Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 3, July 2023
DOI : https://doi.org/10.33395/sinkron.v8i3.12604
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Classification of Tea Leaf Diseases Based on ResNet-50 and Inception V3

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Submitted : Jun 26, 2023 | **Accepted** : Jun 30, 2023 | **Published** : Jul 1, 2023

Abstract: Technological advances have made a major contribution to controlling plant diseases. One method for resolving issues with plant disease identification is the use of deep learning for digital image processing. Tea leaf disease is a plant disease that requires fast and effective control. So, in this study, we adopted the Convolutional Neural Network (CNN) architectures, namely ResNet-50 and Inception V3, to classify six types of diseases that attack leaves. The amount of data used was 5867, which were divided into six classes, namely healthy leaf, algal spot, brown blight, gray blight, helopeltis, and red spot. The process of distributing the data involves randomly splitting it into three portions, with an allocation of 80% for training, 10% for validation, and 10% for testing. The process of classification is carried out by adjusting the use of batch sizes in the training process to maximizehyperparameters. The batch sizes used are 16, 32, and 64. Using three different batch size scenarios for each model, it shows that ResNet-50 has better performance on batch size 32 with an accuracy value of 97.44%, while Inception V3 has the best performance on batch size 64 with an accuracy of 97.62%.

Keywords: Batch Size, Deep Learning, Inception V3, ResNet-50, Tea

INTRODUCTION

Tea is a plant that has its own characteristics because it is only cultivated in certain climatic conditions and regions. Compared to other types of plants, tea is a plant that is very easy to find on almost every hill (Latha et al., 2021). However, in its growth process, the tea plant does not always run smoothly. Farmers face obstacles because of the emergence of diseases that attack tea leaves. Tea leaf diseases are a constant source of worry because they have a direct impact on the product's quality and yield when the harvesting season begins (Pandian et al., 2023). Fungi, bacteria, algae, viruses, or bad environmental conditions are basically the causes of disease in tea leaves (Rosyidah et al., 2023)**.** So far, experts have identified several symptoms of a disease that attacks tea leaves by visually observing the leaves, which include physical size, leaf texture, bone structure, and the color of the leaves themselves (Ramdan et al., 2019). This is very difficult for tea farmers to do alone. The results are highly individualized because farmers must only rely on their personal experience to identify diseases that affect tea leaves (Bao et al., 2022). Inappropriate anticipation in detecting diseases, such as using inappropriate pesticides or other chemicals, can cause pathogens that attack plants to become stronger, and the tea plant's immunity to fight disease will decrease (Gayathri et al., 2020). As a result, a more accurate and trustworthy method of disease diagnosis in tea leaves is required (Mathew & Mahesh, 2022).

Advances in computing technology, such as the use of deep learning and digital image processing, can be used for the detection and identification of diseases in plants. Many studies have proven this by adopting machine learning, especially deep learning in digital image processing, for the detection of leaf diseases, such as diseases in rice leaves (Julianto et al., 2022), tomato leaves (Saputra et al., 2023), and

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JURNAL & PENELITIAN TEKNIK INFORMATIKA
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e-ISSN : 2541-2019
p-ISSN : 2541-044X

other plant leaf diseases. The most commonly used deep learning method today is the convolutional neural network (CNN). One of the studies that adopted CNN was (Chen et al., 2019). This research uses one of the CNN models, namely LeafNet, and makes comparisons with two other models, namely Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP), for classification and identification of disease types in tea using leaf images consisting of 7 classes. The three methods were evaluated individually for each class and obtained an average classification accuracy of 90.19% for the LeafNet model, 60.62% for SVM, and 70.77% for MLP.

In addition, (Ramdan et al., 2020) conducted another study using VGGNet, ResNet, and Xception for tea leaf disease classification. The results of the research conducted revealed that the application of fine-tuning to the model used proved to be effective, and accuracy was obtained using Resnet-50 (94.05%), VGG16 (91.26%), and Exception (91.71%). Although the above architecture has good performance, the number of parameters generated by the model is quite large. The CNN model does produce quite good performance; however, the performance can still be improved by using the appropriate hyperparameters. One of the hyper parameter settings that need interest is batch size. A batch size that is too high can make the network take too long to reach convergence. But, using a batch size that is too low will cause the network to iterate repeatedly and not achieve optimal performance (Kandel & Castelli, 2020).

By utilizing jump connections, the ResNet-50 CNN model addresses performance issues and facilitates deeper networking. As the network grows deeper, this aids in maintaining solid performance (Zahisham et al., 2020). In contrast, Inception V3 is more concerned with the use of parallel convolutional operations. It helps to extract rich information from input data by capturing intricate and complex features at various scales (Mujahid et al., 2022). As a result, the two will approach the study of image features and solving problems in the classification task in different ways.

Based on the description above, this study aims to evaluate the performance of ResNet-50 and Inception V3 in classifying tea leaf diseases and to improve the accuracy of research conducted by (Datta & Gupta, 2023) with paying attention to the use of batch sizes to obtain optimal results. The use of ResNet-50 and Inception V3 architectural models is expected to assist tea farmers in identifying and classifying tea leaf diseases quickly and precisely so as to prevent crop failure due to decreased quality and quantity.

LITERATURE REVIEW

Before conducting research related to the identification of diseases in tea leaves, the researcher first reviewed the literature related to research that previous researchers had carried out as a reference in developing the research to be conducted. From the literature review conducted, several previous research studies related to the research to be carried out were obtained. Research conducted by (Datta & Gupta, 2023) applied the use of Deep CNN to classify diseases of tea leaves into six classes consisting of five types of diseases and one class for healthy leaves. Deep CNN is used because it has many hidden layers, so it can be considered to classify diseased tea leaves into different categories. The use of Deep CNN helps the network detect more features, so the accuracy of disease detection will increase. Based on experimental findings, the suggested method is capable of detecting tea leaf diseases with a fairly high accuracy of 96.56%.

A similar study was also carried out by (Hardi, 2022) using MobileNet and Nasnet Mobile to classify tea leaf diseases into six classes. The classification was carried out using batch sizes of 32 and 10 epochs. From the results of the comparison using the MobilNet and NasNet Mobile methods, accuracy was obtained at 88% and 95%, respectively. Another study conducted by (Hu et al., 2021) offered a deep learning approach to enhance the detection and analysis of tea leaf blight disease severity. Tea leaf blight was identified using a framework for deep learning, namely Faster R-CNN, to enhance the accuracy of the identification of fuzzy, clogged, and small diseased leaves. The detected tea leaf blight will be inserted into the VGG16 network for analysis. In the testing phase, a recall value of 93.92%, precision of 95.74%, and AP value of 91.22% were obtained. The experimental results show that the average precision of the suggested approach is increased by more than 6% and 9%, respectively.

Another study was also conducted by (Gayathri et al., 2020) to classify tea plant diseases into four classes using CNN, namely the LeNet model. In addition, the classification process is also carried out

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by combining the Color Co-occurrence method to extract color packages. The study employs data augmentation to improve the amount of data in all existing classes. By using the softmax activation function, an accuracy of 90.23% and an MCA of 90.16% were obtained.

METHOD

A study always has a research design model or workflow that is used to describe the research flow. Figure 1 illustrates the research stages, which consist of five processes that will be passed: dataset collection, data preprocessing, building architectural models, model training, and testing or evaluation.

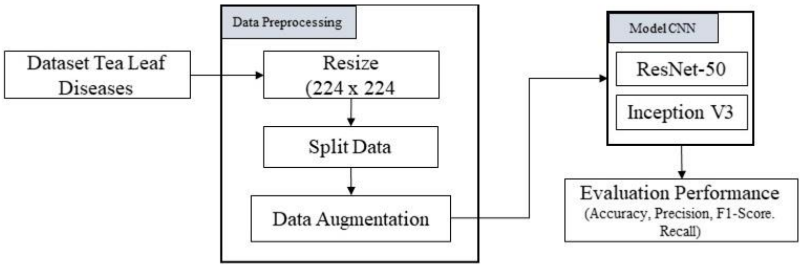

Figure 1. Research Workflow

a. Dataset

The dataset used is secondary data obtained through research conducted by (Datta & Gupta, 2023) with a total of 5867 images of tea leaves divided into six classes with details of 1000 healthy leaves, 1000 algal spots, 867 brown blights, 1000 gray blights, 1000 helopeltis and 1000 red spots. Figure 2 is a visualization of the dataset used in this research.

Healthy Algal Spot Brown Blight

Gray Blight Helopeltis Red Spot

Figure 2. Tea Leaf Dataset.

b. Preprocessing Data

At the preprocessing stage, several processes arecarried out, namely resizing, splitting data, and data augmentation. The resizing process is carried out on the entire dataset so that each image has the same size. This process will adjust the input data to the system so that an error does not occur due to an imbalance in the size of the data. At this stage, the image will be resized from the previous 256x256 pixel image to 224x224 pixels. In the split data process, the dataset will be randomly divided into 3 parts: 80% for data training, 10% for data validation, and 10% for data testing. Furthermore, the augmentations carried out are rotation range, zoom range, vertical flip, and horizontal flip. The augmentation results can be viewed in Figure 3.

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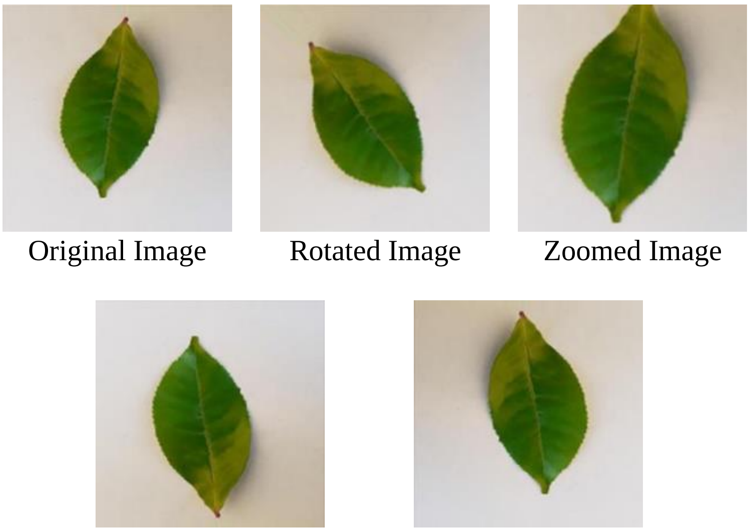

Figure 3. Augmentation Data Preview

c. ResNet-50

After going through the preprocessing stage, the next step is to build an architectural model. The architectural model used in this study is ResNet-50. Overall, the structure of the ResNet-50 architecture consists of five stages of the convolution process, which are then continued by average pooling and end with a fully connected layer as a prediction layer (Faiz Nashrullah et al., 2020). The ResNet-50 architecture can be viewed in Fig 4 (He et al., 2016).

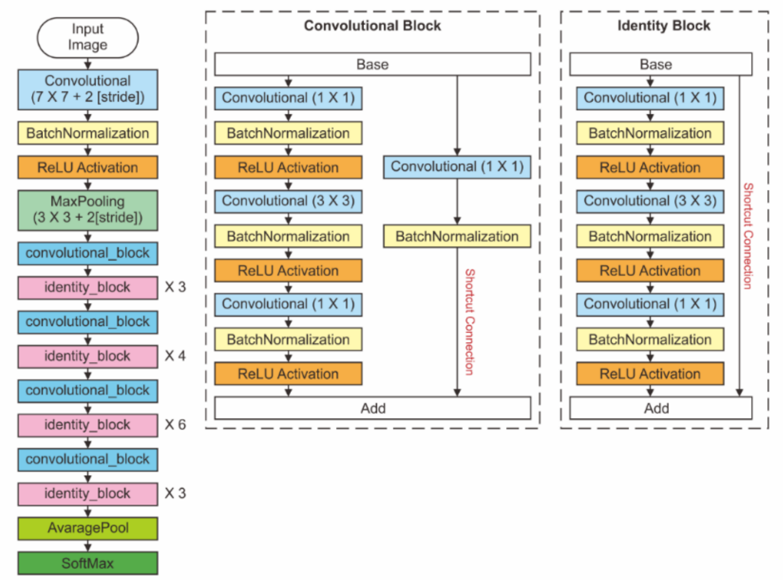

Figure 4. ResNet-50 Architecture

However, there are differences between the ResNet-50 architecture used in this study and the original architecture. Slightly different from Figure 4, in this study several layers were added, namely, one hidden layer (fully connected layer) with 1024 nodes, and use ReLU to activate the function. Then we included a dropout with a size of 0.5 to overcome the overfitting. Furthermore, the number of outputs on hidden layer (fully connected layer) from 1000 classes is changed to 6 classes with the softmax.

d. Inception-V3

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Besides using ResNet-50, the architecture used in this research is Inception V3. Overall, the structure of Inception V3 consists of several steps that are carried out, including convolution, Average Pool, max pool, dropout, fully connected, and softmax (Rochmawati et al., 2021). The Inception V3 architecture can be viewed in Fig 5 (Szegedy et al., 2016).

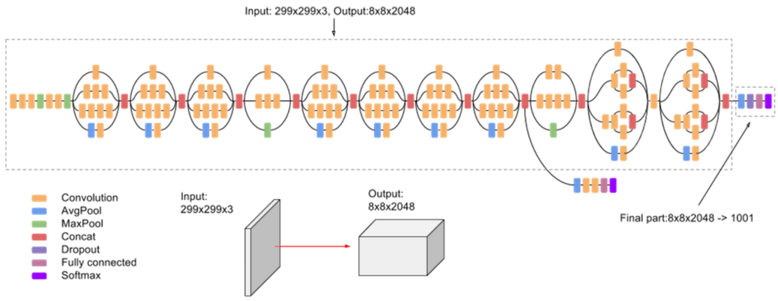

Figure 5. Inception V3 Architecture

However, there are differences between the Inception V3 architecture used in this study and the original architecture on Figure 5, in this study several layers were added, namely, one hidden layer (fully connected layer) with 1024 nodes, and use ReLU to activate the function. Then we included a dropout with a size of 0.5 to overcome the overfitting. Furthermore, the number of outputs on hidden layer (fully connected layer) from 1000 classes is changed to 6 classes with the softmax.

e. Training

In the training process, several hyperparameter configurations are set beforehand. The hyperparameters used are learning rate, optimizer, epoch, and three batch size configurations. Hyperparameter configuration details can be viewed in Table 1.

Table 1. Hyperparameter Configuration Details

Learning rate	Optimizer	Epoch	Batch Size
Reduce Learning Rate (lr = 1e-4 to 1e-6; with factor = 0.5)	Adam	100	16, 32, 64

In addition to using hyperparameters as in Table 1 to improve accuracy, this study also applies a callback function. The functions used for training are the checkpoint model to save the model periodically during training, early stopping to stop training early if there is no increase, and reduced learning rate to adjust the learning rate to achieve better convergence.

f. Evaluasi Performance

After conducting training and testing, the next stage is performance evaluation. At this stage, the model evaluation is visualized using a confusion matrix. Statistical data obtained through the confusion matrix is then used to calculate accuracy (1), recall (2), precision (3), and F1-Score (4).

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \text{ x } 100\% \quad (1)$$

$$\text{Recall} = \frac{TP}{(FN+TP)} \text{ x } 100\% \quad (2)$$

$$\text{Precision} = \frac{TP}{(FP+TP)} \text{ x } 100\% \quad (3)$$

$$\text{F1 Score} = \frac{2 \text{ x } (\text{recall x presisi})}{(\text{recall} + \text{presisi})} \; x \; 100\% \quad (4)$$

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Based on equations (1), (2), and (3), TP represents the count of correctly classified positive instances of tea leaf disease by the system. On the other hand, TN denotes the number of correctly classified negative instances of tea leaf disease. FP signifies the count of negative samples that are mistakenly identified as positive, while FN indicates the number of positive samples that are mistakenly identified as negative.

RESULT

The process in this study was carried out using 5867 datasets. The researchers divided the datasets into 80% for training, 10% for validation, and 10% for testing. The architectural model used is ResNet-50 and Inception V3 with different batch sizes, namely 16, 32, and 64. Each experiment on the batch size value will experience the same approach, namely using 100 epochs, the Adam optimizer, and using three callback functions, namely checkpoint model, reduce learning rate, which starts at a value of 0.0001 to 0.000001, and early stop. The results of the implementation of different batch sizes are illustrated in Table 2.

Table 2. Comparison of Accuracy and Loss

Model	Batch Size	Training		Validation	
		Acc	Loss	Acc	Loss
ResNet-50	16	98.93%	3.67%	96.76%	10.86%
	32	**98,97%**	**3.32%**	**97.10%**	**9.50%**
	64	98.64%	4.51%	96.59%	10.14%
Incepion-V3	16	38.85%	149.02%	44.97%	144.14%
	32	36.60%	154.21%	42.93%	145.63%
	64	**98.62%**	**4.93%**	**96.42%**	**10.67%**

First of all, we will discuss the results obtained on ResNet-50. In the scenario of using batch sizes, the accuracy is not much different. The highest accuracy was obtained by batch size 32 with 98.97% training accuracy and 97.10% validation accuracy. In batch size 16, the training and validation accuracy obtained is quite high, namely 96.76%. However, the accuracy and validation loss graphs produced in Figure 5 are unstable. Unstable conditions of accuracy and validation loss may indicate that the model may not reach convergence or still have high fluctuations in performance in each epoch. So, it is necessary to do an experiment on a batch with a larger size to see a comparison of the graphics rate as well as the resulting performance. However, when we tried batch size 64, it turned out that the accuracy obtained had decreased compared to batch size 32. Thus, the ResNet-50 model to be evaluated is the model with batch size 32. To see the difference, a graphic illustration for comparing accuracy and loss values in training data and validation data using a batch size of 16 can be seen in Figure 6 while using a batch size of 32 can be seen in Figure 7. The X-axis value indicates the number of training iterations that have been processed during the model training process, while the Y-axis shows the accuracy or loss level of each iteration. In the second scenario, it can be seen on the graph that the iterations are running more consistently and do not increase or decrease too much.

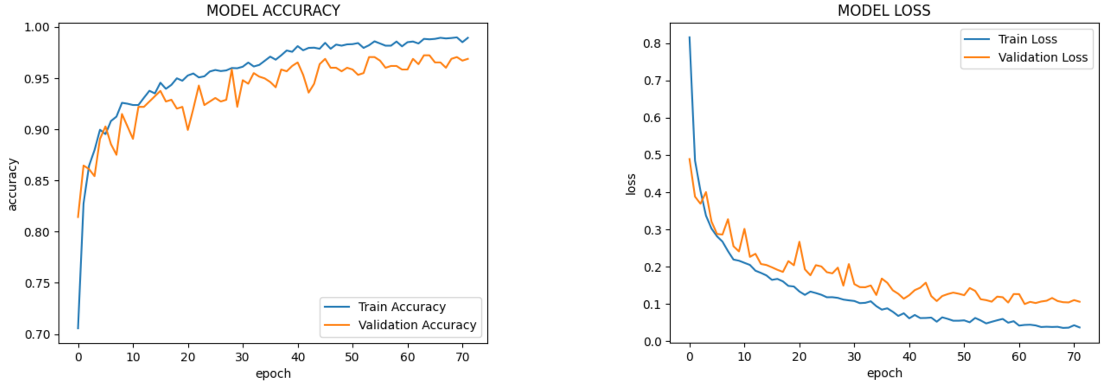

Figure 6. Accuracy and Loss ResNet-50 for Batch Size 16

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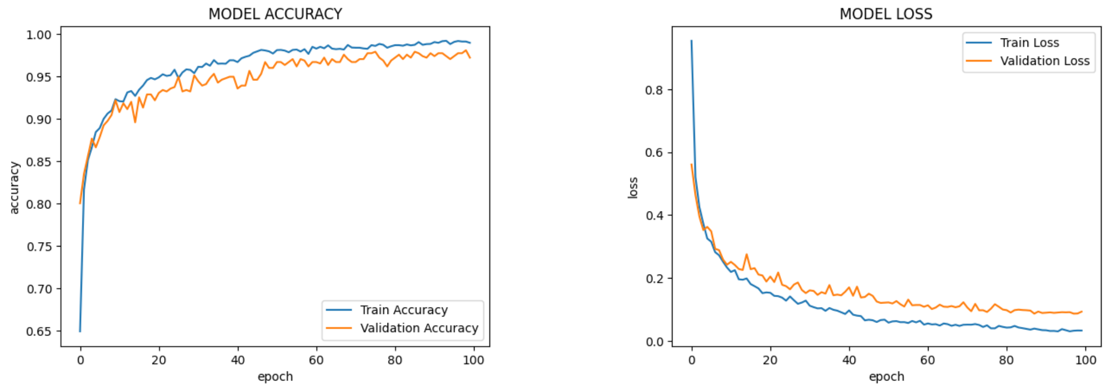

Figure 7. Accuracy and Loss ResNet-50 for Batch Size 32

As seen in Figure 7, the accuracy and loss validation using batch size 32 has a more stable graph compared to batch size 16 in Figure 6. Based on the highest accuracy results obtained in the training process, the next step is to do data testing to find out the accuracy produced in the testing process. The confusion matrix for data testing is shown in Figure 8.

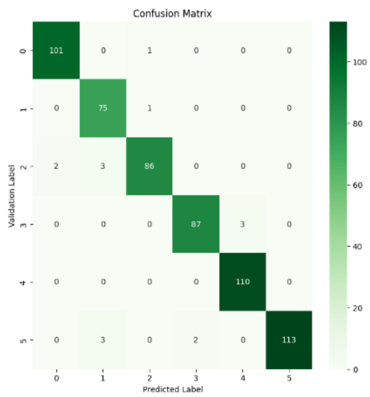

Figure 8. Confusion Matrix for Batch Size 32 with ResNet-50

Based on the results of the confusion matrix in Figure 9, with a batch size of 32, it can be seen that there are 572 images of tea leaves that are correctly identified and 15 images that are not correctly identified. In confusion matrix, 0 represents Algal Spot disease, 1 represents Brown Blight, 2 represents Gray Blight, 3 represents Healthy Leaves, 4 represents helopeltis, and 5 represents Red Spot.

Next up is the Inception V3 model. The Inception V3 model is run using the same parameters as ResNet50. As seen in Table 2, the accuracy and loss for training and validation were obtained with a batch size of 64. In contrast to ResNet-50, there is a significant difference in accuracy and loss in Inception V3. The different model structure is one of the contributing factors. A graphic illustration for comparing accuracy and loss values in training data and validation data using a batch size of 64 can be seen in Figure 10. The X-axis value indicates the number of training iterations that have been processed during the model training process, while the Y-axis shows the accuracy or loss level of each iteration. In the second scenario, it can be seen on the graph that the iterations are running more consistently and do not increase or decrease too much.

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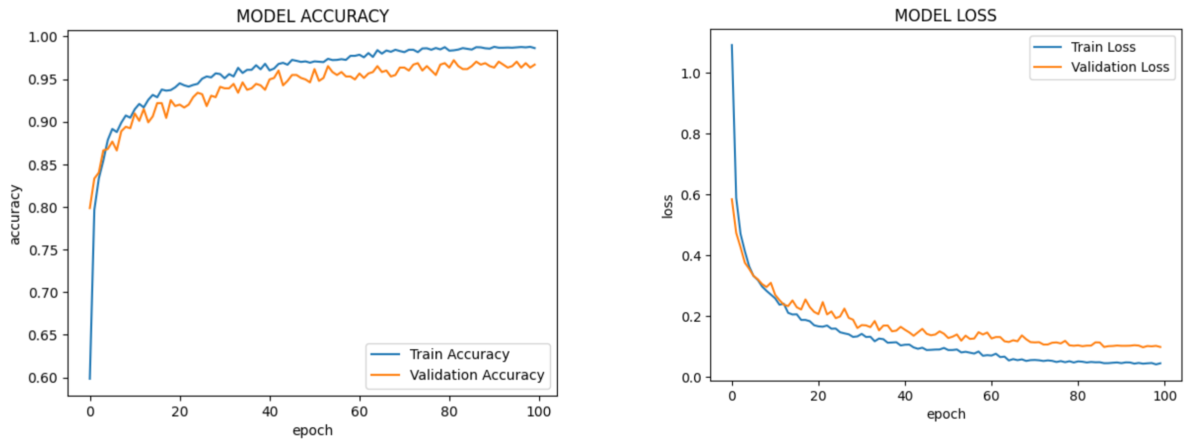

Figure 9. Accuracy and Loss Inception V3 for Batch Size 64

Based on the highest accuracy results obtained in the training process, the next step is to do data testing to find out the accuracy produced in the testing process. The confusion matrix for data testing is shown in Figure 11.

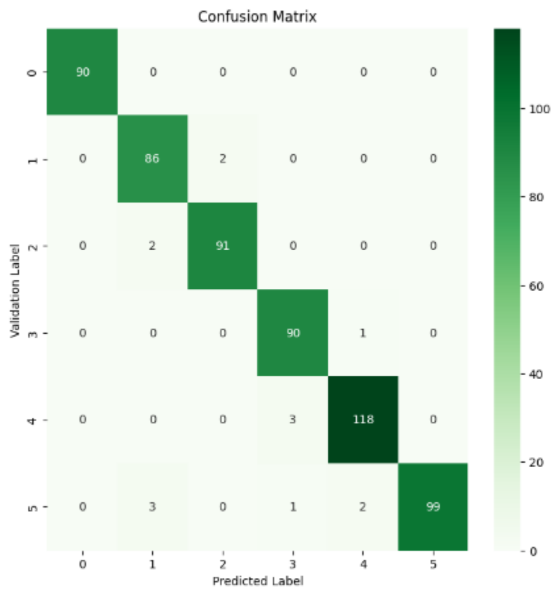

Figure 10. Confusion Matrix for Batch Size 64 with Inception V3

Based on the results of the confusion matrix in Figure 11, with a batch size of 64, it can be seen that there are 574 images of tea leaves that are correctly identified and 14 images that are not correctly identified. Based on the confusion matrix in Figure 8 and Figure 10, the values for accuracy, precision, recall, and f1-score are obtained as shown in Table 3.

Table 3. ResNet-50 and Inception V3 models Performace Result

Model	Accuracy	Precision	Recall	F1-Score	Support
ResNet-50 + batch size 32	97.44%	97.33%	97.66%	97.5%	587
Inception V3 + batch size 64	97.62%	97.83%	97.83%	97.66%	588

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DISCUSSIONS

To compare the performance of ResNet-50 and Inception V3, can be seen by using the performance metrics used in this study as shown in Table 3, which displays the accuracy, precision, recall, and F1-Score values of each model. Based on the results of this study, the ResNet-50 and Inception V3 Architecture models succeeded in classifying tea leaf disease using three different batch size scenarios. The best results for ResNet-50 were obtained for batch size 32 with 97.44% accuracy, 97.33% precision, 97.66% recall, and a 97.5% F1-Score. Whereas in Inception V3, the best results were obtained on batch size 64 with 97.62% accuracy, 97.83% precision, 97.83% recall, and a 97.66% F1-Score.

In identifying the type of tea leaf disease, the results obtained in this study succeeded in obtaining more optimal accuracy compared to previous studies (Datta & Gupta, 2023). Details of the accuracy comparison can be viewed in Table 4.

Table 4. Accuracy Comparison

Method	Accuracy (%)
Deep CNN (Datta & Gupta, 2023)	96.56%
ResNet-50 (Proposed Method)	**97.44%**
Inception V3 (Proposed Method)	**97.62%**

However, keep in mind that the results obtained in this study only refer to the conditions and datasets used in the study. Further research can be done by trying other architectures or adding other parameters to improve accuracy with the same or different dataset.

CONCLUSION

In this study, we compared the performance of ResNet-50 and Inception V3 for tea disease classification using leaf imagery. The dataset in this study consisted of 5867 images of tea leaves divided into six classes with details of 1000 healthy leaves, 1000 algal spots, 867 brown blights, 1000 gray blights, 1000 helopeltis, and 1000 red spots. The use of different batch sizes for each model shows that ResNet-50 obtains the highest accuracy on batch size 32 with an accuracy of 97.44%, while Inception V3 obtains the highest accuracy on batch size 64 with an accuracy of 97.62%. The results obtained indicate that the use of batch size affects the resulting accuracy of the architecture used.

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