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Development of a Web-based Application by Employing a Convolutional Neural Network (CNN) to Identify Pests and Diseases on Pakcoy (*Brassica rapa* subsp. *chinensis*)

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ABSTRACT

The development of Pakcoy cultivation holds good prospects, as seen from the demand for vegetable commodities in Indonesia. Its cultivation is consistently rising in terms of volume and value of vegetable imports. However, the cultivation process encounters multiple issues caused by pests and diseases. In addition, the volatile climate in Indonesia has resulted in uninterrupted pest development and the potential decline of Pakcoy's productivity. Therefore, the detection system for pests and diseases in the Pakcoy plant is called upon to accurately and quickly assist farmers in determining the right treatment, thereby reducing economic losses and producing abundant quality crops. A web-based application with several well-known Convolutional Neural Network (CNN) were incorporated, such as MobileNetV2, GoogLeNet, and ResNet101. A total of 1,226 images were used for training, validating, and testing the dataset to address the problem in this study. The dataset consisted of several plant conditions with leaf miners, cabbage butterflies, powdery mildew disease, healthy plants, and multiple data labels for pests and diseases presented in the individual image. The results show that the MobileNetV2 provides a minimum loss compared to GoogLeNet and ResNet-101 with scores of 0.076, 0.239, and 0.209, respectively. Since the MobileNetV2 architecture provides a good model, the model was carried out to be integrated and tested with the web-based application. The testing accuracy rate reached 98% from the total dataset of

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70 testing images. In this direction, MobileNetV2 can be a viable method to be integrated with web-based applications for classifying an image as the basis for decision-making.

Keywords: Deep learning, disease, MobileNetV2, pest, precision agriculture

INTRODUCTION

Pakcoy (*Brassica rapa* subsp. *chinensis*) is a leaf vegetable from China usually used for diet remedies (Li et al., 2022). It is cultivated and consumed worldwide due to edible leaves containing complete nutrients, making it a decent option for maintaining a healthy body. The development of Pakcoy cultivation holds good prospects, considering improved community nutrition, expanded job opportunities, developed agribusiness, and higher state income by escalating export growth.

Pakcoy is easy to grow and has good prospects for increasing farmers' income and community health. However, its cultivation encounters a number of issues caused by pests and diseases. The climate in Indonesia, with frequent changes, leads to the massive growth of pests and diseases (Nair, 2000). This circumstance potentially reduces Pakcoy's productivity and even causes crop failure. To that end, accurate and immediate detection of crop pests and diseases can help farmers determine the proper treatment, thereby reducing economic losses and producing abundant quality crops (Rahman et al., 2020).

To properly treat plants, a technology that can provide early warning and recommendations is needed by utilizing artificial intelligence. Previous studies report the extensive use of artificial neural network (ANN) methods for plant classification (Griffel et al., 2023; Sai et al., 2022). This method is known to be substantially faster, which is why it gains popularity among farmers. However, it may not be sufficiently potent in determining the number of hidden layers, particularly as it takes copious epoch parameters and requires high-performance computations (Putra, Wirayuda et al., 2022). Many methods can perform image processing, including the Convolutional Neural Network (CNN) (Putra, Amirudin, et al., 2022; Sujatha et al., 2021). This method has the ability to process visual information by imitating the image recognition system in the visual cortex in humans. Previous studies on image processing using the CNN method have reported decent accuracy. Studies by Kamal et al. (2019) and Rahman et al. (2020), who investigate disease detection, provide a system accuracy of 93% and 98.34%, respectively.

A previous study has documented that the CNN method has gained traction in identifying plant diseases (Rahman et al., 2020) by using lightweight architecture such as MobileNet, NasNet Mobile, and SqueezeNet, which can achieve an accuracy of 93.3% with lightweight model size. A similar study has also been conducted by Esgario et al. (2022) on identifying pests and diseases of coffee plants. The developed system has managed to attain an accuracy rate of 97%.

Another study employing CNN to detect plant diseases has also been carried out by Kamal et al. (2019). This study aims to identify a model with the best depth-wise separable technique to identify plant pests and diseases. The dataset encompasses 82,161 images and 55 classes of healthy as well as diseased plants. The result has found that the MobileNet architectural model offers a better accuracy rate at 98.34% compared to the VGG model. The research above has demonstrated that the CNN method can accurately identify pests and diseases in plants, even significantly better than other methods.

Several studies (Chen et al., 2021; Kumi et al., 2022) develop and evaluate the models to produce the best accuracy. MobileNet architecture seems affordable and lightweight to be implemented in smartphones rather than in other architectures. However, in this study, the development of a relational database management system was also incorporated. This study aims to a) compare the performance of several well-known CNN architectures to address the issues of pest and disease detection; b) Develop a web-based application and deploy the best CNN to classify images and aid in decision-making to help farmers surmount pest and disease problems in Pakcoy.

MATERIAL AND METHODS

Dataset

The dataset in this study consisted of multiple images containing information about pests and diseases in Pakcoy. The dataset was obtained from the Kaggle platform, which provided various datasets used for further research by data scientists. The dataset consists of 3 pests and diseases on Pakcoy, including cabbage butterfly, leaf miner, and powdery mildew. The Kaggle data set involved 1,793 images of cabbage butterflies, 333 images of leaf miner pests, and 752 images of powdery mildew. The dataset on Pakcoy was derived from Kaggle along with a label on each image using a CSV file (https://www.kaggle.com/giane901/chinese-cabbage-disease-detection). The data were double-checked to re-identify disease availability in each image and store the type of pests and/or disease information. The labeling employed multiple dataset labels, meaning one dataset image could contain more than one infected pest and disease. However, another class, namely the healthy class, was added and collected from local farmers for this purpose. A balanced dataset of four different classes of pest and diseases are required. Thus, 1156 images were used for training and testing for model development. The proposed architectures, namely MobileNetV2, ResNet-101, and GoogLeNet, were carried out using 894 training images and 262 validation images to determine the level of loss function or cost function generated. In addition, 70 images were collected separately from local farmers and unused Kaggle data for model evaluation along with web-based development and implementation.

Models

Convolutional Neural Network. Convolutional Neural Network or CNN is a neural network method in deep learning commonly used for image data (Hendrawan et al., 2022; Koklu et al., 2021). This method can be used to recognize and classify the objects in an image. It integrates several neurons with weight values, activation functions, and bias values almost similar to normal neural networks. Figure 1 shows the base architecture of the CNN.

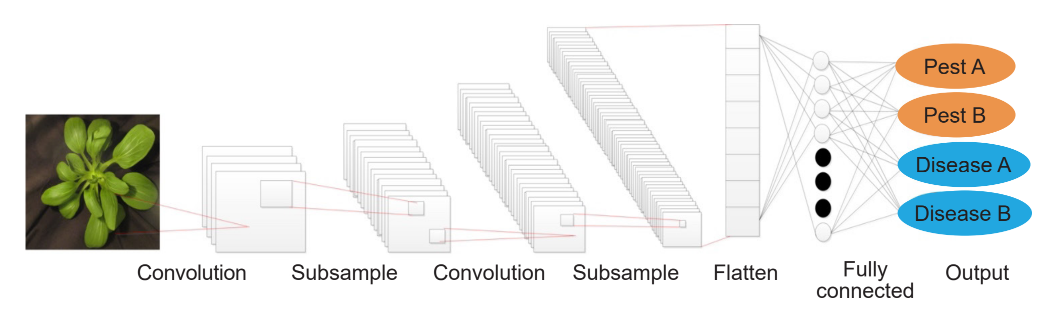

Figure 1. Convolutional neural network

The input layer is the image data input converted into a 3-dimensional matrix with an individual value of each dimension: red, blue, and green. The data are entered at the convolution layer stage, where calculations will occur between the previous layers. As the kernel matrix has been initialized prior to training, the calculation of the number of kernels depends on the number of features generated. Afterward, the rectified linear unit (ReLU) is operative for the activation function. After the activation function, the pooling process will take place. This process is repeated several times until a sufficient feature map is obtained before initiating a fully connected neural network.

MobileNet V2. MobileNetV2 is a convolutional neural network (CNN) architecture used to overcome the need for excessive computing resources (Sandler et al., 2018; Sutaji & Yıldız, 2022). In general, the basic difference between MobileNetV2 architecture and CNN architecture is the use of a convolution layer with a filter thickness corresponding to the thickness of the input image. MobileNetV2 divides convolution into depthwise convolution and pointwise convolution. The MobileNetV2 architecture uses the ReLU6 activation function (Figure 2).

Depthwise separable convolution is a block in deep learning consisting of depthwise and pointwise convolution. This depthwise separable convolution layer reduces complexity and parameters upon generating a smaller model (Howard et al., 2017; Kamal et al., 2019). Depthwise convolution is the result of factorization of standard convolution of a number of inputs, and it is capable of individual channel processing. What follows is the

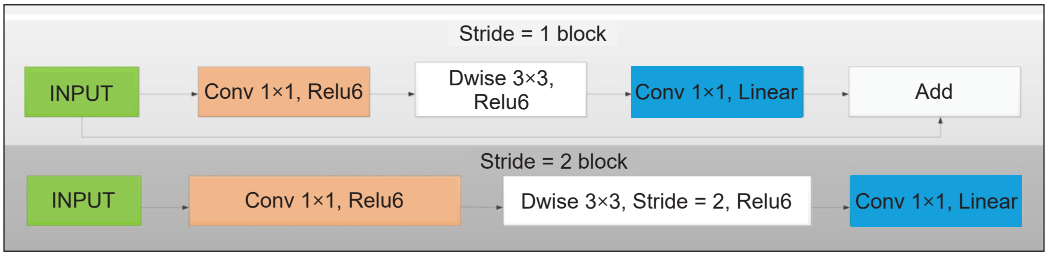

Figure 2. MobileNet V2 architecture

comparison of the total operating costs between depthwise separable convolution and standard convolution. The total cost calculation of standard convolution is formulated as Equation 1.

$$Z_k \,.\, Z_k \,.\, A \,.\, B \,.\, Z_f \,.\, Z_f \quad (1)$$

By contrast, that of depthwise separable convolution employs the Equation 2

$$Z_k \,.\, Z_k \,.\, A \,.\, Z_f \,.\, Z_f + A \,.\, B \,.\, Z_f \,.\, Z_f \quad (2)$$

Zk denotes the size or dimension of the kernel, *A* represents the number of input channels, *B* corresponds to the number of output channels, and *Zf* is the size of the feature or filter. As for standard convolution, the computational cost employs the following Equation 3.

$$\frac{Z_k \,.Z_k \,.A \,.Z_f \,.Z_f + A \,.B \,.Z_f \,.Z_f}{Z_k \,.Z_k \,.A \,.Z_f \,.Z_f} = \frac{1}{B} + \frac{1}{Z_k^2} \quad (3)$$

Equation 3 implies that a 3 × 3 kernel reduces computation by 8 or 9 times (Howard et al., 2017; Kamal et al., 2019).

After the dataset had gone through data labeling and augmentation, a pre-trained model of the MobileNetV2 architecture was prototyped. Each image data followed the MobileNetV2 architecture (Sandler et al., 2018) and performed convolution according to the architecture (Table 1).

Table 1
MobileNetV2 architecture

Input	Operator	Expansion factor	Output channels	Number of repeat	Stride
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2

Table 1 *(continue)*

Input	Operator	Expansion factor	Output channels	Number of repeat	Stride
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1×1	-	1280	1	1
$7^2 \times 1280$	avgpool 7×7	-	-	1	-
1 × 1 × 1280	conv2d 1×1	-	k	-	-

GoogleNet. GoogLeNet is an architecture developed by and has a 22-layer deep convolutional neural network (Szegedy et al., 2015). The GoogleNet architecture usually uses 224 × 224 pixels of each input image. A study conducted by Luo et al. (2021) shows that GoogLeNet works well in classifying weed seeds. However, the use of GoogLeNet needs to be evaluated to classify Pakcoy pests and diseases.

ResNet-101. Resnet-101 is an architecture developed by Microsoft with 101 layers of deep convolution neural networks. Also, the size of the input image of this architecture was 224 × 224 pixels. A study by Wu et al. (2021) shows that ResNet-101 performs better than ResNet-50 in segmenting the abnormal leaves in the plants. For Pakcoy pests and diseases classification, we used a ResNet-101 rather than ResNet-50.

Metrics

As a measuring tool, a confusion matrix is designed to make measurements when analyzing a classifier. It helps to determine whether a classifier is good in terms of recognizing data from different classes. When the classifier is run and generates real-time data, True-Positive and True-Negative values provide that information. Meanwhile, if the classifier encounters an error upon classifying data, the values of False-Positive and False-Negative will provide the required information. In this study, the confusion matrix was employed, and the parameters associated with accuracy (Equation 4), precision (Equation 5), recall (Equation 6), and f1-score (Equation 7). The equations of these constructs are as follows.

$$Accuracy\ (a) = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FN} + \mathrm{FP}} \tag{4}$$

$$Precision\ (p) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{5}$$

$$Recall\ (r) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{6}$$

$$f1 - score\ (f) = \frac{2 \times precision \times recall}{precision + recall} \tag{7}$$

Web-based Development and Implementation

Choosing the Best Model. Three different architectures (MobileNetV2, GoogLeNet, and ResNet-101) were evaluated, and the best metrics were chosen for inclusion in web-based development and deep learning implementation. The model will be re-trained and re-tested for further use if new information/data is provided.

Business Process Model Notation (BPMN). Business Process Model Notation (BPMN) is a graphical representation essential to determine a business process model. BPMN is developed to help readers understand a business process underway. Two main actors, namely user and admin, were involved in the business process. The users can be Pakcoy farmer or stakeholder who wants to predict and recognize the pests and diseases of Pakcoy and its problem-solving. An admin manages users, pests, and disease information, re-train and -tests the model, and applies the best model. Figure 3 shows the BPMN of the pest and disease identification system for Pakcoy in this study.

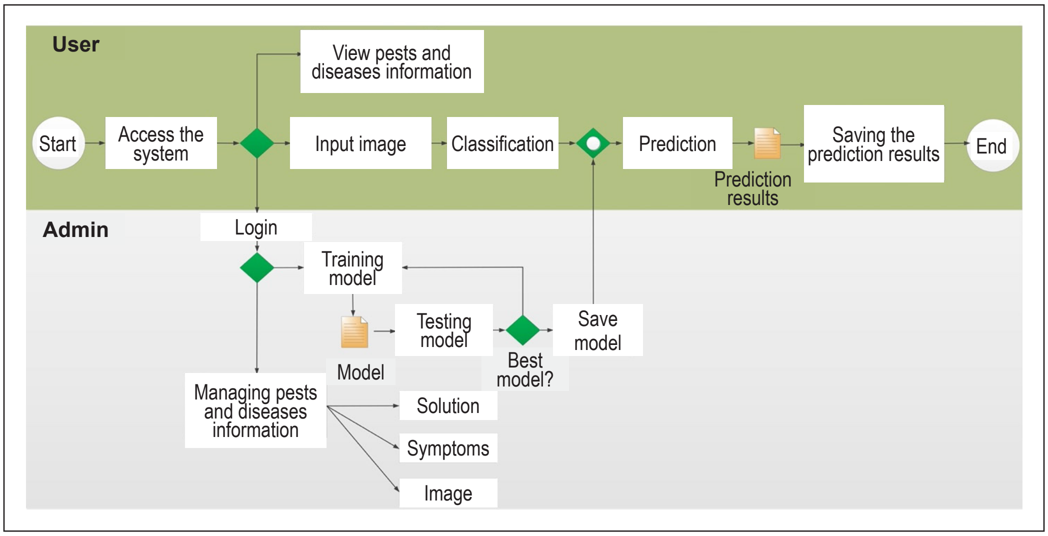

Figure 3. Business Process Model Notation (BPMN)

Workflow. The flowchart describes the detailed convolution process. The process is essential in processing image input using a MobileNet architectural model. It plays a key role in producing new features for identifying pests and diseases on Pakcoy plants. Figure 4 displays how input is engaged in the overall convolution of MobileNet.

Entity Relationship Diagram. Entity Relationship Diagram (ERD) is a diagram for modeling database requirements. The ERD development should be done before developing the web application. The basic tables, namely the image of infected Pakcoy leaf, pest, and disease name, symptoms of each pest and disease, and its solutions, need to be provided for identifying the Pakcoy pest and disease. The ERD of the pest and disease identification system developed in this study can be seen in Figure 5.

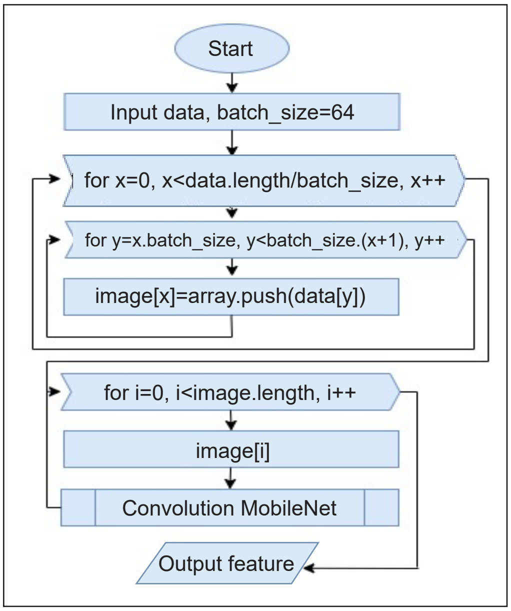

Figure 4. Convolution flowchart

RESULTS AND DISCUSSION

Although several studies provide adequate evidence of those architectures (MobileNetV2, GoogLeNet, and ResNet-101) performance in identifying and classifying the pests and diseases of the plant, based on the principle of precision agriculture, which focuses on site-specific management, each agricultural problem/issue needs to be handled by using the particular treatment and cannot be generalized using the same architecture. Thus, pests and diseases recognition of Pakcoy need to be evaluated.

The Results of Training Model

For this purpose, all well-known architectures, namely MobileNetV2, GoogLeNet, and Resnet101, use batch size, dropout, and early stop patience of 64, 0.085, and 10, respectively. In addition, we also used the learning rate of 0.01, 0.001, 0.0001, and 0.00001 to evaluate the performance of selected architectures and examine the model acquired to

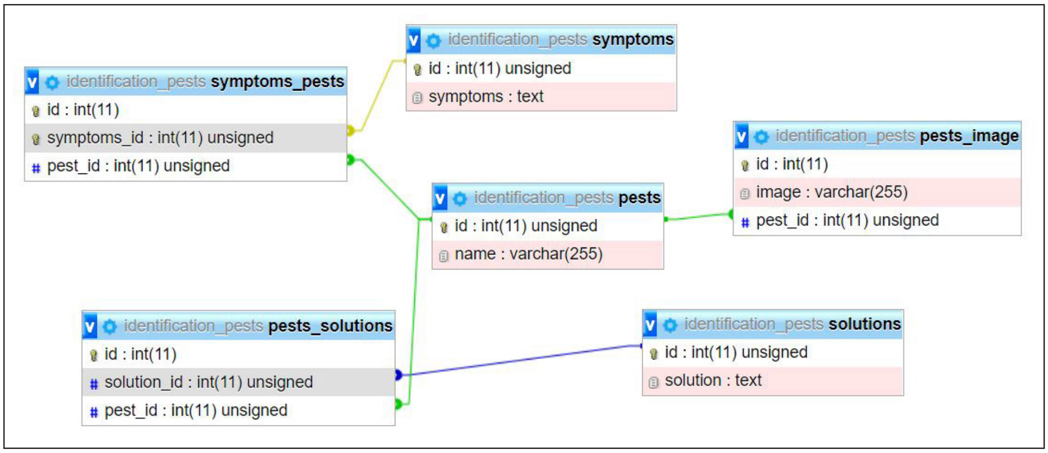

Figure 5. Entity Relationship Diagram (ERD)

recognize the Pakcoy pests and diseases. This study employed multi-label datasets, meaning that one image can indicate more than one pest and disease.

The results have demonstrated that the training process using a learning rate of 0.001 produces the best model and provides the lowest loss function value, especially for MobileNetV2 architecture (Table 2). A good loss function produces the lowest expected error. Since the batch size, dropout, and early stop patience of 64, 0.085, and 10 were used in the training step, these parameter values significantly affect the results, characterized by good results and graphics without overfitting (Figure 6). The results point out that the MobileNetV2 has the best level of loss function compared to ResNet101 and GoogLeNet models. It concludes that the model also markedly affects the success rate of training. Thus, the tested model can be used directly by the user to be implemented into web and mobile applications. Several researchers used a MobileNet architecture for several benefits, such as being lightweight in smartphone implementation and reducing application latency (Chudzik et al., 2020; Li et al., 2021).

Table 2
Loss function value

Learning Rate	MobileNetV2	ResNet101	GoogLeNet
0.01	0.4496	0.4385	0.3396
0.001	0.0764	0.2091	0.2397
0.0001	0.098	0.1048	0.2107
0.00001	0.075	0.1009	0.0829

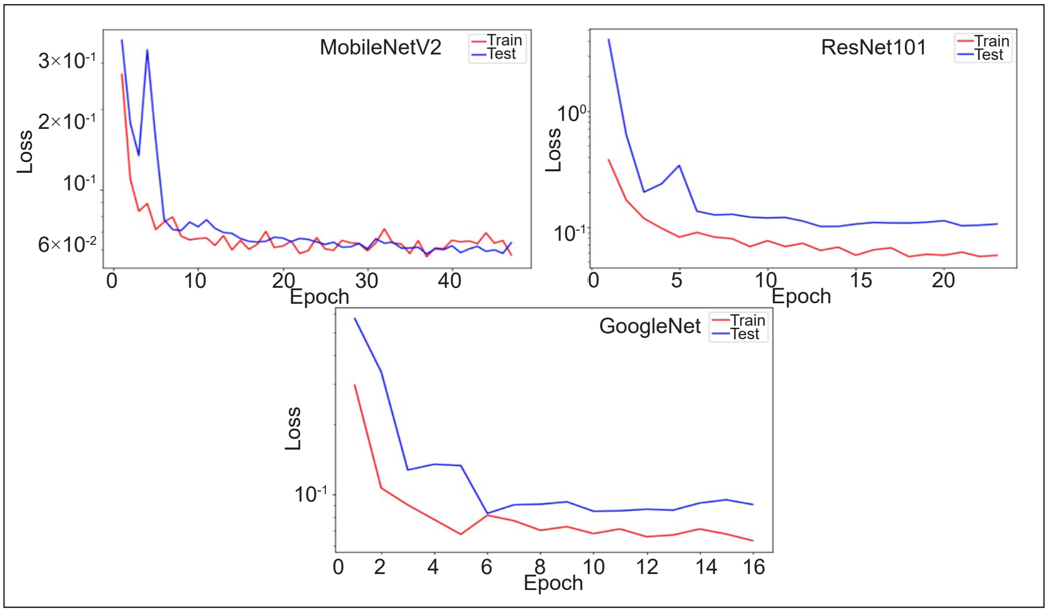

Figure 6. Comparison of different model architectures

The Results of Model Testing

The model testing with MobileNet was carried out using 70 image datasets. Model evaluation determines whether the model tested is sufficiently decent and can be used directly by farmers. In evaluating the model, the researchers calculated accuracy, precision, recall, and f1-score in the form of a confusion matrix. Here are the evaluation results of the model using the confusion matrix (Table 3).

The average precision, recall, and f1-score of each label were calculated using a macro average and a weighted average. As seen in Table 4, each label has a different value but does not imply a significant gap. The findings highlight that the MobileNet architecture model has stable accuracy, precision, recall, and f1-score values, which are essential for identifying pests and diseases. MobileNet is readily applicable for identifying pests and diseases to aid growing Pakcoy.

Table 3
Accuracy, precision, recall, and f1-support

Label	Accuracy (a)	Precision (p)	Recall (r)	f1-score (f)	Number of Label (s)
Healthy	1.00	1.00	1.00	1.00	6
Cabbage butterfly	0.97	0.95	1.00	0.97	39
Leaf miner	1.00	1.00	1.00	1.00	24
Powdery mildew	0.97	1.00	0.90	0.95	20

Table 4
The average of confusion matrix

	Accuracy	Precision	Recall	f1-score	Number of Labels
Macro Avg	98 %	99 %	97 %	98 %	89
Weighted Avg	98 %	98 %	98 %	98 %	89

Implementation Results of Web-based System

In this study, the front end and back end of the system were developed (Figure 7). The front end consists of the homepage and pest and disease prediction page. The landing page is directed to the home page, which users can access. This page has a start button to upload images to predict pests and diseases for the backend used for administration. This page presents information on predicted pests and diseases based on the image uploaded by the user. It informs the pests and diseases that possibly affect a certain plant and the solutions to overcome these pests and diseases. In addition, the administrator can upload the types of pests and diseases, symptoms, and recommendations. For new pests and diseases that are not available in the model, the Administrator will re-train the existing and additional dataset of new pests/diseases, then generate a new model and replace the old model.

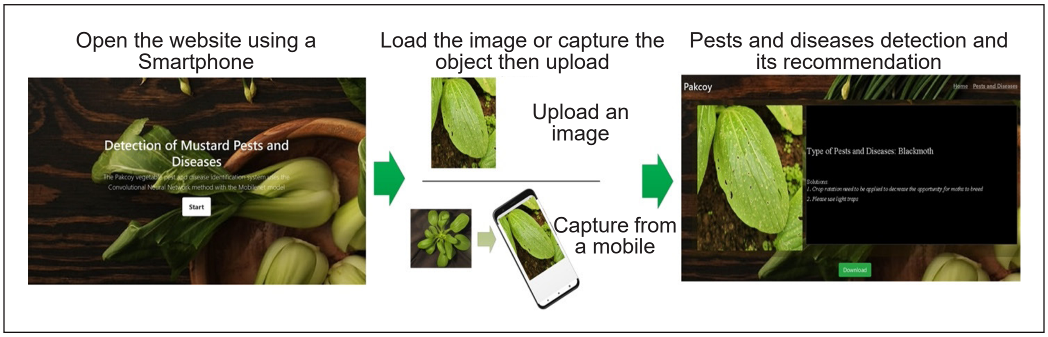

Figure 7. Web-based pests and diseases

CONCLUSION

In this study, we specify four Pakcoy classifications: healthy, cabbage butterfly, leaf miner, and powdery mildew. Several architectures, namely GoogleNet, ResNet, and MobileNet, were evaluated to predict the type of pests and diseases in an image. We also evaluate a single to multilabel criterion of pests and diseases of Pakcoy. A significant model was obtained using MobileNetV2 architecture for pests and disease recognition.

The convolutional Neural Network method using the MobileNet architecture model coupled with several adjusted parameters comprises an effective system to identify pests and diseases on Pakcoy. Based on the training data, the developed model produces an error rate of 0.076 and an accuracy rate of 98%. The model architecture, along with its parameters, has been proven to generate a low error rate without not overfitting. In addition, we successfully developed a web-based application and supported mobile-based applications. Future study is suggested to develop a pest and disease identification system involving many types of pests and diseases affecting Pakcoy including spodoptera litura, spodoptera exigua, Agrotis sp., plasmodiophora brassicae, plutella xylostella, and phytoptora sp.

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