Improving the Accuracy of Chili Leaf Disease Classification with ResNet and Fine-Tuning Strategy

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***Abstract*—Lack of diseases detection in plants frequently results in the spread of diseases that are difficult to treat and expensive. Rapid diseases recognition enables farmers to control the diseases with appropriate treatment. This study aims to support chili farmers in identifying chili plant diseases based on leaf images. This work presents a CNN design based on several existing CNN architectures that have been fine-tuned to achieve the highest possible accuracy. The study found that the ResNet101 model with the Tanh activation function, SGD optimizer, and Reduced Learning Rate (ReduceLR) schedule, achieved a peak classification accuracy of 99.53%. This significant improvement demonstrates the potential of using advanced CNN techniques and fine-tuning strategies to enhance model accuracy in agricultural applications. The implications of this study extend to the field of precision agriculture, suggesting that the proposed model can be integrated into smart farming systems to improve the timely and efficient control of chili leaf diseases. Such advancements not only enhance crop yields but also contribute to sustainable agricultural practices and the economic stability of chili farmers.**

Keywords—Chili leaf classification; convolutional neural network; ResNet10; fine-tuning; precision agriculture

I. INTRODUCTION

Chili has been a flagship commodity in Indonesia's horticultural subsector, earning a solid global reputation. This finding emphasizes chili's enormous potential as a significant export commodity for Indonesia. The unique characteristics and high quality of Indonesian chili have earned global recognition, opening up significant opportunities for export growth and positively impacting the national economy [1], [2]. Chili yields a variety of products, such as fresh chili, dried chili, chili sauce, and chili oil. Dried chili is used as a spice, chili sauce is available in a variety of flavors, and chili oil, produced from chili, is utilized in the food, pharmaceutical, and cosmetic industries [3], [4].

Indonesian chili farmers face significant challenges that could affect production, welfare, and the long-term viability of their farming operations. These problems include environmental and weather fluctuations, which can have an impact on the health and growth of chili plants. In addition to changes in temperature and weather patterns, insect infestations such as thrips, caterpillars, and whiteflies, as well as diseases such as bacterial wilt and anthracnose, pose significant risks that require appropriate management measures [5]–[7]. Pest and disease attacks on chili plants are frequently detected based on the condition or appearance of the leaves, which serve as a food processing area for the plant [8] and poor chili plant development is a direct result of diseased leaves. Monitoring chili infections involves significant effort, and precise agricultural techniques are required to address this issue.

Several prior studies utilized computer vision to classify chili leaves in a variety of ways. Computer vision, which uses cameras and computational power to analyze and understand acquired images, can reliably classify diseases from chili leaves. Currently, the convolutional neural network (CNN) is the most used algorithm for computer vision problems. Transfer learning [9], fine-tuning [10], pruning [11], and new architectures [12] all have the potential to increase CNN performance and achieve high accuracy.

The aim of this study is to solve chili farmers' problems by developing a more efficient and accurate chili leaf disease detection application system utilizing CNN. The findings of this study show that by fine-tuning and optimizing the ResNet101 architecture, the accuracy of chili leaf disease classification may be greatly increased, outperforming previously classification approaches. The increased CNN accuracy attained in this work is intended to help establish a more effective and sustainable precision agriculture system. The study contributes the following:

- Analyzing how activation functions, optimization functions, and learning rate schedules improve CNN accuracy.
- Developing a fine-tuning model to increase CNN accuracy in Chili Leaf Disease Classification.
- Developing a more accurate CNN model suitable for smart farming systems.

II. LITERATURE REVIEW

Chili leaf classification research has advanced alongside developments in machine learning and computer vision technology. CNN has emerged as the preferred method for this purpose because of its ability to extract information from images automatically and accurately. Several methods and approaches have been investigated to increase classification accuracy, with a focus on improving network architecture and using data augmentation. Previous research has demonstrated that selecting of model and preprocessing procedures has a substantial impact on the overall system performance. Table I highlights many studies on chili leaf classification.

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TABLE I. RELATED STUDIES

Metode	Number of Classes	Accuracy
VGGNet [13]	3	97.00%
SVM+RNN [14]	5	92.10%
GLCM+KNN [15]	2	94.00%
Fine Tuning ShuffleNet [16]	2	99.30%
Inception V3 [17]	4	93.00%

The more classes utilized in a classification system, the more diseases that affect chili leaves may be detected and classified. Thus, a more advanced and accurate system can offer more precise information for plant disease control. In this study, five classes were used to classify chili leaf diseases. According to previous studies, the accuracy achieved for the five classes was only 92.10%, showing that there is still space for development and greater accuracy.

This research focuses on enhancing the accuracy of CNNs for chili leaf disease classification by exploring various CNN architectures and optimization techniques. Techniques such as transfer learning and fine-tuning pre-trained models are expected to significantly improve model performance. Additionally, the use of more diverse data augmentation is anticipated to help mitigate overfitting and improve the model's generalization ability to new data. This study aims to contribute to the field of precision agriculture by providing more reliable and efficient solutions for plant disease detection.

III. RESEARCH METHODS

This study was conducted to evaluate several aspects of the implementation and refinement of CNN architectures, with a focus on ResNet. To achieve this goal, a series of experiments were performed, including comparing accuracy on both augmented and non-augmented data, comparing the number of layers in ResNet, and fine-tuning parameters such as activation functions, optimizers, and learning rate schedules. The research workflow began with an evaluation of the effect of data augmentation and continued with a comparison of the performance of CNN models on augmented data. Subsequently, the study investigated the effects of different ResNet layer numbers on accuracy. Experiments with different optimization functions, types of optimizers, and learning rate schedules were also part of the fine-tuning process. Finally, the best results were compared with previous studies to identify improvements achieved.

A. Fine-Tuning Strategy

Fine-tuning is performed to determine the most accurate CNN model. In this work, fine-tuning is performed on an existing CNN that has been tested and produces the highest accuracy, namely the Resnet architecture. Fine-tuning is completed in three stages: activation function tuning, optimizer tuning, and learning rate schedule. The CNN with the best activation function is saved and then fine-tuned by the optimizer. The most accurate activation function and optimizer are reported, and the learning rate schedule is adjusted accordingly. As a result, this study creates the most accurate CNN model. The fine-tuning method is illustrated in Fig. 1.

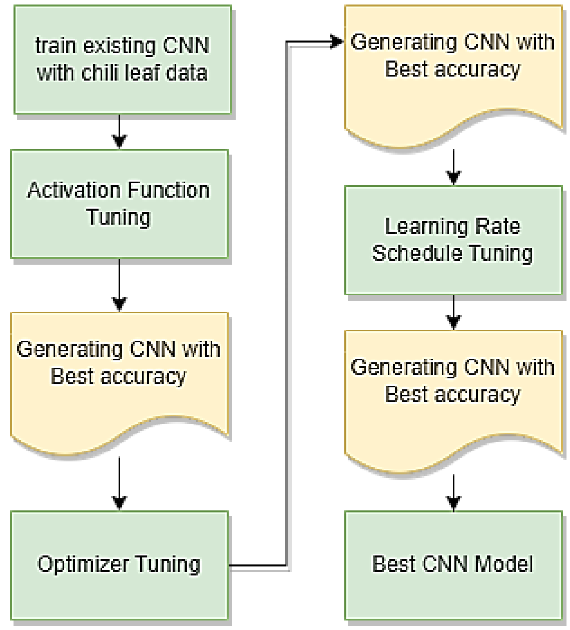


Fig. 1. Fine tuning strategy.

B. Dataset and Augmentation

The dataset used in this research consists of images of diseases affecting red chili leaves, sourced from Mendeley Data, comprising five disease classes [18]. The dataset is divided into two types: augmented and non-augmented. The dataset originally contained 531 images before augmentation, and after augmentation, the dataset expanded to 2,128 images. The details of the augmented dataset are shown in Table II below:

TABLE II. AUGMENTED DATASET

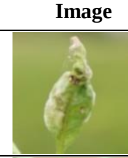
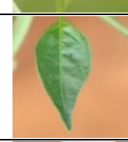
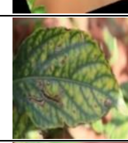
Class Name	Image	Training	Validation	Total
Powdery Mildew		486	122	608
Healthy Leaf		221	55	276
Murda Complex (mites, thrips)		342	86	428
Leaf Spot (Cercospora)		326	82	408
Nutrient Deficiency		327	81	408
Total		1702	426	2128

Table II provides information on the distribution of the augmented dataset used in this research to identify diseases in red chili leaves. This dataset consists of five different disease classes: Powdery Mildew, Healthy Leaf, Murda Complex (mites, thrips), Leaf Spot (Cercospora), and Nutrient Deficiency. Each class contains a number of images that have been divided into subsets for training and validation. The total number of images in the dataset after augmentation is 2,128, which includes 1,702 images for training and 426 images for validation. The original images that have been augmented are shown in Fig. 2.

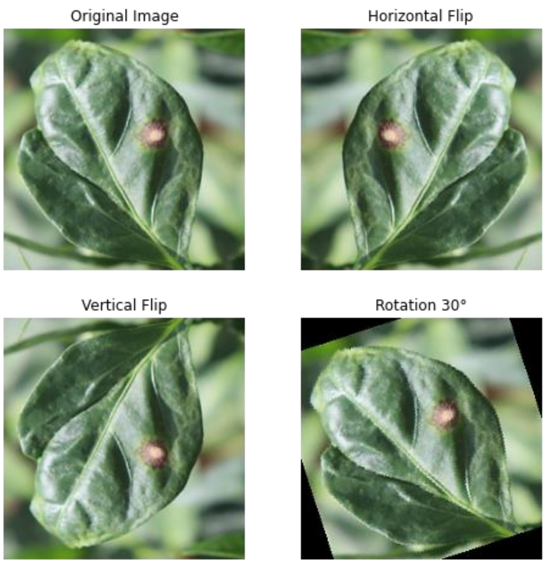


Fig. 2. Data augmentation.

C. Activation Function

The selection of an appropriate activation function in Convolutional Neural Networks (CNNs) is crucial for improving model accuracy, particularly in classification tasks. Activation functions like ReLU, which are popular for their simplicity and effectiveness, help the network learn complex non-linear representations. However, in some cases, ReLU can lead to issues such as dead neurons, which can be mitigated by variants like Leaky ReLU or ELU that introduce a slope or non-linearity on the negative side. Other functions, such as Tanh and Sigmoid, also play important roles, particularly in regulating the output within specific ranges. Tanh maps inputs to values between -1 and 1, while Sigmoid maps inputs to values between 0 and 1. For multi-class classification, Softmax is used to convert outputs into probabilities, enabling more accurate predictions. By understanding the characteristics of these activation functions, we can optimize CNN architectures to achieve the best performance in various classification applications.

The linear activation function returns the input without any modification. It is typically used in the final layer of regression models. The equation for the linear activation function is presented in Eq. (1) [19]:

$$f(x) = a.x \tag{1}$$

ReLU (Rectified Linear Unit) is a highly popular non-linear activation function that returns the input directly if it is positive, and zero if it is negative. The equation for ReLU is shown in Eq. (2) [20].

$$f(x) = \max(0, x) \tag{2}$$

ELU (Exponential Linear Unit) is an activation function similar to ReLU but differs in how it handles negative inputs. ELU introduces non-linearity on the negative side to address the dead neuron problem associated with ReLU[21]. The equation for ELU is presented in Eq. (3).

$$f(x) = \begin{cases} x, & if\ x > 0 \\ \alpha(\exp(x) - 1), & if\ x \leq 0 \end{cases} \tag{3}$$

Leaky ReLU is a variation of ReLU that allows a small gradient when the input is negative [22]. The equation for Leaky ReLU is shown in Eq. (4).

$$f(x) = \begin{cases} x, & if\ x > 0 \\ \alpha x, & if\ x \leq 0 \end{cases} \tag{4}$$

Tanh (Hyperbolic Tangent) is an activation function that maps the input to a value between -1 and 1. It is often used in hidden layers of neural networks [23]. The equation for Tanh is given in Eq. (5):

$$f(x) = \mathrm{Tanh}(x) \tag{5}$$

The Sigmoid activation function maps the input to a value between 0 and 1, which is commonly used in binary classification models [24]. The equation for the Sigmoid function is presented in Eq. (6):

$$f(x) = \frac{1}{1+\exp(-x)} \tag{6}$$

Softmax is an activation function typically used in the output layer for multi-class classification problems [25]. It converts the input values into probabilities. The equation for Softmax is shown in Eq. (7):

$$f(x) = \frac{\exp(x_i)}{\sum_{j=1}^{N} \exp(x_j)} \tag{7}$$

IV. Results and Discussions

A. Accuracy on Augmented and Non-Augmented Datasets

This study utilized two types of chili image datasets: one with augmented data and one without. The augmentation process involved increasing the dataset by applying horizontal flips, vertical flips, and 30-degree rotations. During model training, several key settings influenced how the model learned from the data. One of these was the number of epochs, which represents the number of times the model processes the entire dataset—set to 30 in this case. The batch size, which refers to the number of data samples processed together, was set to 32, impacting the speed and efficiency of the model's learning process. Additionally, the learning rate, fixed at 0.001, determined the magnitude of adjustments made during training to enhance the model's predictions. The momentum, set at 0.9 in the SGDM optimizer, was used to accelerate the convergence of the model. Initial experiments compared the accuracy of the ResNet101 architecture, with the results summarized in Table III.

TABLE III. ACCURACY IMPROVEMENT WITH DATASET AUGMENTATION

No	Method	Training Accuracy	Validation Accuracy
1	Non-Augmented Dataset ResNet101ResNet101	98.35%	89.72%
2	Augmented Dataset ResNet101	97.65%	98.12%

In the experiments using the ResNet101 architecture, two scenarios were compared. In the first scenario, without dataset augmentation, the model achieved a training accuracy of 98.35% and a validation accuracy of 89.72%. In the second scenario, with dataset augmentation, the model reached a training accuracy of 97.65% and a validation accuracy of 98.12%. The effect of augmentation is evident in the unusual outcome where the validation accuracy exceeded the training accuracy. However, applying dataset augmentation led to a significant improvement in the model's performance on the validation set, making it a more advantageous approach.

B. Accuracy on Existing CNNs

Based on the previous testing, it was found that data augmentation successfully improved the accuracy of CNNs in classifying chili leaf diseases. Using the augmented dataset, we tested several existing CNN architectures to determine which one would be more suitable for this classification task. The existing CNNs tested included AlexNet, GoogleNet, VGGNet, and ResNet. Table IV presents the key performance metrics obtained, including training accuracy and validation accuracy.

TABLE IV. ACCURACY OF EXISTING CNNS

No	Method	Training Accuracy	Validation Accuracy
1	AlexNet	93.9%	95.77%
2	GoogleNet	95.12%	96.95%
3	VGGNet16	95.95%	96.95%
4	ResNet 101	97.64%	98.12%

The table above shows the training accuracy and validation accuracy for several convolutional neural network methods used in the experiments. AlexNet achieved a training accuracy of 93.89% and a validation accuracy of 95.77%. GoogleNet demonstrated a training accuracy of 95.12% and a validation accuracy of 96.95%. VGGNet16 reached a training accuracy of 95.95% and a validation accuracy of 96.95%. ResNet101 achieved the highest accuracy, with a training accuracy of 97.65% and a validation accuracy of 98.12%.

C. Accuracy Comparison on ResNet

The comparison of the performance of various layers within the ResNet architecture used in this study aims to evaluate the effectiveness of each ResNet layer in the developed classification model. The comparison results are presented in Table V.

Table V presents a comparison of the training and validation accuracy of various ResNet methods used in the study. The ResNet18 method achieved a training accuracy of 96.42% and a validation accuracy of 95.77%. ResNet34 showed an improvement with a training accuracy of 97.36% and a validation accuracy of 97.18%. The ResNet50 method achieved a training accuracy of 97.83% and a validation accuracy of 97.18%. ResNet101 reached a training accuracy of 97.65% and the highest validation accuracy among the methods, at 98.12%. Finally, the ResNet152 method achieved the highest training accuracy of 98.41%, but its validation accuracy reverted to 97.18%.

D. Fine-Tuning Activation Functions for ResNet101

In an effort to enhance the performance of the ResNet101 model in classifying chili leaf diseases, fine-tuning was performed on the activation functions. Activation functions play a crucial role in determining the output of each layer in a neural network. In this section, various activation functions, such as ReLU, ELU, Leaky ReLU, Tanh, Sigmoid, and Softmax, were trained over 30 epochs. The impact of each activation function on the model's performance was then evaluated. The accuracy results for each activation function are presented in Table VI.

The model was trained using various activation methods, yielding different training and validation accuracies. The Linear method achieved a training accuracy of 97.65% and a validation accuracy of 98.12%. The ReLU method resulted in a training accuracy of 97.30% and a validation accuracy of 97.65%, while the ELU method produced a training accuracy of 97.71% and a validation accuracy of 96.95%. The Leaky ReLU method showed a training accuracy of 98.24% and a validation accuracy of 97.65%. The Tanh method achieved a training accuracy of 97.24% and the highest validation accuracy among all methods, at 99.06%. The Sigmoid method resulted in a training accuracy of 94.65% and a validation accuracy of 95.77%, while the Softmax method achieved a training accuracy of 93.89% and a validation accuracy of 96.48%. The validation results for each epoch are illustrated in Fig. 3.

TABLE V. COMPARISON OF RESNET LAYERS

No.	Method	Training Accuracy	Validation Accuracy
1	ResNet18	96.42%	95.77%
2	ResNet34	97.36%	97.18%
3	ResNet50	97.83%	97.18%
4	ResNet101	97.65%	98.12%
5	ResNet152	98.41%	97.18%

TABLE VI. ACCURACY WITH DIFFERENT ACTIVATION FUNCTIONS

No	Method	Training Accuracy	Validation Accuracy
1	Linear	97.65%	98.12%
2	ReLU	97.30%	97.65%
3	ELU	97.71%	96.95%
4	Leaky ReLU	98.24%	97.65%
5	Tanh	97.24%	99.06%
6	Sigmoid	94.65%	95.77%
7	Softmax	93.89%	96.47%

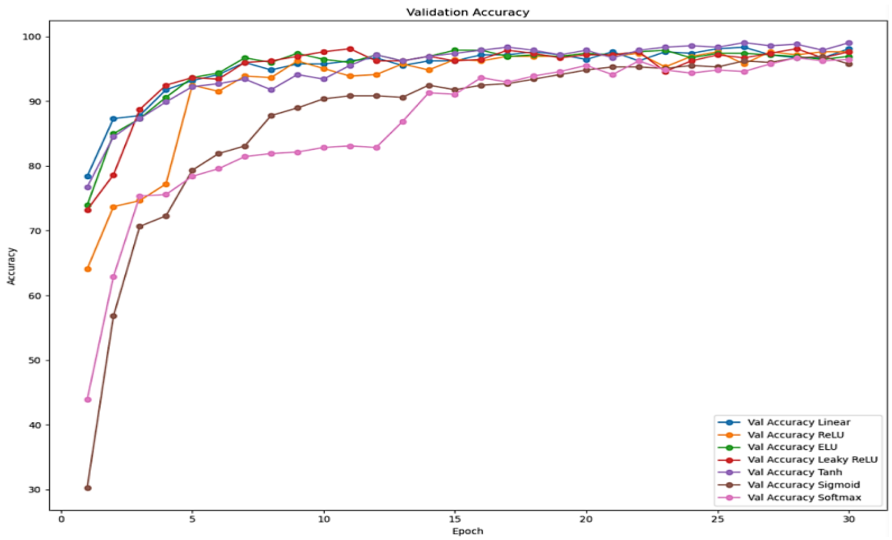


Fig. 3. Graph comparing validation accuracy with different activation functions.

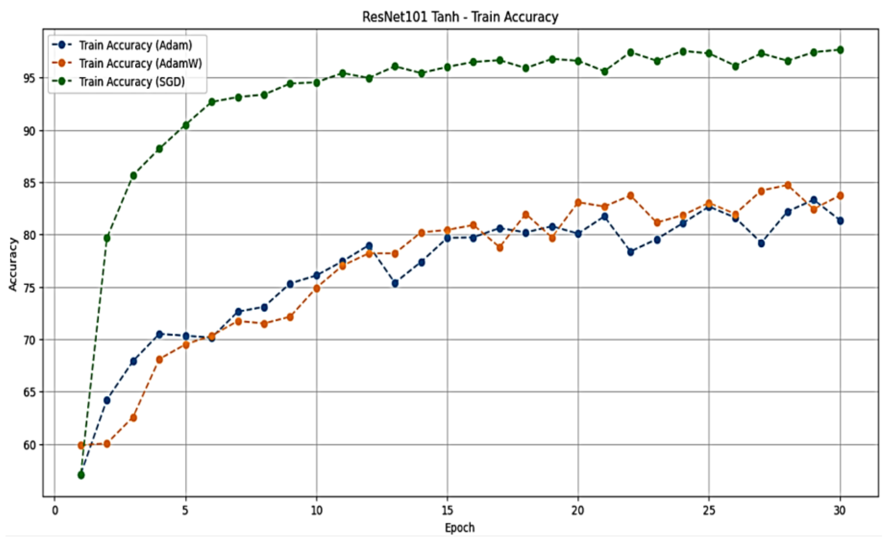


Fig. 4. Comparison of training accuracy using different optimizers.

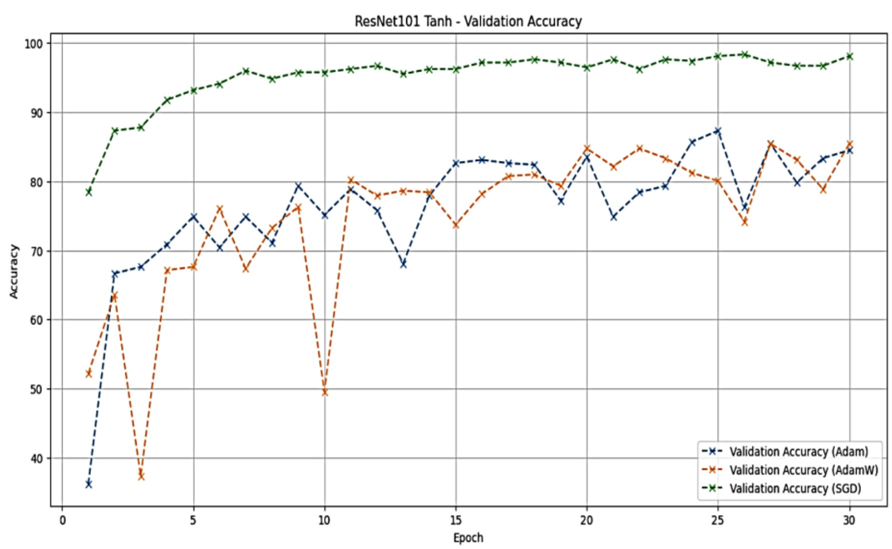


Fig. 5. Comparison of validation accuracy using different optimizers.

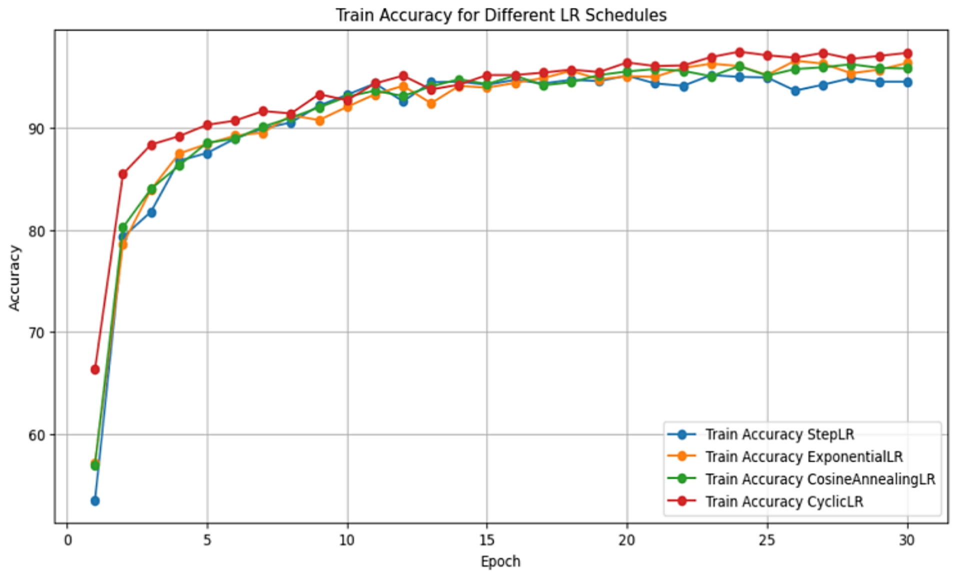


Fig. 6. Comparison of training accuracy across different learning rate schedules.

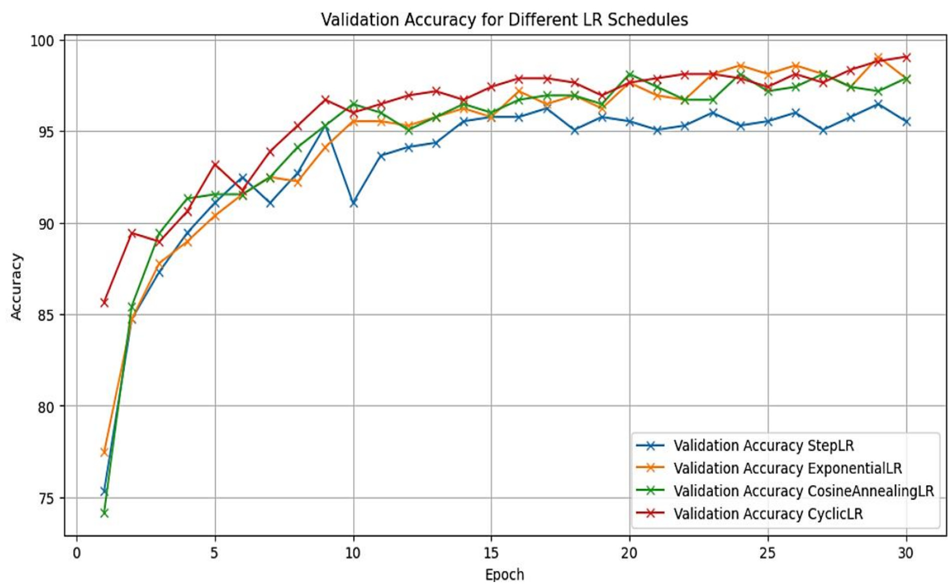


Fig. 7. Comparison of validation accuracy across different learning rate schedules.

E. Fine Tuning Optimizer ResNet101

Based on previous testing, ResNet with the Tanh activation function achieved the highest accuracy. To identify the optimal optimization function, several optimizers were tested while maintaining the Tanh activation function. The initial step involved selecting the appropriate optimizer to effectively handle the task of classifying chili leaf images. The optimizers tested included Adam, AdamW, and SGDM. The results of these tests are presented in Table VII.

Table VII shows the accuracy results of the three machine learning models tested. The different optimization functions yielded varying results. The SGDM optimizer demonstrated the best performance on both training and validation data, with accuracies of 97.24% and 99.06%, respectively. The AdamW model achieved a training accuracy of 84.72% and a validation accuracy of 85.45%, while the Adam model reached a training accuracy of 83.31% and a validation accuracy of 87.32%. Therefore, ResNet101 with the SGDM optimizer achieved the best accuracy in chili leaf classification. The accuracy comparisons for each epoch are presented in the Fig. 4 and 5.

TABLE VII. COMPARISON OF OPTIMIZERS

No	Method	Training Accuracy	Validation Accuracy
1	Adam	83.31%	87.32%
2	AdamW	84.72%	85.45%
3	**SGD**	**97.24%**	**99.06%**

F. Fine Tuning Learning Rate Schedule

In this study, five different learning rate schedules were evaluated to determine their impact on training and validation accuracy. The results of this evaluation are presented in Table VIII below.

TABLE VIII. COMPARISON OF LEARNING RATE SCHEDULES

No	Function	Training Accuracy	Validation Accuracy
1	StepLR	95.1234	96.4789%
2	ExponentialLR	96.3572%	99.0610%
3	ConsineAnnealigLR	96.2397%	98.1221%
4	CyclicLR	97.3561%	99.0610%
5	ReduceLR	97.7673%	99.5305%

Table VIII provides a comparison of the training and validation accuracies for each learning rate schedule model tested. The StepLR model achieved a training accuracy of 95.12% and a validation accuracy of 96.48%. The ExponentialLR model, on the other hand, showed an improved training accuracy of 96.36% and a validation accuracy of 99.06%. The CosineAnnealingLR model attained a training accuracy of 96.24% and a validation accuracy of 98.12%. The CyclicLR model demonstrated further improvement with a training accuracy of 97.36% and a validation accuracy of 99.06%. Finally, the ReduceLR model exhibited the highest performance, achieving the highest training accuracy of 97.77% and the highest validation accuracy of 99.53%, making it the best-performing model among those tested.

The results indicate that different learning rate schedules can significantly affect the performance of the ResNet101 model. While StepLR provided a stable training process, models like ExponentialLR and CyclicLR demonstrated higher validation accuracies, suggesting they were better at generalizing to unseen data. The CosineAnnealingLR schedule showed a balance between training and validation accuracy, but the ReduceLR model outperformed all others by achieving both the highest training and validation accuracies. This suggests that dynamically reducing the learning rate as training progresses may be the most effective strategy for optimizing model performance in this context.

To visualize the impact of these learning rate schedules over the course of training, the accuracy for each epoch is plotted in the Fig. 6 and 7.

These figures illustrate how each learning rate schedule influenced the model's ability to learn and generalize from the data over time. As shown, the ReduceLR schedule not only maintained a high training accuracy but also led to the best validation accuracy, indicating its effectiveness in avoiding overfitting and improving model robustness.

G. Implementation

After completing the model evaluation phase on the test data, this research also implemented the model into an application. The application serves as a platform that facilitates users in classifying chili leaves to identify potential diseases. The classification page of the application is shown in Fig. 8.

Fig. 8. Implementation of chili leaf disease classification.

Fig. 8 illustrates the classification process within the application. The image of the chili leaf, captured by a camera, is successfully classified by the ResNet101 model using the best-performing parameters. The application interface provides clear feedback to the user, indicating the identified disease, thus aiding in quick and accurate diagnosis.

H. Comparison with Previous Research

This study successfully classified chili leaf diseases with high accuracy, surpassing the accuracy achieved in previous studies. The highest accuracy was obtained with the classification of five chili leaf classes. A comparison of the accuracy from this study with that of previous research is presented in Table IX.

TABLE IX. ACCURACY COMPARISON WITH PREVIOUS RESEARCH

Methods	Number of Classes	Accuracy
VGGNet [13]	3	97.00%
SVM+RNN [14]	5	92.10%
GLCM+KNN [15]	2	94.00%
Fine Tuning ShuffleNet [16]	2	99.30%
Inception V3 [17]	4	93.00%
Xception [18]	5	79.56%
Resnet 101 (Best Parameter)	5	99.53%

According to Table IX, ResNet101 with the Tanh activation function, SGD optimizer, and ReduceLR learning rate schedule achieved an accuracy of 99.53%, accepted as the ResNet101 best parameter configuration. This best-parameter ResNet101 outperformed SVM+RNN [14], which used the same number of classes, with a 7.43% increase in accuracy. ResNet101 outperformed Xception [18], on the exactly the same dataset, with a 19.97% improvement. The best-parameter

ResNet101 also outperformed Fine Tuning ShuffleNe [16], which was only classify two chili leaf disease classifications.

V. Conclusion

This study successfully developed and refined a Convolutional Neural Network (CNN) model, especially ResNet101, for classifying chili leaf diseases with reliable accuracy. Through a series of experiments, including the application of multiple activation functions, optimization functions, and learning rate schedules, the model obtained an accuracy of 99.53% when diagnosing five different types of chili leaf diseases. This performance outperforms prior studies that showed the effectiveness of the ResNet101 model using the Tanh activation function, SGD optimization function, and ReduceLR learning rate schedule.

The findings demonstrated that carefully selecting and refining model parameters can greatly increase CNN accuracy in complex classification tasks. The proposed model not only outperformed previous CNN architectures such as VGGNet, Inception V3, and Xception, but it was also more effective in handling several disease classifications than other approaches such as SVM+RNN and Fine Tuning ShuffleNet.

Overall, implementing this model in a practical application-based system has the potential to help farmers and agricultural professionals in accurately diagnosing chili leaf diseases, resulting in improved disease management and crop yields. However, there are limitations to this study. Firstly, the model's performance has not been extensively tested on datasets collected from diverse environmental conditions, which may affect its generalizability in real-world scenarios. Secondly, the computational resources required for training and deploying the ResNet101 model may pose challenges for integration into low-cost, resource-constrained agricultural systems commonly found in rural areas. Further research might explore possibilities into refining the model and applying it to other agricultural fields, while addressing these limitations to enhance its practical applicability and efficiency.

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