ISSN 2961-7758

Transfer Learning VGG16 For Image Classification of Tomato Leaf Disease

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ABSTRACT

Tomatoes (*Solanum lycopersicum*) are one of Indonesia's mainstay horticultural commodities that are exported throughout Southeast Asia. However, the export value of tomatoes in 2021 recorded a decrease of 34.07% from 2020. The decline in the quality and quantity of tomatoes is generally caused by bacteria, fungi, viruses, and mite outbreaks that mostly attack the leaves such as late blight and two-spotted spider mite. This research utilizes one of the image processing methods to classify tomato leaf diseases in 3 labels, namely tomato healthy, tomato late blight, and tomato two-spotted spider mite. The image processing algorithm used in this research is Convolutional Neural Network (CNN) which can extract leaf image features in depth through its layer architecture. The VGG16 transfer learning architecture is used in this study because of its simple structure and can be modified by adding a fully connected layer, namely dropout with a value of 0.5 to adjust the model and improve its performance. Green Channel + CLAHE is also applied at the preprocessing stage with an epoch parameter of 30. The dataset used consists of 1,591 images of healthy tomato leaves, 1,909 images of late blight tomato leaves, and 1,676 images of two-spotted spider mite leaves. Two scenarios were conducted on the model, namely the model with callback function and the model without callback function. Based on the training and evaluation of the model that has been carried out, the model with the callback function is able to produce an accuracy value of 99.03% with precision for the labels tomato healthy 0.99, tomato late blight 1.00, and tomato two-spotted spider mite 0.98, and the number of incorrectly predicted images is only 15. This shows a higher value than the model without the callback function. Against 21 test images from other datasets, the model with callback function was able to produce accurate classification with high prediction values.

Keywords: leaf disease, tomato, late blight, two-spotted spider mite, transfer learning, vgg16

INTRODUCTION

Indonesia is known as one of the producers of horticultural commodities that are exported to the Southeast Asia region. One of the commodities that are widely cultivated and become a mainstay is tomato (*Solanum lycopersicum*) (L. Sahrani, 2021). This plant from the Solanaceae family in 2021 recorded an increase of 2.71% from 2020 with the largest production coming from West Java, North Sumatra, and West Sumatra. However, the export value in 2021 decreased by 34.07% (US$ 538.97 thousand) from 2020 (BPS RI/BPS-Statistics Indonesia, 2021). This is due to a decrease in the quality and quantity of tomato plants that are susceptible to diseases by bacteria, fungi, viruses, and mite outbreaks (Apriyadi et al., 2019).

A common tomato disease is late blight, caused by the fungus *Phytophthora infestans (Mont.) de Bary*, which thrives in cool, moist places. The initial symptoms of this disease are characterized by the appearance of black or brownish lesions on the edges and middle of the leaves as shown in Figure 1 (a) which then continues to spread until it damages the plant (H. Semangun, 1994). The two-spotted spider mite disease originates from *Tetranychus urticae* spider mite outbreaks as a result of excessive insecticide use. The bites of this spider mite cause pale yellow, reddish-brown spots ranging from small to large areas on the upper and lower leaf surfaces as shown in Figure 1 (Kemble et al., 2022).

(a) (b)

Source: Research Result (2023)

Figure 1. Tomato leaf disease (a) late blight (b) two-spotted spider mite

The characteristics of infected leaves tend to be similar, making it difficult for ordinary farmers to identify them. Astiningrum et al., 2020, in their research wrote that plant identification can be done through detecting the shape and texture of leaves through image processing. One of the image processing methods that can handle image classification well with significant results and is very suitable for large amounts of data is the Convolutional Neural Network (CNN) (Wahid et al., 2021). To maximize the performance of the CNN model without training the

ISSN 2961-7758

model from scratch, a transfer learning model is used (Kandel & Castelli, 2020). One of the transfer learning models that can be used is VGG16 with excellent model performance, and has a simple network structure that is relatively easy to modify (Jiang, 2019).

This research classifies tomato leaf diseases with the CNN method where the VGG16 architecture is used to maximize the performance of the classification model and over 5,176 tomato leaf images. So that the classification accuracy obtained is maximum and accurate. This research is expected to be a reference for learning the CNN method with a transfer learning model in future research. It can also help farmers in identifying tomato plant diseases so that later farmers are expected to carry out prevention and further treatment of tomato plants.

LITERATURE REVIEW

Image processing research with the VGG16 transfer learning architecture has been carried out on various datasets. In research conducted by Rismiyati & Luthfiarta, 2021, the VGG16 model was able to classify the quality of salak fruit in 370 salak images in good and bad classes with an accuracy of 95,83%. In a study conducted by Krishnaswamy Rangarajan & Purushothaman, 2020, 1,088 eggplant leaf images were classified with VGG16 into 4 leaf disease classes with an accuracy of 99.4%.

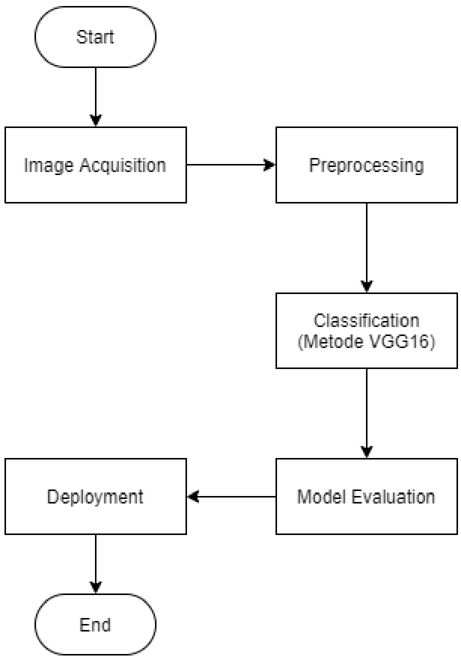
Meanwhile, Tan et al., 2021, have compared the classification of tomato leaf diseases with 10 classes of leaf diseases using machine learning and deep learning resulting in better accuracy of deep learning models than machine learning with an accuracy result for VGG16 of 98.9%. Wahid et al., 2022, have also classified tomato leaf diseases into 10 classes of tomato leaf diseases using InceptionV4 architecture and callback functions for 100 epochs resulting in a model accuracy of only 90%. The tomato leaf disease classification research conducted by Al-gaashani et al., 2022, on 5 classes of tomato leaf diseases with MobileNetV2 and NASNetMobile architecture resulted in model accuracy of 97%.

1. Convolutional Neural Network
   Convolutional Neural Network (CNN) was first introduced by Yann LeCun pada 1988. This method is a development of the multilayer perceptron with neurons connected to each other in different layers. Its ability to find hierarchical patterns in data and assemble more complex pixels from smaller, simpler pixels makes CNNs perform very well in handling the connectedness and complexity of image pixels. (Rasywir et al., 2020).

2. Transfer Learning VGG16
   Transfer learning is a method of knowledge transfer by utilizing models that have been extensively trained before. The existence of this technique makes training time shorter with increased model accuracy (Deep & Zheng, 2019). There are various transfer learning architectures commonly used in image processing, one of which is VGG16. Deng et al., 2009, in their research stated that this architecture has been trained with ImageNet images consisting of millions of images from 1000 classes which can then be used to train other datasets. The earliest architecture that successfully classifies ImageNet images with high accuracy is the Visual Geometric Group (VGG) developed by Oxford University with a total number of 16 layers in it and is known as VGG16.

METHOD

There are several stages in this research to classify tomato leaf diseases with the VGG16 transfer learning model as shown in Figure 2.



Source: Research Result (2023)

Figure 2. Research stages

The initial stage is taking the dataset to be used, then preprocessing the data by changing the color and noise reduction, resizing the image, and dividing the dataset into training data and testing data. The next stage is the classification process with transfer learning where the training data is trained using VGG16 and the final model results are evaluated with the testing data. Furthermore, deployment is carried out on the model that has been evaluated. Each stage is explained as follows.

1. Image Acquisition
   The acquisition of the dataset that will be used in the research is known as image acquisition (Lumute

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Unihehu & Suharjo, 2021). The dataset used for the classification of tomato leaf diseases in this study is secondary data of tomato leaf images obtained from Mahesh Babu's Kaggle which has been updated in June 2022 under the name Tomato Leaf Disease (K. Mahesh Babu, 2022). The image dataset used is a color or RGB (Red, Green, Blue) image with a size of 256x256 pixels and has a .jpg format and is labeled tomato healthy, tomato late blight, and tomato two spotted spider mite with details in Table 1.

Table 1. Tomato Leaf Image Details

Sample	Amount
Tomato Healthy	1.591
Tomato Late blight	1.909
Tomato Two spotted spider mite	1.676
Total	5.176

Source: Research Result (2023)

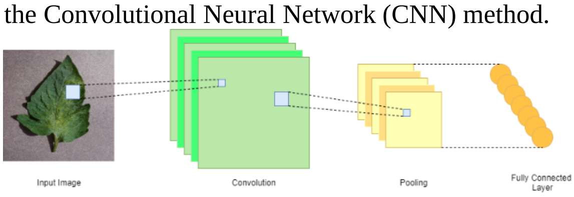
Tomato leaves are usually oval in shape with jagged leaf edges and form pinnate leaf slits (A. Ulfa Martyas, 2021). Healthy leaves have a dark green color and are fluffy (Mugiyanto & Nugroho, 2000). While leaves that have been infected with late blight will appear small spots like wounds that become pale green to brown and quickly expand to cover the leaf area. In humid weather, gray to white pathogens will appear on the lower surface of leaf lesions (Melanson, 2020). Even with two-spotted spider mite leaves, yellow spots will appear on the leaf base to the main leaf bone and can cause reddish leaves like rust when the mites spread. Worse, the lower and middle leaves will fall off, causing the buds to shrink in size. It is common to see white webs covering the leaves in the upper third of the plant causing the plant to die (Fasulo & Denmark, 2016).

2. Preprocessing
The dataset obtained is reduced to remove unnecessary information so that the image conditions are uniform so that the dataset can be used in the classification process is the purpose of the preprocessing stage (Yustika et al., 2019). In this study, the first stage of preprocessing was carried out by resizing the image (resize) from 256x256 pixels to a fixed size of 224x224 pixels. Image sizes that are neither too small nor too large can speed up the training process and use less memory without reducing the resolution (Ekananda & Riminarsih, 2022).

The resized image is extracted to the green channel to get a clearer image of healthy leaves, late blight, and two-spotted spider mite. Green channel is able to produce the best image of the red channel and blue channel (Desiani et al., 2021). Local contrast enhancement in the image is also done to bring out hidden features with the Contrast Limited Adaptive Histogram Equalization (CLAHE) (Kanditami et al., 2014). The resulting image is converted into an array as input to the model.

Next, the dataset is split and labeled with x features and y features. The last stage is to augment the image dataset. This stage aims to overcome overfitting that may occur because CNN memorizes detailed features from training data that cannot be generalized, so that the image dataset will increase without losing the characteristics of each image.

3. Classification with VGG16
The next stage is to classify tomato leaf images with the Convolutional Neural Network (CNN) method.

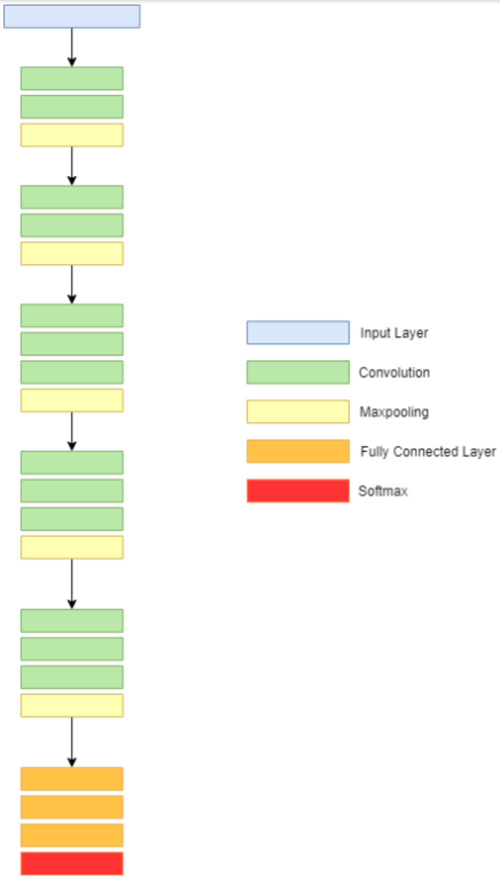


Source: Research Result (2023)

Figure 3. Convolutional Neural Network (CNN) Architecture

Figure 3 is a simple CNN architecture with the first stage layer in the identification process called the convolution layer. This layer will extract the texture from the leaf image and the results will be pooled. The final stage in this method is the fully connected layer which will make decisions based on the features that have been collected by convolution and pooling (Rozaqi et al., 2021).

This research uses the transfer learning model VGG16 to improve the accuracy of the model without its training time. The convolution and pooling layer architecture in VGG16 is deeper than the simple CNN architecture as shown in Figure 4.



Source: Research Result (2023)

Figure 4. VGG16 Architecture

4. Model Evaluation
   The model that has been trained is then evaluated with a confusion matrix based on criteria (Tharwat, 2018) dan equations (Lu et al., 2021):
   a. Precision: indicates the ratio of correct positive predictions to total positive predictions with the formula as shown in equation (1). A high precision value means fewer wrong prediction errors.

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

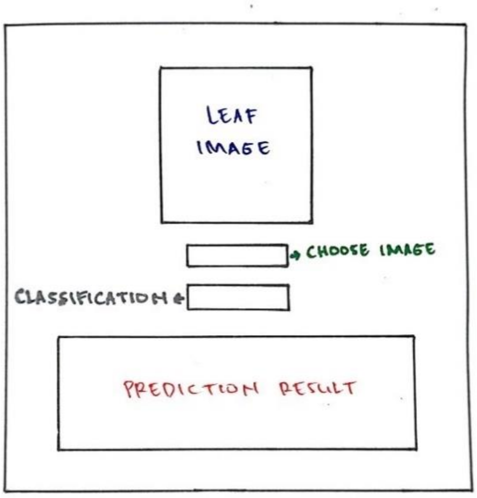
   b. Recall: the ratio of correct positive predictions to all observations in the actual class with the formula as shown as in equation (2). A high recall value means that the model correctly identifies more actual positive observations.

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

   c. F1-score: harmonious average of precision and recall with the function of providing a balance between precision and recall with the formula as shown in equation (3).

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (3)$$

5. Deployment
   The classification model that has been trained is then stored and deployed. Deployment is intended to make it easier for users to understand the process of identifying healthy tomato leaves, late blight, and two-spotted spider mite by utilizing tomato leaf images. Deployment in python is done by creating a Graphical User Interface (GUI) application using QtDesigner, so that the application design is more flexible (Utami, 2021) including image input and accuracy results on images such as Figure 5.



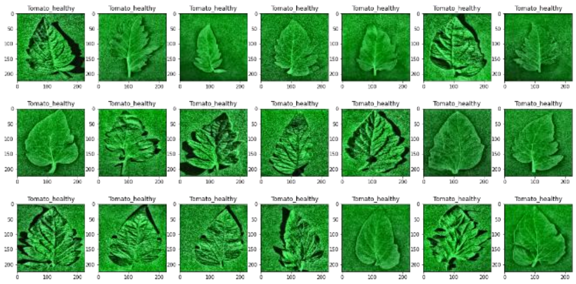
Source: Research Result (2023)

Figure 5. Classification Page Design

RESULT AND DISCUSSION

1. Preprocessing Result

In the preprocessing stage, the image size is changed to 224x224 pixels and then extracted to the green channel and CLAHE to bring up the hidden features with the results as shown in Figure 6.



Source: Research Result (2023)

Figure 6. Green Channel dan CLAHE Result Image

Hidden features aim to detect lesions, spots, or blotches in the leaf image. A clip boundary value of

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3.0 and a grid size of 8.8 are given to control contrast enhancement and control the size of the square region where histogram equalization is applied.

In this study, color spots and lesions on leaves can be detected. Thus, the model can distinguish between healthy leaves and leaves with late blight or two-spotted spider mite. The location and size of spots and lesions on the leaf image also appear more clearly.

Table 2. Split Dataset

Split Data	Data Percentage	Number of Data
Training	70%	3.623
Testing	30%	1.553
Total		5.176

Source: Research Result (2023)

Table 2 shows the percentage split of the dataset that has been labeled with feature x and label y. The data type of the x feature is converted to float32, while the y label is converted to categorical format. The split with the percentages in Table 2 gives the best results according to the empirical analysis (Gholamy et al., 2018).

The next stage in the preprocessing process in this research is augmentation with the aim of avoiding overfitting that may occur. Overfitting is a situation where the accuracy of training data increases until the last epoch, while the accuracy and loss of validation data does not increase due to the small amount of training data in the model (Fadli Gunardi, 2022). There is no specific rule for the amount of augmentation, so this research uses the amount of augmentation shown in Figure 7.

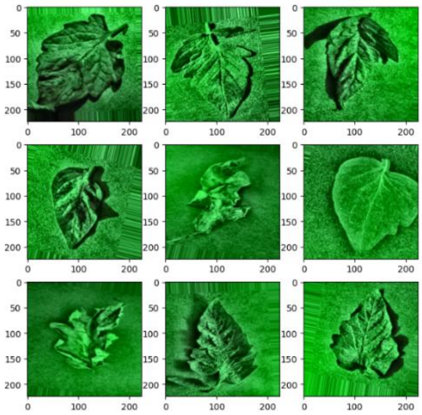
```
datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=15,
    shear_range=0.1,
    zoom_range=0.2,
    width_shift_range = 0.1,
    height_shift_range = 0.1,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
    )
datagen.fit(X_train)
```

Source: Research Result (2023)

Figure 7. Data Augmentation

In this study, the rescale parameter used is 1./255 to change the pixel value from 0-255 to 0-1. This is done so that the range of pixel values becomes smaller to facilitate the model training process. Furthermore, the image rotation degree range is set at 15, which means that at each iteration in each epoch, the image will be randomly rotated in the degree range of -15 to 15 degrees. Furthermore, the shear transformation (shear range) in the image is determined with a range of 0.1 and to zoom in the image is determined with a range of 0.2. To perform horizontal and vertical image shifts, the width shift range and height shift range are set to 0.1.

Furthermore, horizontal flip and vertical flip are set to 'True', which means the image will be randomly flipped horizontally (mirror) or vertically at each iteration in each epoch. With 'nearest' fill mode, pixels in the image that are not covered by the image after transformation will be filled with the nearest pixel value from the original image. Thus, the leaf images for training the model will be more varied. The 9 augmented images are shown in Figure 8.



Source: Research Result (2023)

Figure 8. Augmented Image

2. Classification Result

The training process in this study uses 30 epoch parameters, SGD optimizer, learning rate 0.001, and loss function with category cross entropy. A large number of epochs does not guarantee a better model, so the number of epochs can be reduced to shorten the training process (Valentina et al., 2020). In this study, 2 scenarios were used, namely scenario A without a callback function and scenario B with a callback function which is a function of FastAI to stop the model when it reaches the best accuracy of the model (Uppari, 2020).

Table 3. Function Usage Scenario

Alias	Scenario
SA	Non-callback
SB	Callback

Source: Research Result (2023)

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Based on the SA model training process and SB experiments at 30 epochs, the accuracy and loss plots are obtained with the results in Table 4.

Table 4. Accuracy Results with Scenarios

Scenario	Action	Validation Accuracy	Validation Loss	Epoch
A	Without callback function	96.27%	13.35%	30
B	With callback function	99.03%	2.83%	19

Source: Research Result (2023)

Table 4 shows the SA training process where the model stopped at the 30th epoch. This shows that the model is updated 30 times after going through all the training data, until the validation accuracy is 0.9627 and the validation loss is 13.35%, so the model accuracy is 96.27%. Whereas in SB, the callback function is given a provision if the validation accuracy value is greater than 0.9850 then the message "ACCURACY FULFILLED" will be printed, so that the validation and loss plots are stopped at the 19th epoch with a validation accuracy of 0.9903 and a validation loss of 2.83%, so that the model accuracy is 99.03%. This is because the callback function in PB sets the stop_training attribute of the model object to True. Thus, the training process will stop when the desired accuracy has been achieved. Thus, the callback function affects the accuracy value of the resulting model.

The validation accuracy value in SA and SB appears to be lower than the validation loss value. This means they both perform well and predict labels with a high degree of accuracy. However, there is still a possibility of overfitting or underfitting (Ghojogh & Crowley, 2019), so it is necessary to test on testing data that is not involved in the training process to ensure that the model performs well on new data.

3. Model Evaluation

Model evaluation with precision, recall, and f1-sore metrics can be seen in Table 5 and Table 6.

Table 5. Classification Report SA

Label	Precision	Recall	F1-score
Tomato Healthy	0,97	0,99	0,98
Tomato Late Blight	1,00	0,91	0,95
Tomato Two-spotted Spider Mite	0,92	1,00	0,96

Source: Research Result (2023)

Table 5 shows the SA classification report with precision, recall, and f1-score values for healthy tomato, late blight tomato, and spider mite tomato labels close to 1.

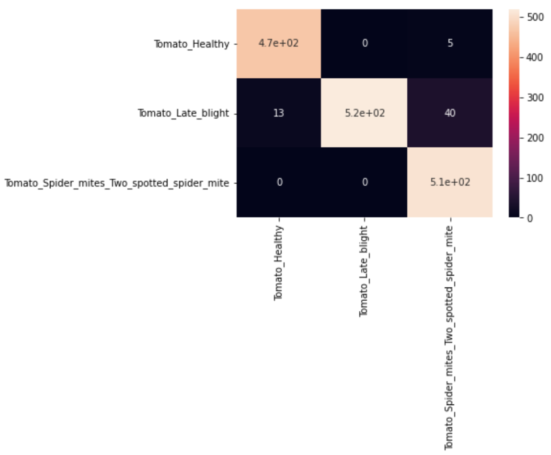
Table 6. Classification Report SB

Label	Precision	Recall	F1-score
Tomato Healthy	0,99	1,00	0,99
Tomato Late Blight	1,00	0,98	0,99
Tomato Two-spotted Spider Mite	0,98	0,99	0,99

Source: Research Result (2023)

Table 6 shows the classification report of SB with precision, recall, and f1-score values for tomato healthy, tomato late blight, and tomato two-spotted spider mite labels close to 1.

Evaluation of the model is also visualized with a confusion matrix to compare the predicted label with the actual label and as an illustration of how well the model works and can be used to calculate its performance measures.



Source: Research Result (2023)

Figure 9. Confusion Matrix SA

Confusion matrix in Figure 9 shows some prediction errors on SA testing data, without callback function. Of the 3 tomato leaf image labels with 1,553 images, 1,495 images were predicted correctly and 58 images were predicted incorrectly which can be seen in Table 7.

Table 7. Prediction Error on Testing Data SA

Label	Correct Prediction	Wrong Prediction

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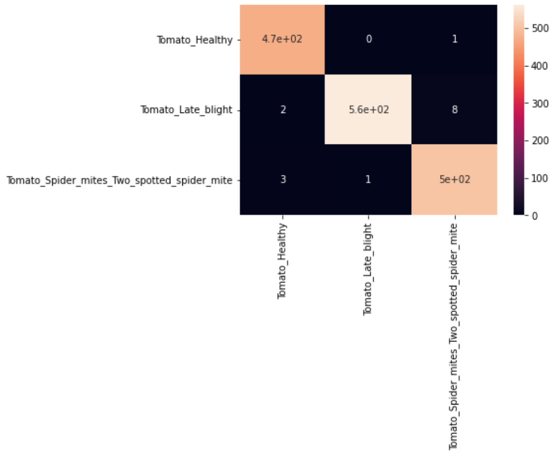
Healthy	469	5
Late blight	519	53
Two-spotted spider mite	507	0
Total	1.495	58

Source: Research Result (2023)

Furthermore, the confusion matrix for the SB model can be seen in Figure 10.



Source: Research Result (2023)

Figure 10. Confusion Matrix SB

Confusion matrix in Figure 10 shows some prediction errors on SB testing data, with the callback function. Of the 3 tomato leaf image labels with 1,553 images, 1,538 images were predicted correctly and 15 images were predicted incorrectly which can be seen in Table 8.

Table 8. Prediction Error on Testing Data SB

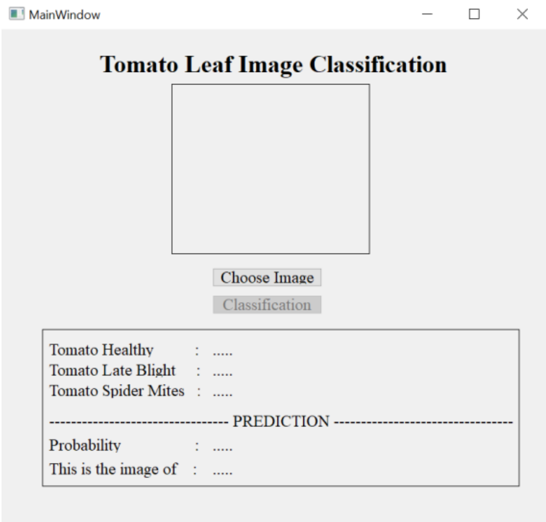
Label	Correct Prediction	Wrong Prediction
Healthy	473	1
Late blight	562	10
Two-spotted spider mite	503	4
Total	1.538	15

Source: Research Result (2023)

Classification reports of SA and SB show the precision, recall, and f1-score values of the three labels are almost close to 1, which means that both models have good performance (Chicco et al., 2021). However, the precision, recall, and f1-score values of SB with callback function are higher than SA without callback function. Also, the prediction error of SB is only 15 images while SA reaches 58 images. Thus, SB is a better classification model than SA.

4. Deployment

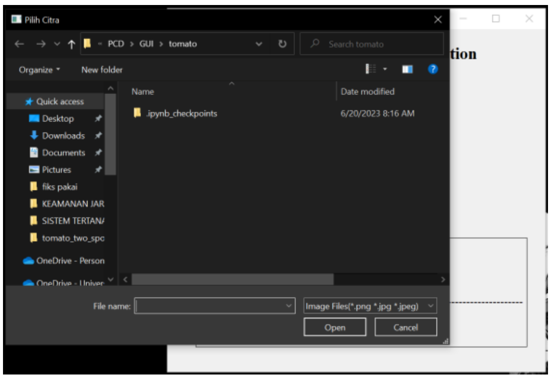
In this study, deployment was carried out to facilitate users in classifying late blight and two-spotted spider mite leaf diseases. The model stored and deployed is the scenario B (SB) classification model, which is a model with a callback function that produces better accuracy than the scenario A (SA) classification model without a callback function. The deployment view of tomato leaf disease classification can be seen in Figure 11.



Source: Research Result (2023)

Figure 11. GUI Interface

Next, the image is selected by pressing the 'Choose Image' button and will be directed to the 'File Explorer' for the location of the leaf image to be input. After the image is selected, the user can press the 'Open' button. The display looks like in Figure 12.



Source: Research Result (2023)

Figure 12. 'Choose Image' Menu Interface

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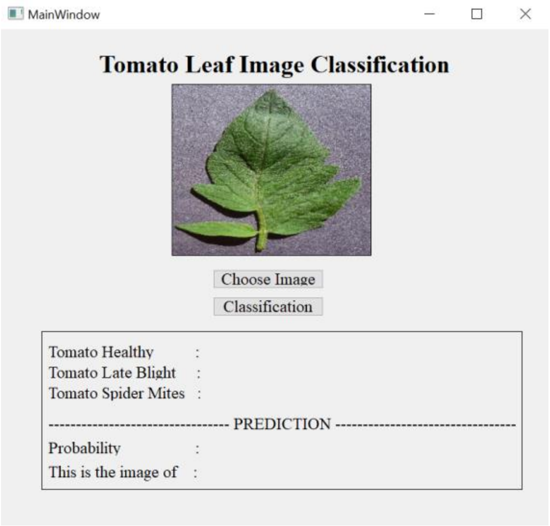
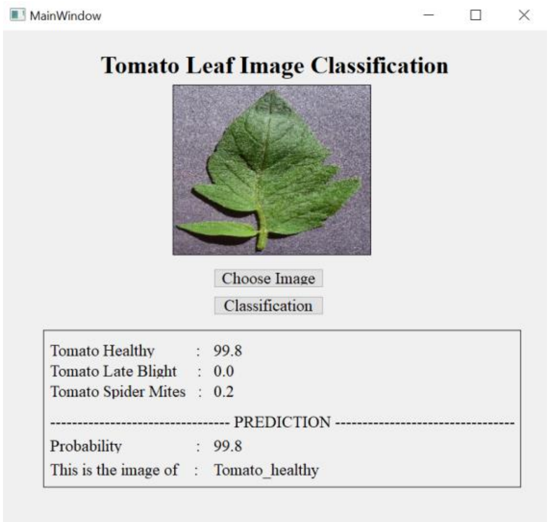
The successfully inputted image is shown in Figure 13. The user can then press the 'Classification' button and the model will identify and predict the image.



Source: Research Result (2023)

Figure 13. Input Image Interface

The prediction results on the input leaf image as shown in Figure 14. There is a description of the percentage of the 3 detected leaf labels. The percentage of tomato healthy shows a greater value than tomato late blight and tomato spider mite, so the leaf image is identified as a healthy leaf.



Source: Research Result (2023)

Figure 14. Prediction Result Interface

Furthermore, testing experiments on the model were carried out by inputting 21 images of tomato leaves from 3 labels, namely tomato healthy, tomato late blight, and tomato two-spotted spider mite which were different from the dataset used for model training. The dataset was taken from Romir Mehta's Kaggle and updated April 3, 2023 under the name potato-tomato-strawberry (Romir Mehta, 2023). The results of testing 21 tomato leaf images can be seen in Table 9, Table 10, and Table 11 with probability values for tomato healthy (H), tomato late blight (LB), and tomato two-spotted spider mite (TSM).

Table 9. Tomato Healthy Test Result

Image	Scenario	H	LB	TSM	Prediction
	SA	99.9	0.0	0.1	Tomato_healthy
	SB	97.0	0.1	3.0	Tomato_healthy
	SA	100.0	0.0	0.0	Tomato_healthy
	SB	99.6	0.0	0.4	Tomato_healthy
	SA	100.0	0.0	0.0	Tomato_healthy
	SB	98.3	1.3	0.4	Tomato_healthy
	SA	99.9	0.0	0.1	Tomato_healthy
	SB	99.6	0.1	0.3	Tomato_healthy
	SA	98.6	0.0	1.3	Tomato_healthy
	SB	6.8	0.1	93.1	Tomato_Spider_mites
	SA	100.0	0.0	0.0	Tomato_healthy
	SB	100.0	0.0	0.0	Tomato_healthy
	SA	98.7	0.0	1.3	Tomato_healthy
	SB	65.6	1.9	32.5	Tomato_healthy

Source: Research Result (2023)

Table 9 shows the test results for 7 images of healthy tomato leaves with SA and SB. Based on the test results, SB produces 1 prediction error, where the healthy tomato leaf is detected as a tomato two-spotted spider mite with a fairly high probability value.

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Table 10. Tomato Late Blight Test Result

Citra	Scenario	H	LB	TSM	Prediction
	SA	7.2	17.3	75.5	Tomato_Spider_mites
	SB	0.0	99.9	0.0	Tomato_Late_blight
	SA	45.6	53.7	0.7	Tomato_Late_blight
	SB	0.0	100.0	0.0	Tomato_Late_blight
	SA	0.5	91.4	8.1	Tomato_Late_blight
	SB	0.0	100.0	0.0	Tomato_Late_blight
	SA	99.9	0.1	0.0	Tomato_healthy
	SB	1.5	98.5	0.0	Tomato_Late_blight
	SA	0.1	99.6	0.3	Tomato_Late_blight
	SB	0.0	100.0	0.0	Tomato_Late_blight
	SA	92.5	7.5	0.0	Tomato_healthy
	SB	0.0	100.0	0.0	Tomato_Late_blight
	SA	97.2	2.8	0.0	Tomato_healthy
	SB	0.2	99.7	0.0	Tomato_Late_blight

Source: Research Result (2023)

Table 10 shows the test results of 7 images of tomato late blight leaves with SA and SB. Based on the test results, SA produced 4 mispredictions, where 1 image was detected as tomato two-spotted spider mite and 3 images were detected as tomato healthy with a high probability value.

Table 11. Tomato Two-spotted Spider Mite Test Result

Citra	Skenario	H	LB	TSM	Prediction
	SA	0.0	0.0	100.0	Tomato_Spider_mites
	SB	0.0	0.1	99.9	Tomato_Spider_mites
	SA	0.0	0.0	100.0	Tomato_Spider_mites
	SB	0.0	0.0	100.0	Tomato_Spider_mites
	SA	0.5	0.0	99.5	Tomato_Spider_mites
	SB	0.1	10.7	89.2	Tomato_Spider_mites
	SA	0.5	0.0	99.5	Tomato_Spider_mites
	SB	0.0	0.2	99.7	Tomato_Spider_mites
	SA	0.1	0.0	99.9	Tomato_Spider_mites
	SB	0.0	0.0	100.0	Tomato_Spider_mites
	SA	0.1	0.0	99.9	Tomato_Spider_mites

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	SB	0.0	3.8	96.2	Tomato_ Spider_ mites
	SA	0.0	0.0	100.0	Tomato_ Spider_ mites
	SB	0.0	0.1	99.9	Tomato_ Spider_ mites

Source: Research Result (2023)

Table 11 shows the test results of 7 tomato two-spotted spider mite leaf images with SA and SB. Based on the test results, both SA and SB successfully predicted the image as tomato two-spotted spider mite.

The results of testing 21 tomato leaf images from 3 labels, both SA and SB models are able to provide predictions of tomato healthy, tomato late blight, and tomato two-spotted spider mite with a fairly high accuracy. However, SA, a model with a non-callback scenario, made 4 errors in the tomato late blight test, while SB, a model with callback, only made 1 prediction error in the tomato healthy test. The magnitude of the probability value produced in the SB model is more specific than that of SA. Thus, the SB model is better at predicting both tomato healthy leaves and tomato late blight and tomato two-spotted spider mite.

CONCLUSION AND RECOMMENDATION

Based on the results of research on the classification model of 5,176 tomato leaf images from 3 labels, namely tomato healthy, tomato late blight, and tomato two-spotted spider mite with epoch parameters of 30, SGD optimizer, learning rate 0.001, and loss function with category cross entropy using Convolutional Neural Network (CNN) architecture and VGG16 transfer learning implementation, it can be concluded that the model is able to provide excellent results with an accuracy rate of 99.03%. The use of green channel + CLAHE, and augmentation in preprocessing can provide a variety of datasets in the model training process and make the image clearer. The model modifications made in this study also improved the performance of the model. The use of non-callback model scenarios and callback models also affects the accuracy value or the resulting probability value. In testing 21 images from 3 labels, it shows that the model scenario with the callback function provides more accurate and specific prediction results compared to the non-callback model. The use of CNN method with VGG16 transfer learning is certainly very effective in image processing. The simple and modifiable architecture of VGG16 can improve the performance of the model to adapt to different datasets and produce a more accurate model in predicting image labels.

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