MaTangDetect: Identification of Potato Pests using Freezing Layers Ensemble-based Deep Learning

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MaTangDetect: Identification of Potato Pests Using Freezing Layers Ensemble-Based Deep Learning

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Abstract **– One of the challenges in the agricultural world is pest attacks that cause crop failure. Potatoes are one of the crops that are often attacked by pests. Early identification of potato pests is crucial because it significantly helps farmers implement appropriate and effective control measures. This not only increases crop yields but also reduces economic losses caused by pest attacks. This study introduces MaTangDetect, a pest detection system that uses an ensemble-based deep learning model with a freezing layer technique. The proposed system uses a freezing layer on the ensemble of DenseNet201, EfficientNetB5, and InceptionV3 models, to improve classification accuracy. By applying the freezing layer technique, the system utilizes previously learned features to the maximum, thereby accelerating the training process and improving overall performance. MaTangDetect was evaluated using various potato pest images and had an accuracy rate of 93%. These results demonstrate the effectiveness of deep learning based on the freezing layer ensemble-based model in identifying potato pest species.**

In addition, this system offers great potential for application in the field, providing practical and innovative solutions for farmers in pest management in potato cultivation, and contributing to increased yields and reduced economic losses.

Keywords **– Freezing layer, deep learning, potato pests, identification, ensemble model-based.**

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1. Introduction

Potatoes are one of the important food commodities in the world, including Indonesia. As the main source of carbohydrates and raw materials for the food industry, the demand for potatoes continues to increase every year [1]. Potato plant productivity is often disrupted by pest attacks that can result in a significant decrease in crop yields. Pests such as *Phthorimaea operculella* (Potato Borer Moth), *Amrasca devastans* (Cotton Planthopper), *Aphis gossypii Glover* (Aphids), *Agrotis ipsilon* (Black Armyworm), *Brachytrypes portentosus Lichtenstein* (Necklace Cricket), *Bemisia tabaci* (Whitefly), *Epilachna vigintioctopunctata* (28-Spot Beetle), *Myzus persicae* (Green Aphid) are the main causes of potato yield losses in several agricultural areas [2].

Early identification of potato pests is essential to ensure the quality and quantity of production. Pest identification in potato plants is generally done manually by farmers and agricultural experts [3]. This method not only requires a lot of time and effort but also relies heavily on individual expertise in recognizing pest types [4]. Errors in identification can lead to ineffective use of pesticides that can harm the environment and human health [5].

Currently, plant pests can be successfully identified, particularly with the use of deep learning and transfer learning methods [6]. Transfer learning and deep learning are techniques that utilize knowledge obtained from other tasks and have been previously studied, thereby accelerating the training process and increasing accuracy values [7].

Plant disease and pest identification are only two of the many agricultural applications where transfer learning and deep learning models have been successfully used [8].

Previous research conducted using a deep learning model, namely VGG16, was successfully implemented in identifying plant pests [9], Other research using the VGG16 and Resnet50 models as transfer learning methods used to detect plant pests, the research conducted showed that the VGG16 and Resnet50 models can be adapted to detect plant pests with various conditions and provide high flexibility in agricultural applications [10], [11]. Other research, where combining the VGG16, Resnet50, and inseptionV3 methods successfully identified plant pests was conducted [12], [13]. Then, other research successfully identified plant pests using the DenseNet, NasNetLarge, and NasNetMobile methods [14]. Another transfer learning method, EfficientNet, was used and successfully identified plant diseases [15]. The mobileNet model has also been successful in identifying plant pests [16]. In this study, a comparison was conducted on the EfficientNetB5, InceptionV3, NasNetLarge, DenseNet201, MobileNetV2, Xception, CNN VGG16, ResNet50, NASNetMobile models and compared the good models in identifying potato plant pests.

The identification process of potato plant pests has several problems, namely the limitations of the plant pest image dataset, and the presence of overfitting in the data. Research [9] uses augmentation techniques to overcome the limited potato plant pest dataset. In research, [13] developed the customized Tunned InceptionV3 technique to overcome the problem of overfitting potato plant pest data. Therefore, in this study, in dealing with the problem of limited data and overfitting data, augmentation techniques were used and models were developed by performing freezing layers on ensembled three models that have high accuracy values in identifying pests in potato plants called MaTangDetect.

Research significantly advances the identification of pests in potato crops. In order to maximize variance and decrease overfitting, this study assembled a dataset of photos of potato crop pests and used data augmentation techniques. To guarantee correct model evaluation, the dataset was separated into training, validation, and testing data. The data was trained using a number of top deep learning models, and three models with the highest accuracy values were chosen for the ensemble, which combines the benefits of each model and enhances detection performance. Standard criteria were used to assess the performance of the final ensemble model, MaTangDetect, which was suggested as the best model. Farmers and researchers now have a useful tool to better identify and manage potato pests thanks to the development and implementation of the MaTangDetect model-based pest detection system.

2. Methodology

Early detection of potato pests is very important in agriculture. The proposed MaTangDetect model is effective for detecting potato pests. The research stages can be seen in Figure 1.

The research steps depicted in Figure 1 include data preparation, data division into training, validation, and testing data, augmenting training and validation data, training and comparing eight models using training and validation data, choosing the top three models, performing the freezing layer ensemble stage on the top three models, known as MaTangDetect, evaluating the MaTangDetect model, testing the MaTangDetect model with testing data, and finally constructing a potato plant pest identification system using the developed model.

Figure 1. Research method

The following provides a more thorough explanation of these stages:

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2.1. Data Preparation

The dataset utilized in this study was obtained from kaggle.com, a public repository. The dataset was acquired via Google as well as the repository. In this study, 1,040 photos of eight different kinds of potato plant pests were employed. Table 1 shows specifics on the quantity of photos used.

Table 1. Potato plant pest image data

No	Class name	Initial Dataset	Additional Datasets	Sub Total
1	*Phthorimaea operculella* (Potato Borer Moth)	42	88	130
2	*Amrasca devastans* (Cotton Planthopper)	62	68	130
3	*Aphis gossypii Glover* (Aphids)	37	93	130
4	*Agrotis ipsilon* (Black gobbler)	103	27	130
5	*Brachytrypes portentosus Lichtenstein* (Necklace Cricket)	35	95	130
6	*Bemisia tabaci* (Whitefly)	35	95	130
7	*Epilachna vigintioctopunctata* (28 Spot Beetle)	70	60	130
8	*Myzus persicae* (Green Aphid)	75	55	130
	Total	459	581	**1040**

Some examples of images used in this study can be seen in Figure 2. Where in the image there are eight types of pests, namely: *Phthorimaea operculella* (Potato Borer Moth), *Amrasca devastans* (Cotton Planthopper), *Aphis gossypii Glover* (Aphids), *Agrotis ipsilon* (Black Armyworm), *Brachytrypes portentosus Lichtenstein* (Necklace Cricket), *Bemisia tabaci* (Whitefly), *Epilachna vigintioctopunctata* (28-Spot Beetle), and *Myzus persicae* (Green Aphids).
The dataset collected from the Kaggle repository and Google data was then divided into training data, validation data and testing data where the division was 80%:10%:10% [17]. Details of the data division can be seen in Table 2.

2.2. Data Augmentation

Pest image collection is very difficult, especially for potato plant pest images [18]. In the process of image identification using deep learning models, the more datasets, the greater the effectiveness of the model used [19]. Image augmentation is a technique that can increase the number of images.

This technique affects the reduction of overfitting in a model. Augmentation techniques not only reduce overfitting but also increase model accuracy and overcome regulation problems [20].

In order to avoid overfitting and enhance model generalization, this work used the data augmentation strategy. The first step in the augmentation process is to use a rescale of 1.0/255 to normalize the image pixel values from a range of 0 to 255 to 0 to 1. Additionally, a number of transformations are used to add variation to the training data: Rotation range 30 for rotation up to 30 degrees, width shift range 0.2 and height shift range 0.2 for horizontal and vertical shifts of 20%, shear range 0.2 for shearing transformation, zoom range 0.2 for zooming up to 20%, and horizontal flip. True for horizontal flipping. Additionally, the image's brightness is altered between 70% and 130% of its initial brightness using a brightness range of 0.7 to 1.3. The total number of training photos after augmentation is 3,734. Figure 3 shows one instance of augmentation applied to the Bemisia Tabachi pest.

Table 2. Training, validation, and testing dataset

Training	Validation	Testing
832	104	104

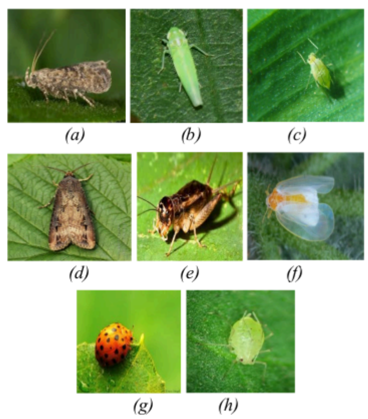


Figure 2. Image of potato pests:
(a) Phthorimaea operculella (Potato Borer Moth),
(b) Amrasca devastans (Cotton Planthopper),
(c) Aphis gossypii Glover (Aphids),
(d) Agrotis ipsilon (Black grasshopper),
(e) Brachytrypes Lichtenstein portentosus (Necklace Cricket),
(f) Bemisia tabaci (Whitefly),
(g) Epilachna vigintioctopunctata (28 Spot Beetle),
(h) Myzus persicae (Green Aphid)

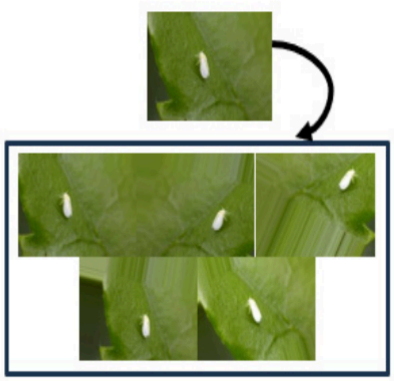


Figure 3. Example of augmented image

2.3. Training and Comparison Model

Designing a new effective model requires a large dataset. However, there are not many datasets available for potato pests [13]. One way to get beyond this obstacle is through deep learning. The practice of applying knowledge acquired from addressing one problem to solve related ones is known as deep learning [21]. Smaller datasets can benefit from feature extraction using deep learning models trained on datasets like ImageNet [22]. This method enhances model accuracy, decreases overfitting in the model, and shortens training time [23]. Eight pre-trained models—EfficientNetB5, InceptionV3, NasNetLarge, DenseNet201, MobileNetV2, CNN VGG16, ResNet50, and NasNetMobile were used in this investigation. The Adam optimizer was used to train the eight models with varying dropouts and learning rates.

Table 3. Parameters and value

Parameters	Value
Optimizing	Adam
Learning Rate	0,00001- 0,1
Dropout Rate	0,5 - 0,4

Table 3 is a table of parameters and values trained to eight models, where the table explains the parameters and values used in model training. Where the parameters employed are optimizing using Adam, learning rate from 0.00001 to 0.1, and dropout rate 0.5 and 0.4. In addition, this process also uses 50 epochs and after that, the results of the model training are compared.

After training eight models, a comparison was carried out on the model and the three best models were selected.

2.4. Freezing Layer Ensemble Model-Based

The trained dataset is data with overfitting conditions so it requires some modifications to the model used [24]. A flow of the freezing layer ensemble model based on the top three models is shown in Figure 4. By employing an ensemble technique, the freezing layer ensemble model enhances the performance of deep learning models. The model's layers are all frozen, meaning that the weights of the three models will not change while training [25]. The freezing layer formula used in this study can be seen in formula (1).

$$\frac{\partial L}{\partial W} = 0 \tag{1}$$

where:

L = symbolizes the loss function that assesses how accurately the model forecasts the desired result.

W_l = weights in the neural network model's inner layer.

$\frac{\partial L}{\partial W}$ = The loss function L's partial derivative with regard to weight W_l illustrates how much L changes when W_l varies little.

Following the freezing layer, the convolutional model's output dimension is reduced to a more compact form using a pooling technique called Global Average Pooling (GAP), which is carried out prior to the convolutional model being entered into the dense or fully connected layer [26]. The formula used in the GAP process of the model can be seen in formula (2).

$$GAP(y) = \left[\frac{1}{H \times W} \sum_{i=1}^{H} \sum_{i=1}^{W} y_{i,j,c}\right]_{c=1}^{C} \tag{2}$$

where:

$y_{i,j,c}$ = value at position (i,j) in channel C of the output tensor y.

H = height of the output tensor,

W = width of the output tensor,

C = number of channels in the output tensor.

After GAP is performed on each model, concatenation is performed. This is done to combine features extracted from various models that have been processed using GAP. The purpose of concatenation is to utilize the strengths of several models to improve feature representation [27].

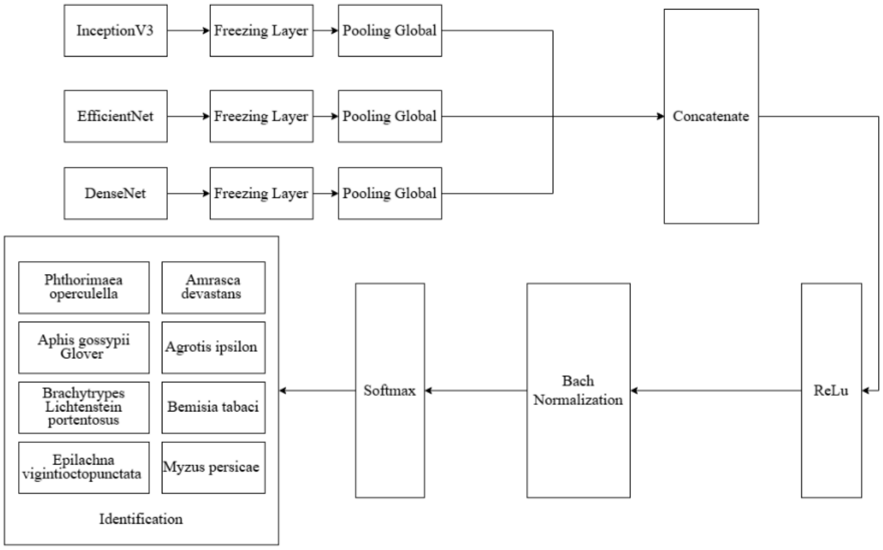


Figure 4. Model-based ensemble layer freezing flow

After concatenation is performed, ReLU is then performed to assist in training deeper and more complex models by accelerating the loss function reduction and reducing the vanishing gradient problem [28].

Next, Bach normalization is performed which can help in stabilizing training, accelerating convergence, and improving model performance [29]. By reducing the internal covariate shift problem, improving training stability, and allowing the use of more efficient activation functions.

Then, sfotmax is performed which aims to change the model output which may not be directly measurable into class probabilities which can be interpreted and used for evaluation and prediction making [30]. This makes the model provide more informative predictions and function well in the context of the loss function.

The final step in the freezing layer ensemble model-based process is to identify the images into eight types of pests, namely *Phthorimaea operculella* (Potato Borer Moth), *Amrasca devastans* (Cotton Planthopper), *Aphis gossypii Glover* (Aphids), *Agrotis ipsilon* (Black Armyworm), *Brachytrypes portentosus Lichtenstein* (Necklace Cricket), *Bemisia tabaci* (Whitefly), *Epilachna vigintioctopunctata* (28-Spot Beetle), and *Myzus persicae* (Green Aphid).

2.5. Evaluation Model

The purpose of model evaluation is to evaluate a model's performance. This is to gauge the model's ability to categorize fresh data. A confusion matrix, a table that can describe a deep learning model's performance on an identification task by contrasting the predicted class label with the actual class label on the testing dataset, was used in this study to evaluate the model [31]. In this work, a confusion matrix was used to evaluate the model, where the number of accurately predicted positive cases is known as true positives (TP). The number of accurately predicted negative occurrences is known as true negatives (TN). The number of positive cases that were mispredicted is known as false fositives (FP). The quantity of negative cases that are mispredicted is known as false negatives (FN).

In addition to using the confusion matrix, precision, recall, f1-score, and accuracy calculations are also carried out. Precision aims to see the proportion of TP on all positive prediction samples.

The precision formula can be seen in formula (3).

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

Recall aims to help assess how well the model is at finding all true positive examples. The formula for recall can be seen in formula (4).

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \text{x} 100 \qquad (4)$$

F1 - score aims to provide an overview of the performance of a classification model by balancing precision and recall. The formula for the F1-score can be seen in formula (5).

$$\mathrm{F1-score} = 2\mathrm{x}\frac{\mathrm{Precision+Recall}}{\mathrm{Precision+Recall}}\mathrm{x}100 \quad (5)$$

Accuracy provides an overview of how well a classification model predicts the correct labels overall. The accuracy formula can be seen in formula (6).

$$\mathrm{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}\mathrm{x}100 \quad (6)$$

3. Results

The implementation and evaluation of the proposed model in this study uses collaboratory supported by GPU. The available storage disk is 100 GB and RAM is 51 GB. The programming language used is Python along with the libraries, pandas, numpy, matplotlib, keras, and tensorflow. These libraries are used to build and train the developed deep learning model.

This study aims to develop a deep learning model that is able to identify potato pests effectively.

To achieve this goal, eight deep learning models are used, namely EfficientNetB5, InceptionV3, NasNetLarge, DenseNet201, MobileNetV2, CNN VGG16, ResNet50, NasNetMobile. The eight models are trained using several parameters and values, and after training it is found that at a dropout rate of 0.4. With a learning rate of 0.0001 and using the Adam optimizer, the seven models produce high accuracy, this is because the dropout rate of 0.4 prevents overfitting and improves generalization, while the small learning rate ensures stable and effective weight updates for fine-tuning the pre-trained model. The Adam optimizer, with its adaptive learning rate, can help fast and stable convergence. In addition, these models are trained on a large dataset with pre-trained weights that provide a strong foundation for specific tasks, and their sophisticated architecture captures various types of features from image data, improving overall performance. Another model that has a high accuracy value at a learning rate of 0.00001 is CNN VGG16, this is due to the deep VGG16 architecture with many layers. Small updates are more suitable for this architecture compared to larger learning rates, which can cause divergence in learning. An explanation of the model training can be seen in Table 4.

Table 4. Training model

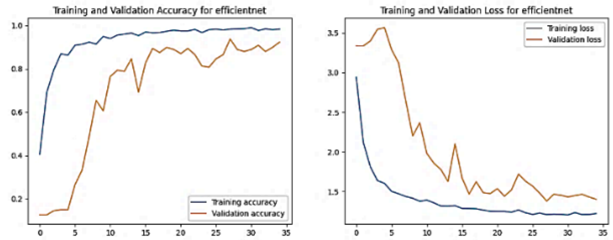
Model	Dropout rate	Learning rate	Optimizer	Val Accuracy	Val Loss
EfficientNetB5	0,4	0,0001	Adam	0,87	1,5
InceptionV3	0,4	0,0001	Adam	0,83	1,8
NasNetLarge	0,4	0,0001	Adam	0,79	1,4
DenseNet201	0,4	0,0001	Adam	0,89	0,9
MobileNetV2	0,4	0,0001	Adam	0,79	1,2
CNN VGG16	0,4	0,00001	Adam	0,73	0,9
ResNet50	0,4	0,0001	Adam	0,24	5,1
NasNetMobile	0,4	0,0001	Adam	0,77	1,4

After training eight models, then a model comparison was carried out and three models were taken with an accuracy value of more than 0,80. This was done because adding a model with an accuracy value of less than 0,80 can affect the accuracy value of the ensemble model results to be smaller. The results of the analysis of the three models that have an accuracy value of more than 0,80 can be seen in Figure 5, which shows the accuracy curve, accuracy validation, loss, and validation loss. It can be seen from the 50 epochs of training that the model stops at a certain epoch which indicates that after that epoch there is no increase in the accuracy value.

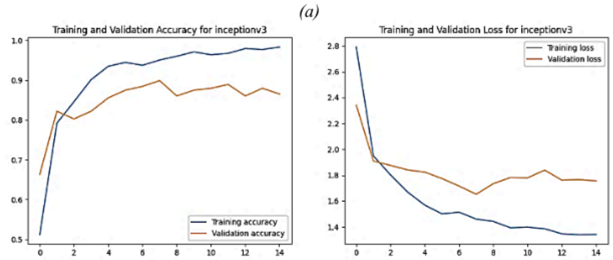
When viewed in Figure 5, the accuracy values of the three models are increasing, and the loss values of the three models are decreasing.

However, the model is still indicated as overfitting, this is because the loss value is still higher than the accuracy value, so it is necessary to develop the model in order to solve this problem.

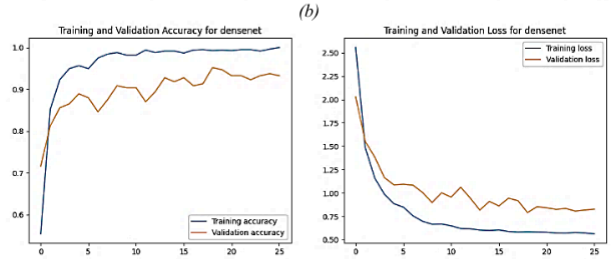
Freezing Layer in the ensemble process of the EfficientNetB5, InceptionV3, DenseNet201 models is used to help prevent data from overfitting, where the freezing layer process is carried out after training the EfficientNetB5, InceptionV3, DenseNet201 models, then the GAP process is carried out for the three models, and concatenate (ensemble), ReLU, batch normalization, softmax is carried out, and finally, the results of the identification appear.



(a)



(b)



(c)

Figure 5. Accuracy, val accuracy, loss and val loss curve (a) EfficientNetB5, (b) InceptionV3, (c) DenseNet201

Freezing Layer ensemble model EfficientNetB5, InceptionV3, DenseNet201 was then evaluated and the results of the evaluation can be seen in Figure 6.

In Figure 6, it can be seen that the accuracy value increases the loss value decreases, and the loss value is smaller than the accuracy value. It can be said that the Freezing Layer ensemble model of EfficientNetB5, InceptionV3, DenseNet201 is better than the model without the Freezing Layer ensemble.

After training the model, the model performance evaluation is carried out using the testing dataset.

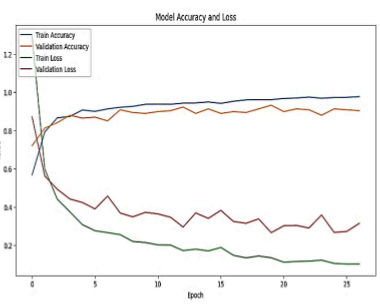


Figure 6. Accuracy, val accuracy, loss and val loss curve Freezing Layer ensemble model EfficientNetB5, InceptionV3, DenseNet201

Following evaluation with the convolution matrix, the MaTangDetect model is evaluated using classification metrics. Accuracy, precision, recall, and F1-score are the categorization measures that are employed. Each distinct class is used to calculate the metrics. Four values for precision, recall, and F1 score per model are obtained from these metrics, which are computed on each distinct class. Table 5 displays the outcomes of every model metric, demonstrating MaTangDetect's superior performance across the board.

Table 5. Performance evaluation models

Model	**Precision**	**Recall**	**F1-core**	**Accuracy**
EfficientNetB5	87%	87%	87%	87%
InceptionV3	82%	83%	83%	83%
DenseNet201	89%	89%	89%	89%
CTInceptionV3 [13]	91%	91%	91%	91%
Freezing Layer Ensemble Model EfficientNetB5, InceptionV3, DenseNet201 (MaTangDetect)	96%	95%	95%	93%

The MaTangDetect model which has been tested with testing data, is then applied to the system to identify potato plant pests. Figure 7 is a display of the Potato Plant Pest Identification system page, where the new image inputted into the system can be identified as a *Bemisia tabaci* image with a confidence level of 0.98. This indicates that the system with the MaTangDetect model can be used and can help potato farmers detect potato plant pests in agricultural areas early.

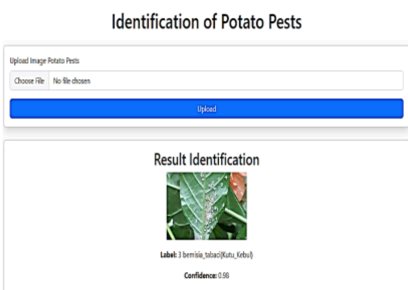


Figure 7. MaTangDetect system

4. Discussion

From the analysis results, it can be seen that the adjusted model can be trained well. Research [32] concluded that CNN is better than traditional machine learning, this is because the parameters in the training are large and the computing time is longer. Therefore, this study focuses on CNN. After training, the accuracy results obtained using CNN VGG16 were 60%, this is indicated because the number of datasets is small but the model used is complex. So the model was changed to deep learning based on the results of research [33]. In addition to the small amount of data, the problem faced is also the overfitting of data in the deep learning model. The solution to the problem of overfitting is modified by performing freezing layers and ensembles on three models that have accuracy values of more than 90%, namely the EfficientNetB5, InceptionV3, and DenseNet201 models. From the results of model training, during training, an experiment was carried out using 50 epochs in each experiment to find the best model. Table 5 is a description of the best parameter combination used during training using 8 models, which were then used in the freezing layer and ensemble of EfficientNetB5, InceptionV3, and DenseNet201 models which are the solution to dealing with data overfitting and obtaining high accuracy values.

The performance of the model in training and testing can be seen in the accuracy and loss curves in Figure 6 and Figure 7. In the figure the difference between the accuracy curve can be seen, accuracy val, loss and val loss in the EfficientNetB5, InceptionV3 and DenseNet201 models with the accuracy curve, accuracy val, loss and val loss in the Freezing Layer Ensemble Model EfficientNetB5, InceptionV3 and DenseNet201 (MaTangDetect).

The difference in accuracy and val accuracy of the Freezing Layer Ensemble Based Model (MaTangDetect) training is between the range of 0.98 - 0.93 = 0.05 and the difference in loss and val loss between the range of 0.38 - 0.18 = 0.2. This indicates that MaTangDetect can learn well and can be applied to a potato plant pest identification system.

5. Conclusion

The purpose of this study is to detect pests of potato plants. In order to find comparable issues, this study started by reading up on pertinent research and examining earlier approaches. The MaTangDetect model was proposed in this study along with the EfficientNetB5, InceptionV3, and DenseNet201 models that were pre-trained by incorporating Freezing Layer Ensemble for potato plant pest diagnosis. The pre-trained model is developed by adding freezing layers, substituting a global average pooling layer for the fully connected layer, and identifying potato plant pests using concatenation, ReLu, Bach Normalization, and Softmax. With a 93% F1-score, the MaTangDetect model outperformed the others in terms of classification accuracy, precision, recall, and F1-score. This finding has significant ramifications for the agriculture sector since farmers can act quickly to identify pests.

To increase the accuracy of the potato pest identification model, more studies can employ deep learning techniques and data preprocessing approaches other than augmentation. The outcomes of the MaTangDetect model can also be applied in a real-world setting by developing an AI-based system.

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10