimizers such as Adam, RMSprop, and SGD is needed to clarify effects on classification accuracy and training stability for plant disease detection. Addressing this research gap through focused performance evaluations enables identification of more optimal strategies for accurate and efficient plant disease detection. Filling this gap will guide the development of automated systems for practical deployment in real-world agricultural environments.

This study aims to evaluate the performance of optimizers in maize leaf disease classification by identifying which optimizer among Adam, RMSprop, and SGD achieves the highest training accuracy and stability through the application of transfer learning and MobileNetV3-Small architecture. Recommendations for selecting the optimal training strategy are developed by thoroughly examining the classification accuracy, model efficiency, and learning consistency. The results of

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this study empower farmers to make timely decisions and help minimize crop losses. In addition, there is potential for intelligent disease detection systems to be integrated into mobile devices and modern agricultural technologies so that the adoption of smart farming practices can progress more rapidly.

2. METHODS

The research flow consists of several key stages that guide the development and assessment of the proposed model as shown in Figure 1. Each stage is structured to ensure the model is accurate and reliable for maize leaf disease classification.

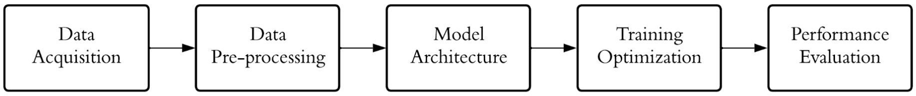

Figure 1. Research Flow

2.1. Data Acquisition

The dataset used in this study was obtained from the Dataset for Crop Pest and Disease Detection [15], which contains plant images in both healthy and diseased conditions. Since the original dataset includes images of various diseases and pests affecting different types of crops, only images related to maize leaf diseases were selected for this research to ensure relevance to the study objectives. All images were captured using high-resolution cameras and saved in JPG format, with dimensions ranging from 400 by 400 to 4032 by 3024 pixels. From the total of 3,244 available images, a subset of 2,850 images was chosen proportionally from three maize leaf disease categories in order to avoid bias during model training. These selected images represent three distinct disease categories, which are Maize Leaf Blight, Maize Leaf Spot, and Maize Streak Virus. Each of these disease categories is shown in Figure 2 with corresponding sample images.

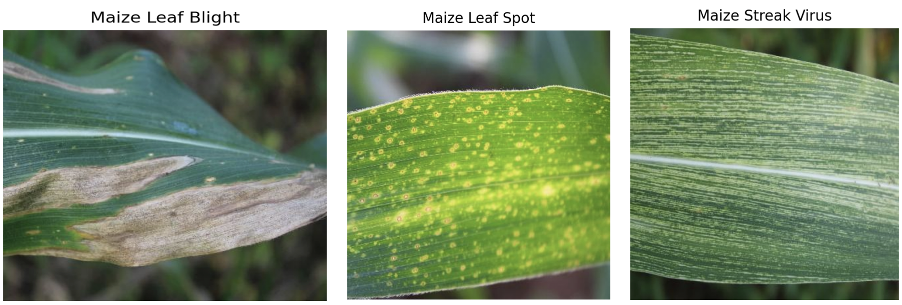

Figure 2. Maize Leaf Disease

2.2. Data Pre-processing

Pre-processing is an essential step that ensures the data are properly prepared for classification purposes. Improving image quality at this stage allows the model to learn more effectively during training [16]. In this study, specific techniques were used to optimize the dataset for the modeling process. The data pre-processing steps consisted of image resizing, data augmentation, and data splitting. This preparation ensures the input data are well suited for training and supports better performance of the classification model.

2.2.1. Image Resizing

The maize leaf disease images in the dataset have various dimensions, so it was important to standardize the image sizes for this study. Adjusting the dimensions of each image creates a uniform dataset and is expected to reduce computation time during model training [17]. Every image was resized to 224 x 224 pixels to match the standard input size required by the model. Figure 3 shows results of the resizing process by providing a clear comparison between images before and after adjustment.

Figure 3. Image Size Adjustment

2.2.2. Data Augmentation

Augmentation provides an effective way to build models that are generalizable and enhance system robustness, especially when the amount of training data is limited [18]. Various image transformations were used to enrich the dataset by applying suitable parameter values for each technique. Images were randomly rotated up to 40 degrees, shifted horizontally and vertically by 0.2, subjected to shear and zoom of 0.2, with only horizontal flipping applied and brightness adjusted within a range from 0.6 to 1.0 to improve illumination conditions. Figure 4 shows examples of

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images produced through this augmentation process. The dataset size for each class was increased twofold to help prevent overfitting during model training. Increasing data diversity in this manner enables the model to better recognize a wide range of visual patterns.

Figure 4. Data Augmentation Examples

2.2.3. Data Splitting

After augmentation, the dataset was split to achieve balanced representation for each class. The data were divided into three subsets, assigning 80% for training, 10% for validation, and 10% for testing. Proportional sampling was applied to ensure that each subset included the same class distribution as the overall dataset. During the splitting process, images were randomly selected within each class to reduce selection bias and ensure fairness in model assessment. By maintaining balanced class proportions throughout all subsets, the evaluation results provide an accurate reflection of model performance. Details of the data distribution are shown in Table 1.

Tabel 1. Distribution of Maize Leaf Disease

Name of Disease	Original	Augmented	Train	Val	Test	Total
Maize Leaf Blight	950	950	1,520	190	190	1,900
Maize Leaf Spot	950	950	1,520	190	190	1,900

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Name of Disease	Original	Augmented	Train	Val	Test	Total
Maize Streak Virus	950	950	1,520	190	190	1,900
Total	2,850	2,850	4,650	570	570	5,700

2.3. Model Architecture

Convolutional Neural Network (CNN) was developed to read digital information and extract features for computer vision tasks such as image classification [19]. MobileNetV3 stands out as a lightweight Convolutional Neural Network (CNN) architecture introduced by Google in 2019 as an improvement over previous model. This architecture integrates Squeeze and Excitation (SE) modules with channel attention, residual connections and depth wise separable convolutions to reduce parameters while also enhancing overall network performance [20]. Image classification is carried out using MobileNetV3-Small as the backbone network. MobileNetV3-Small was selected for its efficiency and its capability to maintain high accuracy, even when applied to datasets of limited size. Employing this model facilitated the extraction of distinctive features from maize leaf disease images, contributing to reliable classification outcomes.

2.4. Training Optimization

Optimization became an important part of neural network training to improve model stability, generalization, and convergence rate [21]. A transfer learning strategy was adopted by utilizing MobileNetV3-Small as the pre-trained base model on the ImageNet dataset. Transfer learning offers an efficient approach, removing the need to construct and train a model from scratch. The pre-trained model provides a broad set of features that are useful for diverse computer vision problems [22], including the classification of maize leaf diseases. Model parameters learned from the pre-trained neural network are transferred to the target model to facilitate training with new data [19]. During this process, the final layers of the pre-trained model are excluded so the network operates as a feature extractor [23], and the extracted features are processed by newly added classification layers to generate predictions. This approach enables faster and more accurate model training even when working with limited data [24]. To further optimize the process, three optimizers were applied, namely Adam, RMSprop, and SGD. Adam provides an adaptive learning rate and efficiently handles sparse gradients [25], RMSprop enables robust and consistent training for non-stationary environments [26], and SGD offers simplicity and stable performance [27]. Each optimizer was assessed using the same hyperparameter settings to evaluate the impact on final model performance.

2.5. Performance Evaluation

Model performance evaluation was conducted using a confusion matrix, which presents classification results based on the number of correct and incorrect predictions for each maize leaf disease class. Each confusion matrix enabled comparison of model performance across all optimizers and disease classes. The confusion matrix provides values for True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are then used to calculate accuracy, precision, recall, and f1-score using equations (1), (2), (3), and (4) [28].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2\ x\ Recall\ x\ Precision}{Recall + Precision} \tag{4}$$

3. RESULTS AND DISCUSSION

This section presents the experimental results and analysis of maize leaf disease classification using transfer learning with the MobileNetV3-Small architecture. Various evaluation metrics are used to show the accuracy and reliability of the model across different optimizers. All models were trained using the same hyperparameter settings, including 100 epochs, an initial learning rate of 0.0001, and a batch size of 32, to ensure consistency during evaluation. The analysis focuses on how well the model classifies images into each leaf disease category. Furthermore, a comparison of optimizer performance is included to highlight the effectiveness of different approaches within the classification task.

3.1. Performance with Adam Optimizer

The model was trained using the Adam optimizer and reached a training accuracy of 0.9543 with a loss of 0.1464. For validation, the model achieved an accuracy of 0.9456 and a loss value of 0.1614. Both the accuracy and loss for training and validation changed in a similar pattern over the training process. Figure 5 shows the full curves of accuracy and loss for both training and validation phases.

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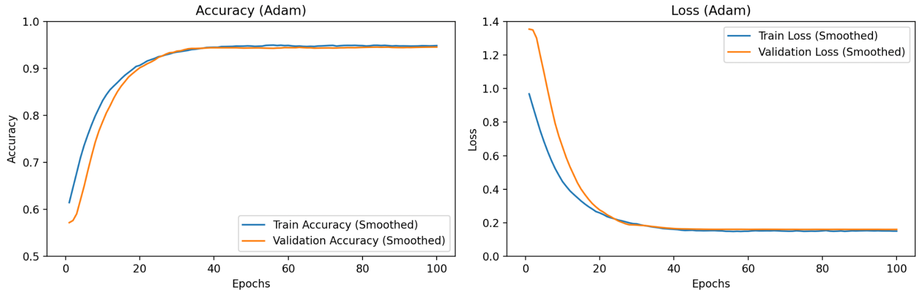
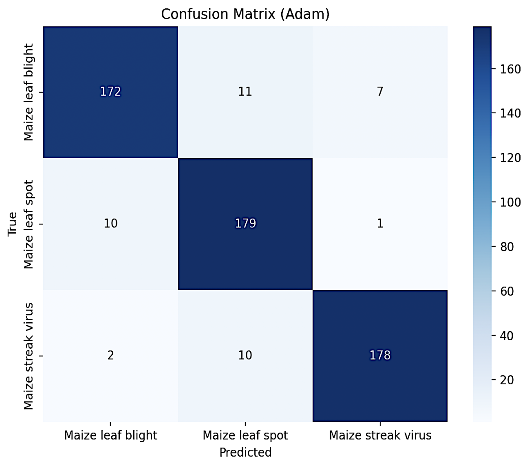


Figure 5. Adam Training Result

On the test data, the confusion matrix shows that 172 samples of Maize leaf blight were classified correctly, while 11 were labeled as Maize leaf spot and 7 as Maize streak virus. In Maize leaf spot, 179 were correct, with 10 as Maize leaf blight and 1 as Maize streak virus. For Maize streak virus, 178 were classified correctly, while 2 were assigned to Maize leaf blight and 10 to Maize leaf spot. The classification report lists precision, recall, and f1-score for each class. Maize leaf blight has 0.93, 0.91, and 0.92, Maize leaf spot has 0.90, 0.94, and 0.92, and Maize streak virus has 0.96, 0.94, and 0.95. Overall accuracy reached 0.93, with macro and weighted averages also at 0.93 for all metrics. These results with the confusion matrix and classification report are shown in Figure 6.

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Classification Report (Adam):
                    precision    recall  f1-score   support

 Maize leaf blight       0.93      0.91      0.92       190
   Maize leaf spot       0.90      0.94      0.92       190
Maize streak virus       0.96      0.94      0.95       190

          accuracy                           0.93       570
         macro avg       0.93      0.93      0.93       570
      weighted avg       0.93      0.93      0.93       570
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Figure 6. Adam Classification Results

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3.2. Performance with SGD Optimizer

Training with the SGD optimizer yielded a training accuracy of 0.8695 and loss of 0.3680. Validation accuracy reached 0.8772 with a loss of 0.3254. The training graph shows validation accuracy quickly exceeded training accuracy and stayed higher throughout, while validation loss remained below training loss after early epochs. Figure 7 presents the complete accuracy and loss curves during training.

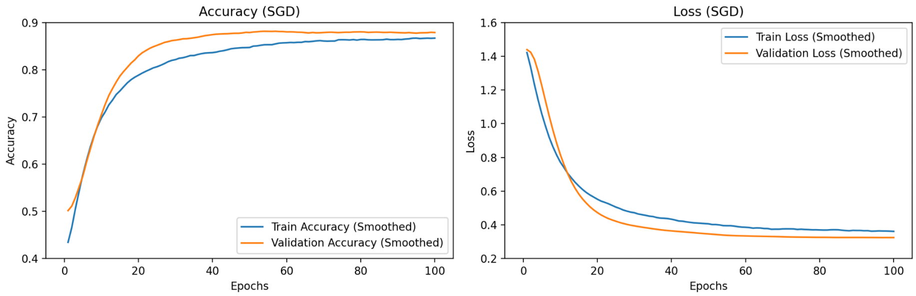
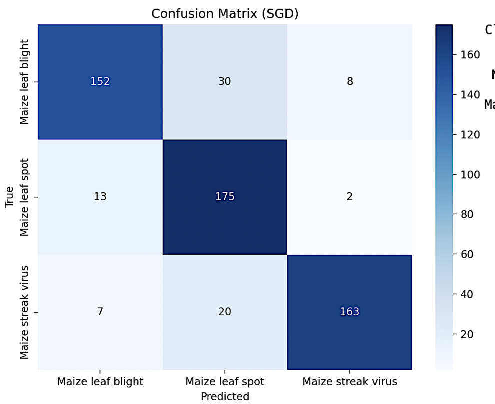


Figure 7. SGD Training Result

Based on the results, 152 samples from the Maize leaf blight class were predicted correctly, while 30 were classified as Maize leaf spot and 8 as Maize streak virus. The Maize leaf spot category had 175 correct predictions, with 13 in Maize leaf blight and 2 in Maize streak virus. In the Maize streak virus group, 163 samples were identified accurately, with 7 assigned to Maize leaf blight and 20 to Maize leaf spot. Precision, recall, and f1-score for Maize leaf blight are 0.88, 0.80, and 0.84, for Maize leaf spot are 0.78, 0.92, and 0.84, and for Maize streak virus are 0.94, 0.86, and 0.90. Overall accuracy is 0.86, with macro and weighted averages for precision of 0.87, recall and f1-score each 0.86. Figure 8 presents these results along with the confusion matrix and classification report for the SGD optimizer.



Classification Report (SGD):

	precision	recall	f1-score	support
Maize leaf blight	0.88	0.80	0.84	190
Maize leaf spot	0.78	0.92	0.84	190
Maize streak virus	0.94	0.86	0.90	190
accuracy			0.86	570
macro avg	0.87	0.86	0.86	570
weighted avg	0.87	0.86	0.86	570

Figure 8. SGD Classification Results

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3.3. Performance with RMSprop Optimizer

The RMSprop optimizer was used to train the model, yielding a training accuracy of 0.9527 and loss of 0.1422. On the validation set, accuracy reached 0.9368 with a loss of 0.1767. The training curve indicates accuracy and loss for both sets progressed consistently, with validation closely tracking those of training across epochs. These accuracy and loss curves for both sets are shown in Figure 9.

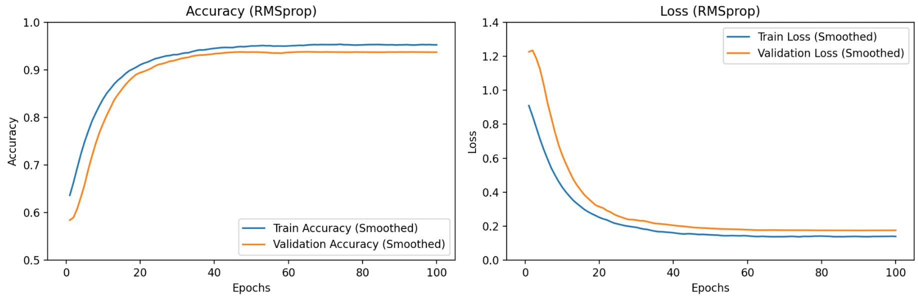
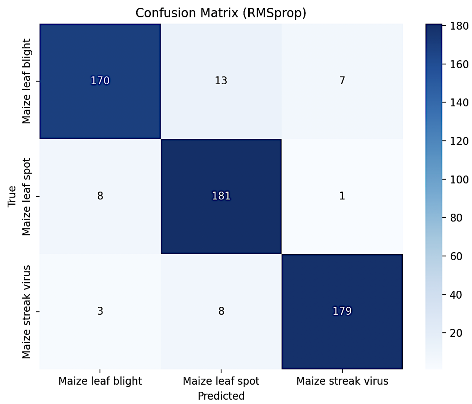


Figure 9. RMSProp Training Result

The confusion matrix for the RMSprop optimizer shows 170 Maize leaf blight samples classified correctly, with 13 as Maize leaf spot and 7 as Maize streak virus. For Maize leaf spot, 181 were correct, while 8 were Maize leaf blight and 1 as Maize streak virus. In Maize streak virus, 179 matched the correct label, while 3 were Maize leaf blight and 8 as Maize leaf spot. The classification report gives precision of 0.94, recall of 0.89, and f1-score of 0.92 for Maize leaf blight. Maize leaf spot has values of 0.90, 0.95, and 0.92, while Maize streak virus yields 0.96 for precision, 0.94 for recall, and 0.95 for f1-score. Total accuracy is 0.93, with macro and weighted averages for all metrics also 0.93. Figure 10 contains both the confusion matrix and the classification report for the RMSprop optimizer.



Classification Report (RMSprop):

	precision	recall	f1-score	support
Maize leaf blight	0.94	0.89	0.92	190
Maize leaf spot	0.90	0.95	0.92	190
Maize streak virus	0.96	0.94	0.95	190
accuracy			0.93	570
macro avg	0.93	0.93	0.93	570
weighted avg	0.93	0.93	0.93	570

Figure 10. RMSprop Classification Results

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3.4. Optimizer Performance Overview

The model performance analysis focused on the classification results of each training scenario in the application of transfer learning using the MobileNetV3-Small architecture for maize leaf disease classification. Table 3 contains the results obtained from each scenario, presenting the variation in performance produced by each optimizer. Key evaluation metrics such as accuracy, precision, recall, and f1-score are included to show how each optimizer contributes to the classification process. Results for each metric represent the outcomes achieved for the model with the corresponding optimizer. All of this information serves as a reference for comparing model performance across different scenarios.

Tabel 2. Comparison of Optimizer Performance

Evaluation Metrics	**Optimizers**		
	Adam	**SGD**	**RMSProp**
Accuracy (%)	92.81	85.96	92.98
Precision (%)	92.89	86.79	93.08
Recall (%)	92.81	85.96	92.98
F1-Score (%)	92.82	86.04	92.98

As presented in Table 2, Adam resulted in an accuracy of 92.81%, with precision and recall reported at 92.98 and 92.81%, and f1-score of 92.82 %. When using the SGD optimizer, the model achieved an accuracy of 85.96%, precision of 86.79%, recall of 85.96%, and an f1-score of 86.04%. RMSprop achieved 92.98% accuracy, while its precision, recall, and f1-score reached 93.08%, 92.98%, and 92.98% respectively. The metrics reported in the table reflect the classification outcomes produced by the model when evaluated with the specified optimizer in each scenario.

3.5. Discussion

The performance evaluation of the model trained with transfer learning and MobileNetV3 Small compared outcomes across various training scenarios using different optimizers for maize leaf disease classification. Using Adam resulted in stable training and effective feature extraction, which produced balanced results for all classes. RMSprop showed similar behavior, delivering consistent learning and reliable predictions. In contrast, models trained with SGD displayed greater fluctuations in accuracy and loss, often requiring more training epochs to achieve convergence. The classification report and confusion matrix indicated that RMSprop achieved the highest accuracy, precision, recall, and f1 score for each class, with Adam yielding closely similar results. More frequent errors in class assignment occurred with SGD, especially between classes that shared similar

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visual patterns. This pattern emphasizes that optimizer selection significantly influences classification performance for maize leaf disease detection.

Beyond the choice of optimizer, broader factors play an important role in the model's ability to generalize and maintain reliable performance. The high visual similarity among maize leaf disease images makes it challenging for the model to separate one class from another, which increases the risk of misclassification even when a suitable optimizer is used. Ensuring balanced sample counts for each class and maintaining high image quality help produce better learning outcomes. Careful adjustment of training parameters such as batch size, learning rate, and total epochs supports stable and accurate predictions. Regular monitoring of prediction outcomes and ongoing review of model behavior are essential to identify and resolve issues like overfitting, underfitting, or persistent misclassifications during training. By prioritizing these factors, models can be developed that are robust, capable of generalizing to new data, and able to provide dependable results in practical applications.

While the optimizers delivered strong performance overall, some limitations remain when considering individual classes. Overfitting can occur in classes with limited data, resulting in a model that performs well during training but has difficulty with unseen samples. Underfitting is also possible when an optimizer does not capture distinct features in visually comparable classes, which can lead to more frequent misclassifications. To address these issues, it is important to focus not only on overall accuracy but also on achieving reliable predictions for each class. Training strategies such as data augmentation and regularization are valuable for helping the model learn complex visual patterns and for reducing the risks of overfitting or underfitting. Robustness to real-world data must also be considered, as changes in background, lighting, and symptom appearance add complexity to disease classification. Considering both the limitations in individual classes and the need for model robustness is essential for achieving practical and effective results.

In addition to classification accuracy, efficiency in computation is an important consideration for real-world deployment. Adam often leads to faster convergence and stable training, though it can require more memory and processing power compared to other optimizers. RMSprop enables steady progress during training but may offer a different balance of speed and resource use, depending on the dataset and task complexity. SGD typically needs more epochs to reach a similar level of accuracy but can provide advantages in computational simplicity and faster execution per epoch. Selecting the appropriate optimizer is particularly important when resources are limited or when models need to operate in real time. The decision should balance high classification performance with efficient use of available hardware and operational requirements. Achieving both strong model performance and sustainable deployment depends on careful alignment between training strategies and practical constraints.

Based on the results of evaluation across multiple training scenarios, selecting an appropriate optimizer is crucial for model reliability and successful classification outcomes. Comparison of optimizers demonstrates clear differences in learning stability, prediction consistency, and the model's ability to distinguish between classes with comparable features. Evaluation of performance also shows that not all optimizers can address every challenge present in the dataset and that some are better at supporting the model's capacity to learn and generalize. A systematic assessment of optimization strategies provides a solid foundation for advancing model development and informs decisions that are supported by experimental evidence. Utilizing these evaluation results ensures the alignment of optimization methods with specific classification tasks and contributes to the enhancement of model quality.

4. CONCLUSION

This research comprehensively evaluates optimizer performance for maize leaf disease classification using transfer learning with MobileNetV3-Small. RMSProp achieved the highest accuracy, precision, recall, and f1-score, while Adam and SGD showed lower and less consistent results. These findings indicate that optimizer selection significantly influences learning stability, convergence, and prediction consistency across disease categories. By enabling earlier and more accurate detection of maize leaf diseases, RMSProp has the potential to support timely management decisions and reduce crop losses. Improved identification of disease symptoms can enhance maize crop productivity by supporting better crop management practices. Unfortunately, the evaluation used a relatively small dataset containing only three categories of maize leaf diseases which may affect consistency of classification performance in more complex or varied conditions. Future research should adjust hyperparameters, explore advanced optimization strategies or alternative model architectures, and incorporate additional data sources such as weather data, soil conditions, pest information, or real-time monitoring to further improve performance and strengthen the implementation of smart agriculture systems.

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