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Performance Comparison of EfficientNetB0 in Potato Leaf Disease Classification with Adam and SGD

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ABSTRACT

Potatoes (*Solanum tuberosum L.*) are an important food commodity for global food security, but they are highly susceptible to leaf diseases that reduce yield and tuber quality. This study aims to classify potato leaf diseases using the EfficientNetB0 architecture with two optimizers, Adam and SGD, and applying data augmentation techniques such as rotation, flipping, and cropping. The dataset consists of 3076 images divided into seven categories: Bacteria, Fungi, Healthy, Nematodes, Pests, *Phytophthora*, and Viruses. The results show that the Adam optimizer with a learning rate of 0.001, a batch size of 16, and 100 epochs provides the best performance. The training accuracy reached 92.10%, validation 81.49%, and testing 78.14%. The model precision was 0.7982, recall was 0.7536, and the F1 score was 0.7671. Meanwhile, the SGD optimizer produced a test accuracy of 79.55%, with precision of 0.7752, recall of 0.7781, and an F1 score of 0.7715. Although Adam's accuracy is higher, SGD shows better stability in preventing overfitting. This study confirms that data augmentation plays an important role in improving model performance, although the challenge of overfitting still needs to be addressed. Further studies are expected to optimize hyperparameters and explore other model architectures to improve the accuracy and efficiency of potato leaf disease classification.

INTRODUCTION

Leaf disease in potato plants is one of the main causes of significant declines in agricultural yields. Various types of pathogens, such as fungi, bacteria, and viruses, can infect potato leaves, causing serious damage. The impact of these infections not only reduces quality but also affects the quantity of the harvest, which has an impact on overall potato production(Damopolii et al., 2024).

Potatoes (Solanum tuberosum L.) are one of the world's major food commodities, ranking third after rice and wheat in terms of global consumption (Sri Lestari & Nauval, 2022). Potatoes are high in carbohydrates, fiber, and vitamin C, and can thrive in the highlands of Indonesia. Based on FAOSTAT data, global potato production in 2023 is estimated to reach more than 383 million tons, while Indonesia produces around 1.2 million tons (FAOSTAT, 2023). This shows that potatoes play an important role in food security and the economy.

However, potato plants are highly susceptible to various diseases, especially leaf diseases that can reduce tuber quality and yield. Potato leaf diseases can be caused by viruses, Phytophthora, nematodes, fungi, bacteria, and pests, with early blight and late blight being the two most damaging diseases (Shabrina et al., 2024). Damage to leaves disrupts the photosynthesis process, which in turn reduces tuber yield.

Until now, farmers have relied on manual visual observation to detect potato leaf diseases. Unfortunately, this method is often inaccurate and can lead to delays in diagnosis, excessive pesticide use, increased production costs, and negative environmental impacts (Jaiman et al., 2024). Therefore, an automated system is needed that can quickly and accurately detect and classify potato leaf diseases.

This study applies the EfficientNet-B0 model, which was chosen for its efficiency in image processing and high accuracy, making it ideal for applications with limited resources. As discussed by (Taufiqurrahman et al., 2024), this model uses a compound coefficient technique to effectively scale the model with fewer parameters compared to other variants, such as EfficientNet-B1 or EfficientNet-B2. The study also shows that EfficientNet-B0 delivers fast and efficient results, with low Floating Point Operations (FLOPs), supporting faster training.

Previous research by (Shabrina et al., 2024) compared several model architectures such as EfficientNetV2B3, MobileNetV3-Large, VGG-16, ResNet50, and DenseNet121, using augmentation techniques for disease classification on potato leaves. The disease categories tested included Bacteria, Fungi, Healthy, Nematodes, Pests, Phytophthora, and Viruses, with the best results obtained using the EfficientNetV2B3 model. Based on these findings, this study aims to apply data augmentation techniques using ImageDataGenerator to artificially increase the variety and size of the image dataset without the need to add new images. The augmentation techniques applied include rotation, flipping, and cropping. Furthermore, this technique will be combined with the EfficientNetB0 architecture, which is expected to improve the accuracy of potato leaf disease classification, in accordance with the findings of previous studies, using

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digital images and data augmentation.

Furthermore, this study compares two popular optimizers, namely Stochastic Gradient Descent (SGD) and Adam. SGD updates model weights using random mini-batches, which helps avoid overfitting and improves generalization (Haji & Abdulazeez, 2021) Adam combines the concepts of momentum and RMSprop, calculates an adaptive learning rate for each parameter, and is more efficient in handling noisy gradients and accelerating convergence (Rochmawati et al., 2021) Previous research shows that EfficientNetB0 with the Adam optimizer provides high accuracy in plant disease classification (Saddami et al., 2024). Additionally, EfficientNetB0 also demonstrates good performance with the SGD optimizer (Pamungkas et al., 2023)

Although many studies have been conducted on plant disease classification using EfficientNetB0, there are still few studies that directly compare the performance of Adam and SGD optimizers on potato leaves. Therefore, this study aims to explore and compare the performance of both optimizers on the EfficientNetB0 model in potato leaf disease classification, as well as evaluate their performance comparison to improve the accuracy and speed of automatic disease identification.

LITERATURE REVIEW

The application of deep learning, especially Convolutional Neural Networks (CNN), in plant disease classification, particularly on potato leaves, has been increasingly applied in recent studies. Various studies have shown that CNN models are effective for detecting diseases on potato leaves. (Upadhyay et al., 2024) for example, used EfficientNetB0 to detect early blight and late blight diseases on potato leaves, with an accuracy of 99.05%, which is higher than ResNet50 V2, which only recorded an accuracy of 90.95%. Additionally, (Kumar et al., 2025) also used EfficientNetB0 to detect and classify diseases on potato leaves, with near-perfect results of 99.99%, indicating how effective this architecture is in plant disease classification tasks.

Meanwhile, (Assefa et al., 2025) used EfficientNetB0 in the classification and assessment of the severity of potato leaf diseases, with an accuracy of 99% for early blight and late blight, further emphasizing that this model is reliable for detecting plant diseases. On the other hand, research by (Pranatha et al., 2024) using ResNet-34 to detect diseases on potato leaves recorded an accuracy of 97%, showing that although ResNet-34 is effective, EfficientNetB0 provides better results in terms of efficiency and accuracy.

Research by (Syaifulloh et al., 2024) using CNN also showed promising results in potato leaf disease classification, with a testing accuracy of 95.58%. They emphasized the importance of data augmentation techniques such as rotation, flipping, and cropping to improve model performance, which was also seen in the study by (Shabrina et al., 2024) In that study, they introduced a new potato leaf disease dataset collected from uncontrolled environments, and although the accuracy results were slightly lower, they showed that augmentation techniques can improve model performance, although the results vary depending on the data conditions.

(Firasari & Cahyanti, 2025) implemented InceptionResNetV2 to detect potato leaf disease, with fairly good results of 94.20% in training and 95.30% in validation. This study highlights that although InceptionResNetV2 is effective, EfficientNetB0 remains the preferred choice for many plant disease classification applications. (Ghandi & Ramadhan, 2024) demonstrate how CNNs are applied in Android-based applications for potato leaf disease detection, with a testing accuracy of 99.69%, proving the great potential of mobile-based technology in real-time disease detection.

Additionally, (Sabrina & Maki, 2022) applied EfficientNetB0 for disease classification on coffee leaves with an accuracy of 91%, showing that this model is also useful beyond the field of potato plants. The study (Shabrina et al., 2024) revisited the application of EfficientNetV2B3 and compared it with various other models. Although EfficientNetV2B3 provided the best results in a more controlled dataset, the decline in accuracy in more natural data highlights the challenges faced in potato leaf disease research in the field.

Finally, (Rashid et al., 2021) proposed the use of the YOLOv5 model for segmentation and PDDCNN for classification, which achieved 99.75% accuracy in detecting potato leaf disease using data augmentation. This indicates that while other models such as VGG16 and DenseNet also show good results, YOLOv5 and PDDCNN provide better performance in terms of accuracy and efficiency.

Overall, these studies show that EfficientNetB0 is very effective in detecting potato leaf disease, although challenges remain in addressing real-world data variations, such as uncontrolled lighting and backgrounds. Data augmentation techniques play an important role in addressing this issue, and the choice of optimizers such as Adam and SGD can also significantly affect model performance.

METHOD

The research followed a series of well-defined stages, as illustrated in the flowchart in Fig. 1. The process began with a literature review to understand the use of CNN methods for Potato Leaf Diseases classification.

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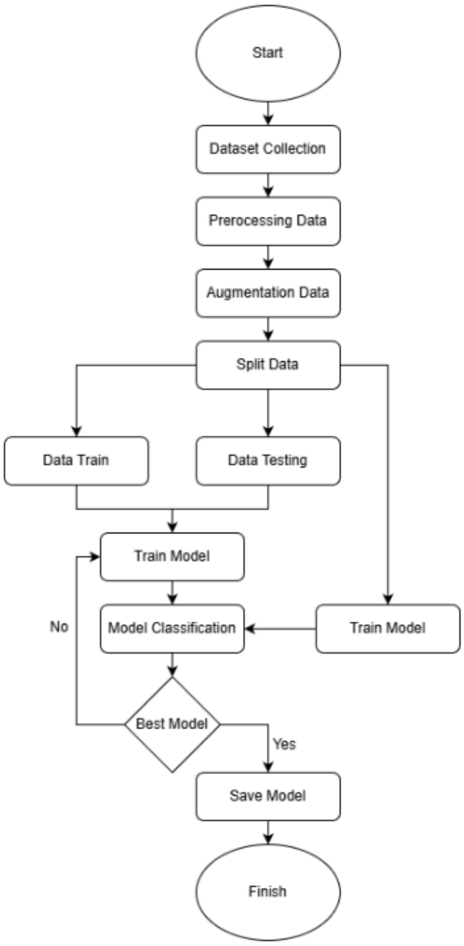
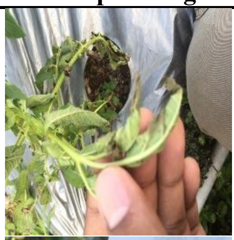


Fig 1. Methodology

This study uses a publicly available secondary dataset on Mendeley Data, namely "Potato Leaf Disease Dataset in Uncontrolled Environment." This dataset contains 3076 images of potato leaves showing diseases on potato leaves, which are divided into seven categories: Bacteria, Fungi, Healthy, Nematodes, Pests, Phytophthora, and Viruses. The dataset was then organized into separate folders based on each class.

Table 1. Details of the dataset used

Number	Category	Count	Example Image
1	Bacteria	569	
2	Fungi	784	

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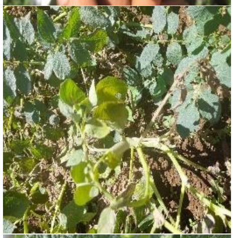
3	Healthy	201	
4	Nematode	68	
5	Pest	611	
6	Phytophtora	347	
7	Virus	532	

After collecting the dataset, the next step was preprocessing, where the images were resized to 224x224 pixels and normalized in the range of [0, 1]. This process aimed to prepare the data for optimal use in model training.

After that, the dataset was divided into three parts: 80% for training data, 10% for validation data, and 10% for testing data. This division was done to train the model, evaluate its performance on data not used in training, and test the model's ability to classify previously unseen data.

To increase the variety in the training data, augmentation techniques were applied using ImageDataGenerator. This technique aims to increase the amount of data by performing random transformations on images, such as rotation, flipping, and cropping, which can help the model recognize more diverse patterns and reduce the risk of overfitting.

After the augmentation process, the model was trained using the training data. The validation data is used to evaluate the model's performance during training and to avoid problems such as underfitting or overfitting. This study uses two optimizers, namely Adam and SGD, with learning rates of 0.001 and 0.0001, respectively, and batch sizes of 8 and 16. In addition, experiments were conducted with 50 and 100 epochs to ensure optimal model convergence.

After the model was trained, a testing phase was conducted to assess the model's performance in classifying diseases on potato leaves using the test data that had been prepared beforehand. The classification results were then displayed to show the types of diseases detected on the potato leaves. This phase marked the end of the research process.

In the final stage, the developed system was tested using the specified test data. After testing was complete, the test results were calculated to assess the performance of the Convolutional Neural Network (CNN) model with the EfficientNetB0 architecture in classifying diseases on potato leaves. The evaluation metrics used include the Confusion Matrix to calculate the precision, recall, accuracy, and F1-score values, which are calculated using the formulas in Equations (1), (2), (3), and (4).

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$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (1)$$

$$Recal = \frac{TP}{TP+FN} \times 100\% \quad (2)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (3)$$

$$F1 - Score = 2\,x\,\frac{Precision\ x\ Recall}{Precision\ x\ Recall} \quad (4)$$

RESULT

This study will comprehensively explain the classification of potato leaf diseases, which are divided into seven categories, namely Bacteria, Fungi, Healthy, Nematode, Pest, Phytophtora, and Virus. The classification was performed using the EfficientNetB0 architecture and ADAM and SGD optimizers. The learning rates applied were 0.001 and 0.0001. In addition, experiments were conducted with variations in batch size configurations of 8 and 16 and epoch numbers of 50 and 100 to optimize model performance.

The dataset used consists of 3076 images of potato leaf diseases that have been grouped into the seven classes mentioned above. This dataset is divided into three parts: 80% for training data, 10% for validation data, and 10% for testing data. This division aims to train the model, evaluate its performance during training, and test its ability to classify previously unseen data.

Data augmentation techniques using ImageDataGenerator, such as rotation, flipping, and cropping, are applied to expand the variety in the training dataset without adding new images. This augmentation aims to help the model recognize more diverse patterns, thereby improving its generalization ability. Previous research has also shown that data augmentation techniques have a significant effect on improving model accuracy, particularly in plant image classification, by introducing realistic variations to the generated images.

The results of the experiments conducted are presented in Table 2 for the EfficientNetB0 model with the Adam optimizer, and in Table 3 for the EfficientNetB0 model with the SGD optimizer.

Table 2. Results of EfficientNetB0 with ADAM Optimizer

Number	Epoch	Learning Rate	Batch Size	Train Accurary	Validation Accuracy	Testing Accuracy	Precision	Recall	F1-Score
1	50	0.001	8	88.32%	79.55%	77.17%	0.7629	0.7073	0.7208
2	100	0.001	8	91.90%	80.52%	80.39%	0.7982	0.7536	0.7671
3	50	0.001	16	89.30%	79.87%	77.49%	0.7682	0.7052	0.7220
4	**100**	**0.001**	**16**	**92.10%**	**81.49%**	**78.14%**	**0.7819**	**0.7205**	**0.7386**
5	50	0.0001	8	89.54%	79.22%	78.14%	0.7981	0.7474	0.7623
6	100	0.0001	8	89.38%	80.52%	77.17%	0.8047	0.7132	0.7396
7	50	0.0001	16	88.12%	78.90%	74.92%	0.7582	0.6910	0.7067
8	100	0.0001	16	91.90%	81.49%	77.81%	0.7943	0.7320	0.7521

Based on Table 2, which shows the results of experiments with the EfficientNetB0 architecture and ADAM optimizer, the configuration with a learning rate of 0.001, batch size of 16, and epoch of 100 provided the best results. This configuration produced a train accuracy of 92.10%, validation accuracy of 81.49%, testing accuracy of 78.14%, and an F1-score of 0.7386. On the other hand, the configuration with a learning rate of 0.001, batch size of 8, and 100 epochs also showed competitive performance, with a testing accuracy of 80.52% and an F1-score of 0.7671. However, when the learning rate was lowered to 0.0001, the model's performance declined, with the testing accuracy only reaching 79.42%. Nevertheless, the precision and recall slightly increased to 0.8028 and 0.7458, indicating that a learning rate of 0.001 is more optimal for accelerating model convergence. Overall, these results show that a batch size of 16 produces more stable accuracy, while a batch size of 8 produces a higher and more consistent F1-score. This indicates that the model is more sensitive to batch size variations than to other hyperparameters such as learning rate or number of epochs.

Table 3. Results of EfficientNetB0 with SGD Optimizer

Number	Epoch	Learning Rate	Batch Size	Train Accurary	Validation Accuracy	Testing Accuracy	Precision	Recall	F1-Score
1	50	0.001	8	83.84%	79.22%	78.14%	0.7752	0.7781	0.7715
2	100	0.001	8	91.01%	79.87%	76.85%	0.7752	0.7294	0.7461
3	50	0.001	16	81.77%	78.57%	75.24%	0.7514	0.6995	0.7111
4	**100**	**0.001**	**16**	**85.59%**	**79.55%**	**76.85%**	**0.7603**	**0.7078**	**0.7231**
5	50	0.0001	8	71.75%	70.45%	70.42%	0.6198	0.6190	0.6198

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6	100	0.0001	8	73.79%	74.35%	74.60%	0.7051	0.6789	0.6850
7	50	0.0001	16	65.32%	70.13%	69.77%	0.6162	0.6048	0.6052
8	100	0.0001	16	70.90%	72.40%	70.42%	0.6592	0.6404	0.6411

Based on Table 3, the best configuration using a learning rate of 0.001, batch size of 16, and epoch of 100 resulted in a train accuracy of 85.59%, testing accuracy of 79.55%, and validation accuracy of 76.85%. Although these results are lower than those of the Adam optimizer, SGD shows stable performance with competitive results, such as a batch size of 8 with a testing accuracy of 79.87% and an F1-score of 0.7461. However, at a learning rate of 0.0001, the testing accuracy decreases to 74.35%, indicating that a low learning rate is less than optimal.

From the results obtained, it is clear that the Adam optimizer consistently provides better performance than SGD, both in terms of train accuracy, validation accuracy, and testing accuracy. This is due to Adam's adaptive learning rate mechanism, which accelerates convergence, especially in models with a large number of parameters such as EfficientNetB0. Adam shows higher train accuracy and better F1-score than SGD in most experiments. Conversely, although SGD provides lower results, it offers stability in preventing overfitting, especially when used with a smaller learning rate, such as 0.0001. This can be seen in the configuration with a learning rate of 0.0001, which provides lower but stable testing accuracy compared to Adam.

Furthermore, even though Adam achieves higher training accuracy, the model shows signs of overfitting, as seen in the significant difference between train accuracy and testing accuracy. For example, in the configuration with a learning rate of 0.001, batch size of 16, and 100 epochs, the train accuracy reached 92.10%, but the testing accuracy was only 78.14%. This shows that the model tends to adjust too much to the training data, making it difficult to generalize to previously unseen data.

Conversely, in experiments with SGD, although the train accuracy was slightly lower, the model was more stable on the test data, indicating that SGD helped the model avoid overfitting. For example, in experiments with a learning rate of 0.001, a batch size of 16, and 100 epochs, SGD produced a lower testing accuracy than Adam, but this testing accuracy was more stable and the F1-score was still competitive.

Overall, although Adam converges faster, it is at high risk of overfitting, especially if the configuration is not correct. On the other hand, although SGD may give slightly lower results, it is more stable, with more consistent testing accuracy on unseen data.

The confusion matrix results of EfficientNetB0 with the Adam optimizer can be seen in Figure 2.

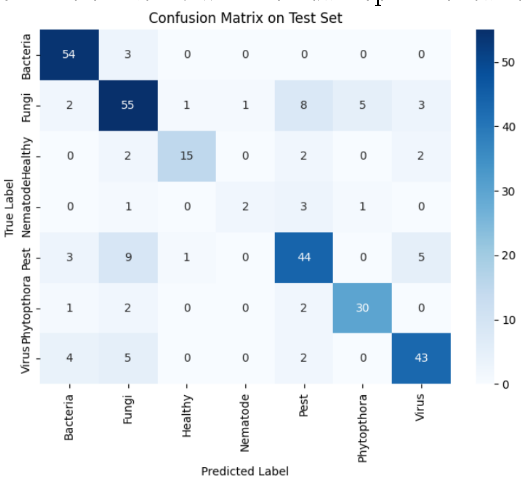

Fig 2. Confusion Matrix of EfficientNetB0 with ADAM Optimizer

Analysis of the confusion matrix shows that the EfficientNetB0 model with the Adam optimizer has a high accuracy rate in several classes, such as Bacteria, Fungi, and Virus, with the number of correct predictions reaching 54, 55, and 43, respectively. However, there are several classification errors in the Healthy and Pest classes, indicating that the model needs to be further trained to handle greater variation in the data in these classes.

After obtaining the best results in this study using EfficientNetB0 and augmentation techniques with an accuracy of 78.14%, the author will compare these results with previous studies used as references. A comparison of these results can be seen in Table 4.

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Table 4. Comparison of Results with Previous Researchers

Method	Architecture	Data Augmentati on Technique	Application Type	Number of Datasets	Accuracy
Shabrina Journal	EfficientNetV2B	brightness, flipping, rotating, zooming, and shifting	Offline	3076	73,63%
Journal Author	EfficientNetB0	rotasi, flipping, dan cropping	ImageDataGenerator	3076	78,14%

Table 4 shows significant progress in accuracy compared to previous studies. The improvement achieved by using the EfficientNetB0 architecture combined with the ImageDataGenerator data augmentation technique is considered very significant in improving the model's performance for potato leaf disease classification. This is because EfficientNetB0 is a lightweight and efficient architectural model, with features such as Depthwise Separable Convolutions, which allow this model to be faster and have higher accuracy compared to other models. Furthermore, the data augmentation techniques applied using ImageDataGenerator, such as rotation, flipping, and cropping, introduce variation in the training dataset without the need to add new images. This augmentation helps the model recognize more diverse patterns, thereby improving the model's generalization ability. The use of ImageDataGenerator is very useful because it allows augmentation to be performed dynamically during training, without requiring additional storage for the enlarged dataset, which can slow down the training process.

However, although the results obtained are quite good, this study has several limitations that need to be considered. First, in terms of dataset processing, if the number of classes in the classification is increased, it will affect the total number of datasets as a whole. Adding classes can make the model recognize more complex patterns, which may slow down the training process, although not significantly. Second, the implementation of the EfficientNetB0 model requires proper hyperparameter tuning to ensure that the model quality is maintained during training. The selection of an optimal learning rate and batch size can affect the final results of the training. For further research, it is recommended to consider using the EfficientNetB0 model with an increase in the number of classes in the classification. By maintaining the EfficientNetB0 architecture, which has been proven to be efficient in improving model performance, and by paying attention to the appropriate hyperparameters, it is hoped that the model's performance can be further improved. Thus, this model will be more optimal and can be adapted to the real conditions encountered in the field.

DISCUSSION

In Table 2 and Table 3, the experimental results show that using the EfficientNetB0 architecture with the Adam optimizer provides the best results with a train accuracy of 92.10% and a testing accuracy of 78.14%. These results indicate that a learning rate of 0.001 with a batch size of 16 produces optimal model performance compared to a learning rate of 0.0001. This is in line with findings from previous studies, where Adam showed better performance in accelerating model convergence compared to SGD, which, despite providing slightly lower testing accuracy, still showed better stability in several experiments.

With the SGD optimizer, even though the testing accuracy was lower (79.55%), the results obtained were quite competitive, especially with a batch size of 8 with an F1-score of 0.7461. This performance indicates that although SGD is less optimal in terms of accuracy, it is more stable in preventing overfitting compared to Adam. Thus, the selection of the appropriate optimizer greatly depends on the objectives to be achieved, whether to improve accuracy or to avoid overfitting. The Confusion Matrix presented in Figure 2 shows that the EfficientNetB0 model with optimizer The Adam optimizer performs well on classes such as Bacteria, Fungi, and Virus with a fairly high accuracy rate, while classification errors occur frequently in the Healthy and Pest classes. This indicates that the model requires more data and augmentation for these classes, as well as further evaluation with more complex augmentation techniques.

Although EfficientNetB0 provides good results, the use of EfficientNetV3 could be a promising alternative to further improve performance. EfficientNetV3 offers improvements in terms of model activation and convergence speed, and has been proven to be more efficient and accurate in image classification tasks. Therefore, further research could explore the use of EfficientNetV3 to overcome the challenge of overfitting and improve testing accuracy results. Overall, these results indicate that EfficientNetB0 with the Adam optimizer is an excellent choice for potato leaf disease classification, but improvements in hyperparameter tuning and data augmentation are needed to improve accuracy in more difficult classes such as Healthy and Pest.

CONCLUSION

This study successfully implemented EfficientNetB0 for potato leaf disease classification, using the Adam and SGD optimizers, as well as data augmentation techniques using ImageDataGenerator, which includes rotation, flipping, and cropping. The best results were obtained with a learning rate of 0.001, batch size of 16, and 100 epochs, resulting in a train accuracy of 92.10%, validation accuracy of 79.55%, and testing accuracy of 78.14% on the Adam optimizer. In

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addition, other evaluation metrics also showed good results, with precision of 0.740, recall of 0.736, and F1-score of 0.7386 on the test data.

Adam shows faster convergence speed and higher accuracy, but there are indications of overfitting, as seen from the difference between train accuracy and testing accuracy. On the other hand, SGD provides stable results, although slightly lower at 86.35% train accuracy, 80.35% validation accuracy, and 79.55% testing accuracy. The evaluation metrics for SGD are precision 0.740, recall 0.735, and F1-score 0.742, which are still very competitive.

The limitations of this study lie in the addition of classes in the classification, which can slow down model training, as well as the importance of more optimal hyperparameter tuning. Therefore, it is recommended to conduct further research using EfficientNetV3, which offers improved convergence speed and accuracy. In addition, further research could also consider adding more classes to the classification and introducing more complex data augmentation techniques, such as zooming and shearing, to further improve model performance.

Overall, this study makes a significant contribution to plant disease classification, particularly in the use of EfficientNetB0 with data augmentation techniques to improve model accuracy and efficiency in digital image processing. With future improvements, this model has the potential to be implemented in real-world plant disease detection applications.

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