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EfficientNetV2M for Image Classification of Tomato Leaf Deseases

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Abstract

Favorable climatic conditions make tomato plants (Solanum Lycopersicon) a widely cultivated horticultural crop in Indonesia. However, the increase in tomato production is often accompanied by a decrease in both the quantity and quality of the plants, which can be caused by a variety of factors such as bacteria, fungi, viruses, and insects like Late Blight and Two-Spotted Spider Mite diseases that attack the tomato leaves. To help farmers identify leaf diseases that have similar characteristics, this study employs image processing with the Convolutional Neural Network (CNN) algorithm and transfer learning models. Specifically, the study uses the EfficientNetV2M transfer learning architecture which has superior parameter efficiency and training speed compared to other transfer learning models. Additionally, this study conducts four experimental scenarios on preprocessing, including green channel + CLAHE, green channel + Gaussian Blur, CLAHE without green channel, and Gaussian Blur without green channel. The dataset used in this study includes 5,176 images with three labels: Tomato Healthy, Tomato Late Blight, and Tomato Two-Spotted Spider Mite. These images were used to train and produce models, which were then tested using a different dataset from the trained dataset. The testing dataset included 30 image samples divided into three labels. Based on the test results of the four models with different scenarios, the best model was found to be the one with the green channel preprocessing scenario + CLAHE, which was able to precisely predict all 30 image samples with high accuracy.

Keywords: *efficientNetV2M, late blight, transfer learning, tomato, two-spotted spider mite*

1. Introduction

As an archipelagic country with a large land area, Indonesia is blessed with endless natural resources. The country's fertile land has made it one of the largest vegetable producers in Southeast Asia, with the tomato plant (Solanum lycopersicum) being one of the most important commodities that must be cultivated and increased each year plant (Felix et al., 2019). With stable selling prices, high consumption rates among the community, and favorable climatic conditions, tomato plants are widely cultivated in Indonesia (Putri, 2021). According to BPS data in 2021, there was a 2.71% increase in tomato plant production compared to 2020 (Badan Pusat Statistik, 2021). However, tomato plants are susceptible to diseases caused by bacteria, fungi, viruses, and insects that can attack various parts of the plant's leaves

The types of diseases that often affect tomato plants include late blight and two-spotted spider mite. Late blight, shown in Figure 1 (a), is caused by the fungus Phytophthora infestans (Mont) de Bary and thrives in cold and damp environments. The initial symptoms of this disease are black or brownish lesions that appear on the edges and middle of the leaves, which then spread and cause damage to the plant (Semangun, 2013). On the other hand, two-spotted spider mite is an infestation of the spider mite Tetranychus urticae caused by excessive use of insecticides. Leaves that have been attacked by the mites will exhibit pale yellow stains and reddish-brown spots ranging from small to large areas on both the upper and lower leaf surfaces, as shown in Figure 1 (b) (Kemble et al., 2022).

(a)

(b)

Source: Research Result (2023)

Figure 1.Diseases of tomato leaves (a) late blight (b) two-spotted spider mite

Identifying the type of disease can be difficult for ordinary farmers, especially when the texture and color characteristics of different diseases are almost the same. To overcome this challenge, technology can be utilized to identify leaf diseases through the introduction of their characteristics. With the advancement of technology, leaf disease identification can be done by utilizing image processing through the Convolutional Neural Network (CNN) method (Wahid et al., 2021). CNN is a neural network designed to process two-dimensional data and is used to recognize objects in an image by using high-dimensional vectors that require many parameters for classification. By utilizing high-dimensional vectors and involving many parameters in their classification, CNN can accurately recognize objects in the image (Nugroho et al., 2020).

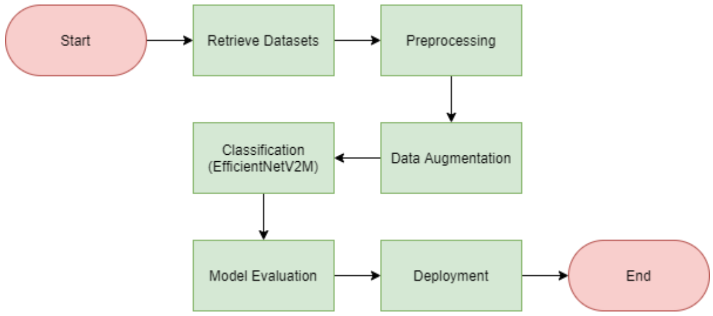
To enhance the performance of the CNN model without retraining from scratch, transfer learning techniques are employed. This technique leverages a pre-trained network as a starting point for learning new (Wonohadidjojo, 2021). One of the transfer learning models that can be utilized is the EfficientNetV2M model, which boasts superior parameter efficiency and training speed compared to other transfer learning models (Tan & Le, 2021).

In research conducted by (Aktürk et al., 2022) on the classification of eye images based on personal details using transfer learning, the EfficientNetV2M model was used and achieved an accuracy of 60.94% for classification based on findings, 88.55% for classification based on gender, and 61.44% for classification based on age. Similarly, (Semwal et al., 2023) used the EfficientNetV2M model for multimodal analysis and modality fusion to detect depression from Twitter data, achieving an accuracy of 63.31%. (García Cortés et al., 2022) used the EfficientNetV2M model for the classification of apple cider varieties and obtained an accuracy of 70.54%. (Mahaputri et al., 2022) used the EfficientNetV2M model for identifying traditional food images and obtained an accuracy result of 83.82%. (Shabrina et al., 2023) used the EfficientNetV2M model to identify nematodes and obtained an accuracy result of 98.66%. Based on the results of previous research, it can be concluded that the EfficientNetV2M model produces good accuracy in image identification.

The classification of tomato leaf disease in this study was carried out using the CNN method of the EfficientNetV2M transfer learning model. The EfficientNetV2M model is used to address overfitting generated in the model training process. It is hoped that this research can help farmers to identify tomato leaf disease.

2. Research Method

In this study, there are several stages to classify the image of leaf disease of tomato plants as shown in Figure 2.



Source: Research Result (2023)

Figure 2. Stages of Research

Figure 2 illustrates the stages involved in the classification of tomato leaf disease images. The first stage involves gathering the dataset, while the second stage involves preprocessing the dataset by resizing images, adjusting color, reducing noise, and splitting the dataset into training, validation, and testing data. The next stage involves data augmentation through the application of various random transformation methods. Subsequently, the training data is classified using the CNN method with the EfficientNetV2M transfer learning model. Afterward, the trained model is evaluated to assess its performance. Finally, the last stage of the study involves deploying the trained model. The further section clarifies each stage of the process as follows.

2.1. Retrieve Datasets

Dataset retrieval is the process of obtaining data that will be used for the image classification of tomato leaf disease. In this study, labeled datasets from each class were used for supervised learning (Rozaqi, Sunyoto, et al., 2021). Therefore, the tomato leaf disease image dataset used in this study has three labels: tomato healthy, tomato late blight, and tomato two-spotted spider mite. This dataset was obtained from Kaggle, uploaded by MAHESH BABU under the name "Tomato Leaf Disease" and last updated in June 2022 (Babu, 2022).

Table 1. Dataset

Lable Name	Number of Images	Dataset Sources
Tomato Healthy	1,591	
Tomato Late Blight	1,909	*Kaggle (Tomato Leaf Diseases)*
Tomato Two Spotted Spider Mite	1,676	
Total	5,176	

Source: Research Result (2023)

The number of images for each label can be seen in Table 1, which includes 1,591 images of tomato healthy, 1,909 images of tomato late blight, 1,676 images of tomato two spotted spider mite, and a total of 5,176 images. In this study, images with a size of 256 x 256 were used, which will be resized in the preprocessing stage.

2.2. Preprocessing

The prepared native dataset classification model needs to undergo preprocessing before it can be trained, as stated by (Yustika et al., 2019). In this study, the preprocessing stage involved resizing the original images to 224 x 224 pixels to increase the speed of the classification process, as suggested by (Ekananda & Riminarsih, 2022). Afterward, the imagery dataset was subjected to 4 scenarios.

Table 2. Scenario

Alias	**Scenario**
SK1	*Green Channel* + CLAHE
SK2	*Green Channel* + Gaussian Blur
SK3	CLAHE tanpa *Green Channel*
SK4	Gaussian Blur tanpa *Green Channel*

Source: Research Result (2023)

The use of green channels in imagery aims to produce a clearer image of the leaves when compared to red channels and blue channels (Desiani et al., 2021). Meanwhile, CLAHE (Contrast Limited Adaptive Histogram Equalization) is used to increase the contrast locally in the image, so that it can bring up hidden features to clarify lesions or spots in the leaf image (Kanditami et al., 2014). In the scenario, Gaussian Blur is also given, which serves to create a foggy effect and reduce details in the image using the autofocus effect (Sinurat & Siagian, 2021). Then the data is divided into 3, namely training data, testing data, and validation data. Training data is data used in the model training process and training data stores more data than testing data and validation data. Data validation is data used for comparison with training data in the model training process. Testing data is data used for evaluation of models that have been trained with training data and validation data (Arsal et al., 2020). The next stage feature x on the dataset is converted to float32, while the y label is converted to a categorical format.

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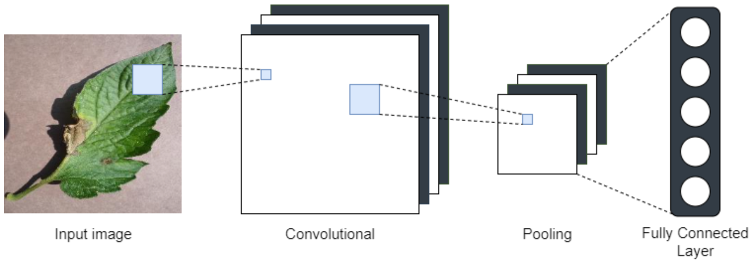
2.3. Data Augmentation

Augmentation process is conducted by applying random transformations to the training data. There are several methods used for augmentation including rescale, rotation range, shear range, zoom range, width shift range, height shift range, horizontal flip, vertical flip, and fill mode (Nisa' et al., 2020). The explanations of each method are as follows:

a. Rescale: rescale or change the value of a predetermined pixel
b. Rotation range: rotates the image
c. Shear range: performs imagery shifting
d. Zoom range: zooming in or zooming on the image
e. Width shift range performs imagery offset horizontally
f. Height shift range: performs imagery shifting vertically
g. Horizontal flip: reverse image horizontally
h. Vertical flip: reverse image vertically
i. Fill mode: fills the missing pixels with the nearest pixel

2.4. Classification (EfficientNetV2M)

After preprocessing, the next stage involves classifying the images of tomato plant leaf diseases using the transfer learning model of Convolutional Neural Network (CNN) method. A simplified overview of the CNN architecture is presented in Figure 3.



Source: Research Result (2023)

Figure 3. Simple CNN Architecture

Figure 3 is a simple CNN architecture that has several layers, namely convolution which is the first layer in the image identification process to extract the texture of the leaf image with the results processed on the pooling layer. In the pooling layer the pixel size of the image is reduced without degrading its quality. The last layer is fully connected which will generate decisions by taking features on convolution and pooling (Rozaqi, Arief, et al., 2021).

Transfer learning is one of the methods used to improve the accuracy of the model in this study. This method leverages pre-defined artificial intelligence on pre-trained models with different datasets. One model that can be used is EfficientNetV2M, which has 740 layers that are used to improve the accuracy in recognizing different types of tomato leaf diseases. In the initial stage of fine-tuning, a new layer is added consisting of a fully connected layer with the number of labels according to the type of disease to be recognized. Then, the top layer of the model is frozen so that it does not change or is not retrained.

2.5. Model Evaluation

In determining the success of a model, evaluation of the model is particularly important. In this study, model evaluation was carried out using *Confusion Matrix*, *Precision*, *Recall*, and *F1-Score* (Wahid et al., 2022).

a. Confusion Matrix is an evaluation metric used in classification problems. Confusion Matrix is generally in the form of a table or visualization that displays the predicted results of the model, both true and false.

Table 1. Confussion Matrix

		Current	
		Positive	Negative
Predictions	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

Source: Research Result (2023)

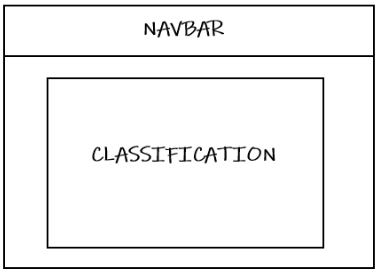
b. Precision is a measure of how many positive predictions are correct from all positive predictions made.

c. Recall is a measure of how many positive cases are correctly detected out of all existing positive cases.

d. F1-score is used to measure how well the model combines the two matrices, namely precision and recall.

2.6. Deployment

In this study, the Flask framework is utilized to deploy the application, providing users with a user-friendly interface to obtain results in the form of healthy tomatoes, tomato late blight, or tomato two spotted spider mite. To begin the deployment process, the necessary libraries are called, including Flask, Keras, TensorFlow, Scikit-image, NumPy, OS, CV2, Datetime, and PIL. The subsequent step involves loading a pre-trained CNN model and saving it to ensure accurate image prediction by the application. Finally, a router is created on the website page, and a source code is generated to classify the image of tomato as healthy, tomato late blight, or tomato two spotted spider mite.



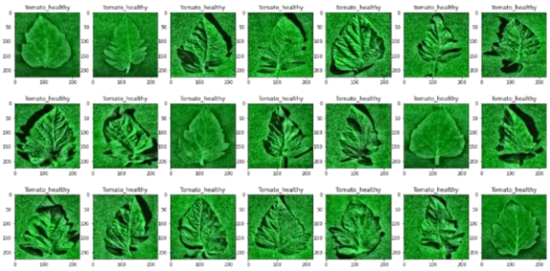
Source: Research Result (2023)

Figure 4. User Interface Design

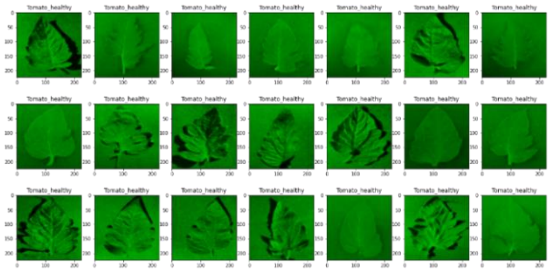
3. Results and Analysis

3.1. Preprocessing Results

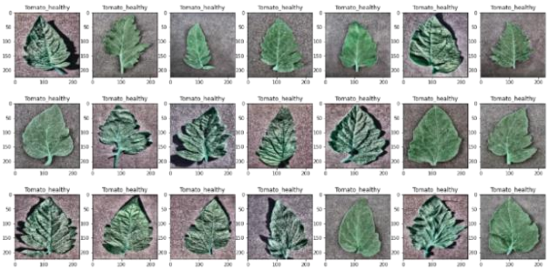
The initial stage of preprocessing is to resize the original image to 224 x 224, then the next stage is the image in the extraction according to the 4 scenarios that have been created. The output of each scenario can be seen in figure 5.



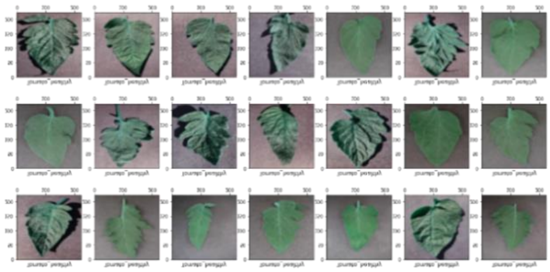
(a) *Green Channel* + CLAHE



(b) *Green Channel* + Gaussian Blur



(c) CLAHE without *Green Channel*



(d) Gaussian Blur without *Green Channel*

Source: Research Result (2023)

Figure 5. Output 4 Scenarios

Furthermore, the data was divided into 3 sets, namely the training set, testing set, and validation set. The training set consists of 55% of the total 3,105 images, the testing set consists of 20% of the total 1,036 images, and the validation set consists of 25% of the total 1,035 images.

3.2. Data Augmentation

In this study, several methods were used for augmentation, including rescale, rotation range, shear range, zoom range, width shift range, height shift range, horizontal flip, vertical flip, and fill mode.

```
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'
    )
```

Source: Research Result (2023)

Figure 6. Data Augmentation

In figure 6, it can be observed that the image data is rescaled using 1./255 which transforms the pixel values to lie between 0 and 1. Additionally, the rotation range is set to 15 degrees, the shear range to 10%, and the zoom range to 20%. The width shift range and height shift range are both set to 10%. The horizontal flip and vertical flip are set to True, which means they are activated. Finally, the fill mode is set to 'nearest', which fills any missing areas with the pixel value closest to the original area of the image.

3.3. Classification Result

This study used 5,176 tomato leaf images from 3 classes, namely tomato healthy, tomato late blight, and tomato two-spotted spider mite. The training process of 4 scenarios used SGD optimization, 30 epochs, batch size of 32, and evaluation on the testing data using verbose of 2, with results shown in Table 4.

Table 2. Trial Results for Each Scenario

No	Scenario	Data Training		Data Validation		Data Testing	
		Loss	Accuracy	Val Loss	Val Accuracy	Loss	Accuracy
1	SK1	0.0443	0.9820	0.0643	0.9807	0.0787	0.9749
2	SK2	0.0549	0.9794	0.1799	0.9362	0.1564	0.9382
3	SK3	0.0307	0.9878	0.0176	0.9942	0.0083	0.9971
4	SK4	0.0229	0.9926	0.0253	0.9894	0.0093	0.9971

Source: Research Result (2023)

Among the 4 scenarios, scenario 1 (SK1) shows an accuracy result of 0.9749, which means it has an accuracy of 97.49% and a loss value of 7.87%. Scenario 2 (SK2) shows an accuracy result of 0.9382, which means it has an accuracy of 93.82% and a loss value of 15.64%. In scenario 3 (SK3), the accuracy result is 0.9971, which means it has an accuracy of 99.71% and a loss value of 0.83%. Scenario 4 (SK4) also shows an accuracy result of 0.9971, which means it has an accuracy value of 99.71% and a loss value of 0.93%. Thus, it can be seen that scenarios 3 (SK3) and 4 (SK4) produce higher accuracy compared to scenarios 1 (SK1) and 2 (SK2).

3.4. Model Evaluation

a. Precision, Recall, and F1-score

After conducting the training process, then evaluate the model of each scenario with confusion matrix, precision, recall, and F1-score. The evaluation of the first model is carried out with precision, recall, and F1-score which can be seen in the following table.

Table 5. Precision, Recall, and F1-score Scenario 1

Lable	**Precision**	**Recall**	**F1-score**
Tomato Healthy	0.95	0.99	0.97
Tomato Late Blight	1.00	0.94	0.97
Tomato Two Spotted Spider Mites	0.97	0.99	0.98

Source: Research Result (2023)

Table 6. Precision, Recall, and F1-score Scenario 2

Lable	**Precision**	**Recall**	**F1-score**
Tomato Healthy	0.87	1.00	0.93
Tomato Late Blight	0.98	0.88	0.93
Tomato Two Spotted Spider Mites	0.97	0.95	0.96

Source: Research Result (2023)

Table 7. Precision, Recall, and F1-score Scenario 3

Lable	**Precision**	**Recall**	**F1-score**
Tomato Healthy	0.99	1.00	1.00
Tomato Late Blight	1.00	0.99	1.00
Tomato Two Spotted Spider Mites	1.00	1.00	1.00

Source: Research Result (2023)

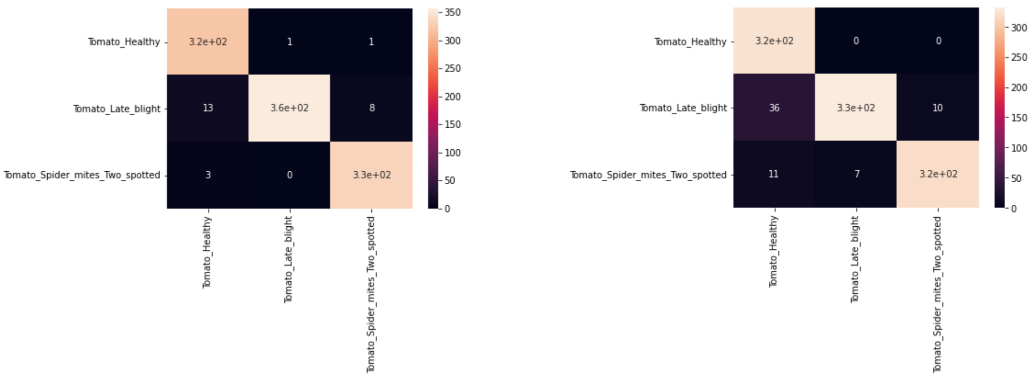
Table 8. Precision, Recall, and F1-score Scenario 4

Lable	**Precision**	**Recall**	**F1-score**
Tomato Healthy	1.00	1.00	1.00
Tomato Late Blight	1.00	0.99	1.00
Tomato Two Spotted Spider Mites	0.99	1.00	1.00

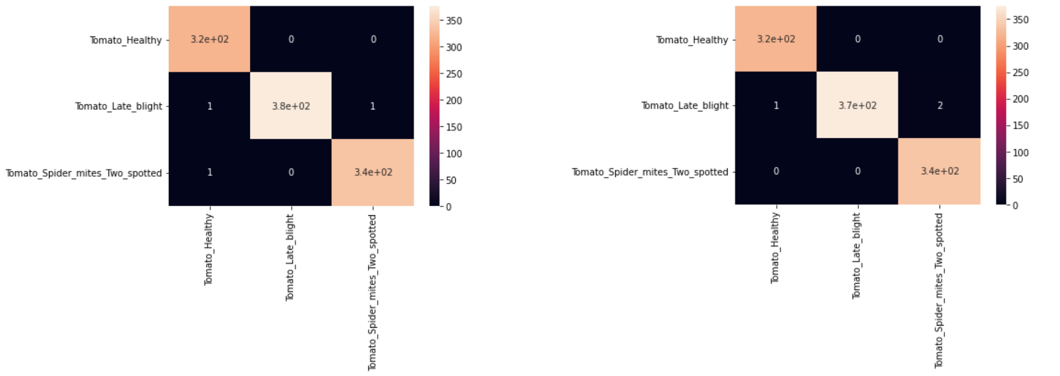
Source: Research Result (2023)

b. Confussion Matrix

Additionally, to evaluate the model's performance, a confusion matrix is used to compare the predicted label with the actual label, as shown in Figure 7.



(a) *Green channel* + CLAHE (b) *Green channel* + Gaussian Blur



(c) CLAHE without *Green Channel* (d) Gaussian Blur without *Green Channel*

Source: Research Result (2023)

Figure 7. Confussion Matrix Result

The confusion matrix in Figure 7 shows some errors in the testing data performed with 4 scenarios as shown in Table 9.

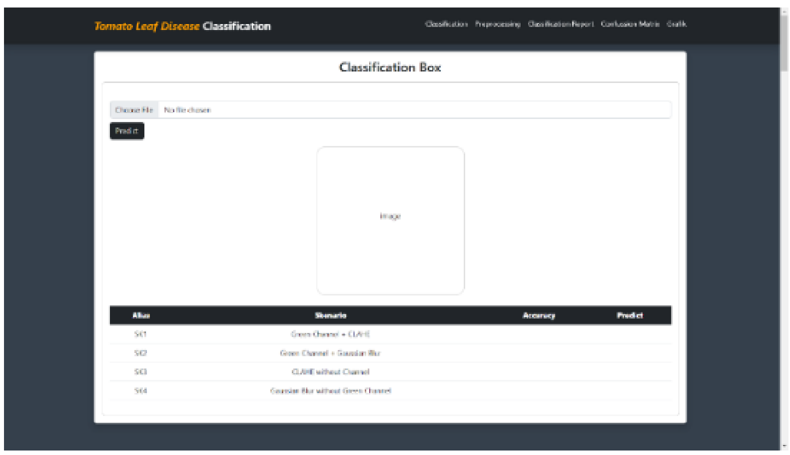
Table 9. Prediction Error in Testing Data

Scenario	Correct Predictions	Wrong Predictions
SK1	1.010	26
SK2	972	64
SK3	1.063	3
SK4	1.063	3

Source: Research Result (2023)

3.5. Deployment Models Already in Training

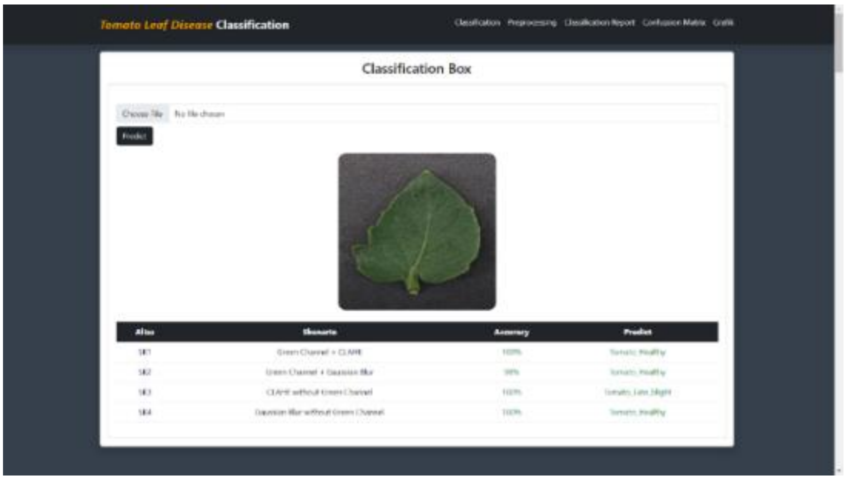
The trained classification model is then saved and deployed. Model deployment is done to turn the model into an application that can be practically used by end-users. Deployment is created using the Flask framework. The results of the deployment can be seen in Figure 8.



Source: Research Result (2023)

Figure 8. Index Page View

In Figure 8, the index page display consists of several sections, namely Classification, Preprocessing, Classification Report, Confusion Matrix, and Graph. The Classification section is used for image classification, where users can input an image of tomato leaves by clicking "Choose File". After the leaf image has been uploaded, users can click "Predict" to get the results. An example of the classification result can be seen in Figure 9. The Preprocessing, Classification Report, Confusion Matrix, and Graph sections are used to display statistics on the results of training models from the 4 scenarios.



Source: Research Result (2023)

Figure 9. Submit Page View

The input image in Figure 9 shows a tomato leaf that is classified as healthy. The model was tested using the four scenarios, and it was found that scenario 1 (SK1) achieved 100% accuracy by using the green channel and CLAHE for preprocessing. Scenario 2 (SK2) achieved 98% accuracy by using the green channel and Gaussian Blur for preprocessing, while scenario 4 achieved 100% accuracy by using Gaussian Blur without the green channel. However, scenario 3 (SK3), which used CLAHE without the green channel, achieved 100% accuracy but misclassified the image.

The next testing was conducted on 4 scenarios using 30 dataset samples from 3 labels obtained from Kaggle under the name [ShiftAcademy] Tomato Disease Ready uploaded by (Mahasin, 2022). This sample dataset is different from the dataset used in the training model. The test results for tomato healthy image samples by (Mahasin, 2022) can be seen in Table 10.

Table 3. Tomato Healthy Test Results

Image	Scenario	Accuracy	Predictions
	SK1	100%	Tomato Healthy
	SK2	95%	Tomato Healthy
	SK3	90%	Tomato Two Spotted Spider Mites*
	SK4	99%	Tomato Healthy
	SK1	100%	Tomato Healthy
	SK2	99%	Tomato Healthy
	SK3	59%	Tomato Late Blight*
	SK4	100%	Tomato Healthy
	SK1	100%	Tomato Healthy
	SK2	98%	Tomato Healthy
	SK3	73%	Tomato Healthy
	SK4	100%	Tomato Healthy
	SK1	100%	Tomato Healthy
	SK2	97%	Tomato Healthy
	SK3	98%	Tomato Healthy
	SK4	96%	Tomato Healthy
	SK1	100%	Tomato Healthy
	SK2	98%	Tomato Healthy
	SK3	53%	Tomato Healthy
	SK4	100%	Tomato Healthy
	SK1	100%	Tomato Healthy
	SK2	90%	Tomato Healthy
	SK3	99%	Tomato Healthy
	SK4	96%	Tomato Healthy
	SK1	98%	Tomato Healthy
	SK2	77%	Tomato Healthy
	SK3	98%	Tomato Healthy
	SK4	98%	Tomato Healthy
	SK1	96%	Tomato Healthy
	SK2	91%	Tomato Healthy
	SK3	81%	Tomato Two Spotted Spider Mites*
	SK4	99%	Tomato Healthy
	SK1	100%	Tomato Healthy
	SK2	97%	Tomato Healthy
	SK3	100%	Tomato Healthy
	SK4	99%	Tomato Healthy

Image	Scenario	Accuracy	Predictions
	SK1	93%	Tomato Healthy
	SK2	98%	Tomato Healthy
	SK3	99%	Tomato Late Blight*
	SK4	100%	Tomato Healthy

*Represents the tomato disease

Source: Research Result (2023)

Based on the test results of 4 scenarios on tomato healthy image samples in Table 10, it can be known that scenario 3 (SK3) using CLAHE without green channel in preprocessing experienced prediction errors 4 times, although the resulting accuracy was high. Furthermore, testing on tomato late blight image samples can be seen in Table 11.

Table 4. Tomato Lite Blight Test Results

Image	Scenario	Accuracy	Predictions
	SK1	99%	Tomato Late Blight
	SK2	99%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	59%	Tomato Late Blight
	SK1	97%	Tomato Late Blight
	SK2	97%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	92%	Tomato Late Blight
	SK1	99%	Tomato Late Blight
	SK2	100%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	65%	Tomato Healthy*
	SK1	97%	Tomato Late Blight
	SK2	97%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	53%	Tomato Late Blight
	SK1	100%	Tomato Late Blight
	SK2	100%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	89%	Tomato Late Blight
	SK1	100%	Tomato Late Blight
	SK2	78%	Tomato Late Blight
	SK3	100%	Tomato Late Blight

Image	Scenario	Accuracy	Predictions
	SK4	93%	Tomato Late Blight
	SK1	100%	Tomato Late Blight
	SK2	68%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	100%	Tomato Healthy*
	SK1	100%	Tomato Late Blight
	SK2	100%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	97%	Tomato Late Blight
	SK1	100%	Tomato Late Blight
	SK2	100%	Tomato Late Blight
	SK3	100%	Tomato Late Blight
	SK4	68%	Tomato Healthy*
	SK1	100%	Tomato Late Blight
	SK2	63%	Tomato healthy*
	SK3	99%	Tomato Late Blight
	SK4	97%	Tomato Healthy*

*Represents the healthy tomato

Source: Research Result (2023)

Based on the test results of 4 scenarios on tomato late blight image samples in Table 11, it can be seen that scenario 4 (SK4) using Gaussian Blur without green channel in preprocessing stage experienced prediction errors 4 times. Scenario 2 (SK2) using green channel + Gaussian Blur in the preprocessing stage experienced a prediction error 1 time. Furthermore, testing on tomato two spotted spider mites image samples can be seen in Table 12.

Table 5. Tomato Two Spotted Spider Mites Test Results

Image	Scenario	Accuracy	Predictions
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	98%	Tomato Healthy*
	SK3	98%	Tomato Two Spotted Spider Mites
	SK4	99%	Tomato Healthy*
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	92%	Tomato Healthy*
	SK3	94%	Tomato Two Spotted Spider Mites
	SK4	52%	Tomato Two Spotted Spider Mites
	SK1	89%	Tomato Two Spotted Spider Mites

Image	Scenario	Accuracy	Predictions
	SK2	64%	Tomato Late Blight*
	SK3	56%	Tomato Two Spotted Spider Mites
	SK4	100%	Tomato Healthy*
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	82%	Tomato Healthy*
	SK3	94%	Tomato Healthy*
	SK4	99%	Tomato Healthy*
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	91%	Tomato Healthy*
	SK3	100%	Tomato Two Spotted Spider Mites
	SK4	100%	Tomato Healthy*
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	98%	Tomato Healthy*
	SK3	96%	Tomato Two Spotted Spider Mites
	SK4	100%	Tomato Healthy*
	SK1	98%	Tomato Two Spotted Spider Mites
	SK2	97%	Tomato Healthy*
	SK3	43%	Tomato Healthy*
	SK4	100%	Tomato Healthy*
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	95%	Tomato Healthy*
	SK3	99%	Tomato Two Spotted Spider Mites
	SK4	100%	Tomato Healthy*
	SK1	100%	Tomato Two Spotted Spider Mites
	SK2	97%	Tomato Healthy*
	SK3	96%	Tomato Two Spotted Spider Mites
	SK4	100%	Tomato Healthy*
	SK1	99%	Tomato Two Spotted Spider Mites
	SK2	96%	Tomato Healthy*
	SK3	50%	Tomato Healthy*
	SK4	100%	Tomato Healthy*

*Represents the healthy tomato

Source: Research Result (2023)

Based on the test results of 4 scenarios on tomato two spotted spider mites image samples in Table 12, it can be seen that scenario 2 (SK2) using green channel + Gaussian Blur in preprocessing experienced 10 prediction errors, although the resulting accuracy was high. Scenario 3 (SK3) using CLAHE without green channel in preprocessing experienced 3 prediction errors. Scenario 4 (SK4) using Gaussian Blur without green channel in preprocessing experienced 9 prediction errors.

4. Conclusion

Based on the research that has been carried out, it can be concluded that the implementation of the CNN algorithm with the EfficientNetV2M architecture for the classification of tomato leaf diseases in 4 scenarios resulted in high accuracy values. The higher the accuracy value, the fewer prediction errors in the model evaluation. Although 4 scenarios resulted in high accuracy, the results of the image sample tests that have been carried out, scenario 1 (SK1) using green channel + CLAHE can predict 30 image samples from 3 labels precisely with high accuracy values compared to other scenarios. The use of green channel + CLAHE greatly affects the introduction of new leaf imagery because the green channel itself produces clearer imagery compared to red channels and blue channels, while CLAHE is used to increase contrast in the image and bring out hidden features (invisible parts) so as to clarify the lesions or spots on the new leaf image.

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Author Contributions

Arazka Firdaus Anavyanto proposed the topic; Arazka Firdaus Anavyanto, Maimunah, and Muhammad Resa Arif Yudianto compiled models and designed experiments; Arazka Firdaus Anavyanto, Maimunah, and Muhammad Resa Arif Yudianto compiled the algorithm; Maimunah, and Muhammad Resa Arif Yudianto analyzed the results.

Conflicts of Interest

The author declare no conflict of interest.

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