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Marigold Flower Disease Prediction through Deep Neural Network with Multimodal Image

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Abstract — *This research aims to develop the convolutional neural network model to predict the marigold flower disease through multimodal image processing. The marigold flower was detected on the image dataset by applying the Fast Approximate Nearest neighbor Search Algorithm, centroids, and GrabCut algorithm. The image segmentation with the watershed and hue saturation value techniques were used to process the image dataset for the neural network modeling. The result showed that the developed model with the watershed dataset has the highest efficiency. The model gave the validation accuracy of 88.03%, the validation loss of 4.21%, and the accuracy of the model testing was 91.67%. Therefore, it could be said that image segmentation processing could optimize flower disease image classification in deep neural networks.*

Keywords — *Deep Neural Network, Marigold, Multimodal image.*

I. INTRODUCTION

Farming the ornamental flower is a very popular and important career that generates income for farmers economically every year. The ornamental flower is used to decorate houses and essential places according to special occasions. The marigold (*Tagetes erecta* or *T. erecta*) has its legend to cause prosperity when brought to the ceremony or planted in the house or various places. The marigold is one of the top-selling plants in the flower market in almost several Asian countries, such as Thailand and India, as a garland used in Buddhist or religious ceremonies. Further, the marigold has insect repellent properties such as mosquitoes [1]. In livestock, it is also used for feed as animal food such as chicken food [2]. In addition, marigold also has medicinal properties or some nutrition. It contains carotenoids such as zeaxanthin and lutein compounds [3] to prevent and control the disease for human health [4][5]. Therefore, it is popular in the food and pharmaceutical industries. For this reason, marigolds are exported to many countries worldwide, and there is a tendency to increase demand.

Even though the marigold flower businesses are booming, the marigold farmers still have problems with some diseases that cause this plant to wilt and die before harvesting, causing much damage to farms. There are several risks associated with cultivating flowers. Plant disease is one of the greatest threats, as it lowers the quality and quantity of flower production. Plants get ill when repeatedly disrupted by a causative agent, resulting in an aberrant physiological process that disturbs the plant's typical structure, growth, function, or other activities [6].

Flowers are one of the plant species that are vulnerable to a variety of diseases. In particular, the marigold flower disease can spread to other flowers in the same plot. The most common marigold flower diseases are flower blight, Botrytis blight or gray mold, and flower bud rot. These diseases are due to mold or some fungal disease, coolness, and humidity, causing some parts of the flowers to turn brown and eventually cause the plant to die. To diagnose a flower's condition, take a good look at it, study the flower, leaves, stem, and occasionally roots, and do some detective work to figure out what is causing it [7]. Experts in this area can help farmers identify flower disease. However, finding well-qualified professionals for detecting and examining flower diseases is difficult (and expensive) since professionals are obliged to keep an eye on flowers at all times. Traditionally, marigold farmers are still using manual techniques to detect and identify floral illnesses, resulting in high production costs. Furthermore, the problem is exacerbated by the fact that professionals work in unfavorable conditions due to pesticides and greenhouses used in the flower production process [8]. Thus, various researches have to occur to analyze and solve diseases that occur with ornamental plants and flowers.

Deep Neural Network (DNN), notably Convolutional Neural Network (CNN), was proposed in 2012 and is now delivering the most expanding applications, including object recognition, detection, biometry, and classification. CNN creates a hierarchy of visual representations, serving as a matching filter [9]. The key aspect of CNNs is the concept of generalization, which refers to the ability to handle data that has never been seen before. Sibiya et al. recommended a CNN model and histogram approaches to classify the maize plant disease [10]. Zhang et al. used ResNet, which is considered the best algorithm among all the CNN, GoogLeNet, and AlexNet algorithms for detecting tomato leaf disease [11]. The LeNet architecture was utilized, and F1 and CA scores were applied to evaluate the banana leaf disease model in grayscale and color models [12]. VGG, AlexNet, Overfeat, and GoogLeNet are five CNN architectures suggested by Ferentinos in 2018. VGG architecture is regarded as the outclassed model among these [13].

However, some studies suggest a generic method that uses artificial neural networks to automatically identify flower disorders and a prediction mechanism for unknown flower samples using image processing techniques, automatic detection of floral diseases is feasible. To develop a knowledge base, uninfected and infected flower photos must be collected and applied to some images pre-processed with segmented to determine the region of interest.

Therefore, this research focused on classifying marigold flower disease by applied a convolutional neural network and multimodal image processing technique for predicting the disease on the flower for further integrating technology that might help to increase marigold productivity and reduce agricultural costs by preventing flower disease problems. Additionally, the production and distribution of marigolds will create a stable income from the extent of agricultural innovations.

II. METHODOLOGY

The research methods for marigold flower disease prediction using neural networks were described as follows.

A. Data Collection

This research focuses on detecting whether marigold flowers are infected or not. Therefore, the authors collected 2,220 images of the marigold flowers from the internet and took the photo via smartphone. These images consist of 1,240 images of marigold flowers in good condition (uninfected) and 980 images of marigold flowers with diseases (infected). There might be one or more marigold flowers in each image which an image dimension is between 400 and 1,920 pixels wide and between 400 and 1,080 pixels high.

B. Multimodal Image Processing

In this step, the previously collected images are arranged through the following image processing as follows.

a) Flower Detection: The marigold flowers have different sizes and positions in the image. This research focuses on finding the flowers that are the most prominent in the image. Thus, the Fast Approximate Nearest neighbor Search Algorithm (FLANN) [14] was conducted to help search the flower on the image in this process. The FLANN cascade classifier was trained for comparing the features and matching the vector of objects in different rectangle sizes on an image. The sample marigold flower images were prepared as templates for cascading classification of the flower location on the image. The green lines were connected to the flower feature matching between the small flower template (top-right) and the flower on the dataset image (left), as shown in Fig. 1.

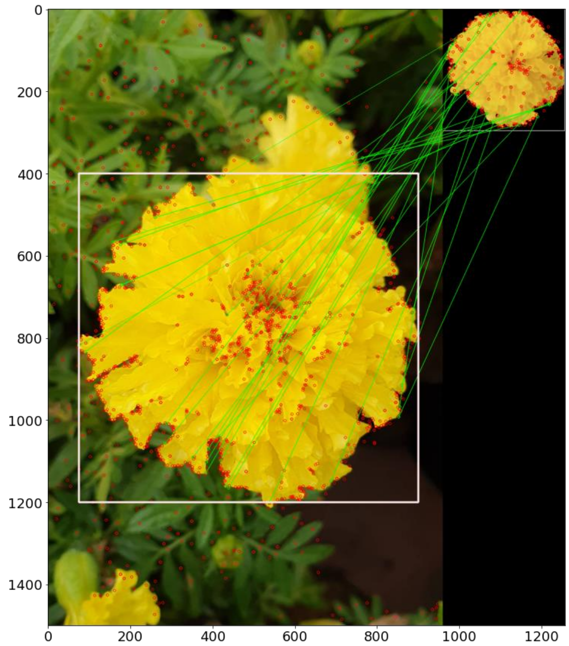


Fig. 1 Flower detection by using FLANN feature detection

***b) Centroid Calculation and Cropping*:** After the flower features are discovered in the image with FLANN, the center point of the flower is calculated using the arithmetic mean centroid principle. The coordinate of the centroid (x_c, y_c) was calculated in (1) and (2) [15].

$$x_c = \frac{\sum_{k=1}^{n} x_k}{n} \quad (1)$$

$$y_c = \frac{\sum_{k=1}^{n} y_k}{n} \quad (2)$$

Where n refers to the total number of points (x,y) which is the coordinate of the flower feature matched.

Therefore, the red circles with a green line connected in Fig. 1 were used to find the centroid of the marigold flower. Moreover, the minimum and maximum values of x and y were applied to calculate the flower boundary. Once the flower area was bounded, the image was cropped into a square for use in the next process.

***c) Background Removal*:** An image of a square-cropped marigold flower is brought to emphasize the region of interest (ROI) by removing the background information. The authors applied the GrabCut algorithm [16] to scope the background as a marking area then remove it from the image. The GrabCut algorithm is based on the graph cut technique for image segmentation by contour the curve of border matting between foreground and background. Thus, the flower only remained on the image in red-green-blue (RGB) color mode, as illustrated in Fig. 2.

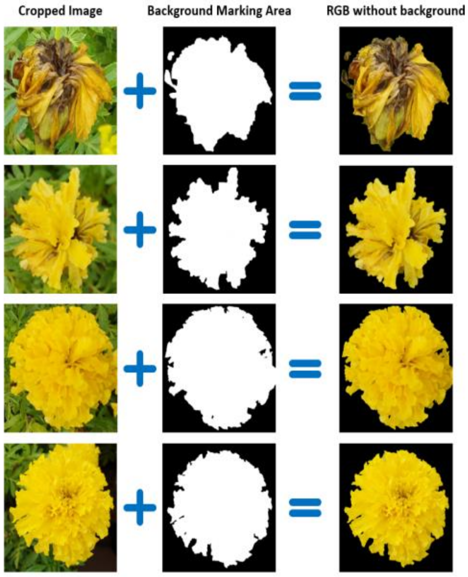


Fig. 2 The sample of the output images without background information (RGB noBG)

***d) Changing Color-Space*:** Images without background data were subjected to a changing color-space process to differentiate between the infective hyperpigmentation and the yellow surface of the marigold flower. The hue-saturation-value (HSV) color model was applied to remaps the RGB primary colors, especially the yellow color on the marigold flower. This work focussed on the hue parameter at 60 degrees for the yellow color range while the saturation and value parameters were set between 60% and 100%, respectively. All yellow color ranges on the flower were found and converted to gray, while the black color ranges were converted to the white color range. The output image after changing the color space was shown in Fig. 3.

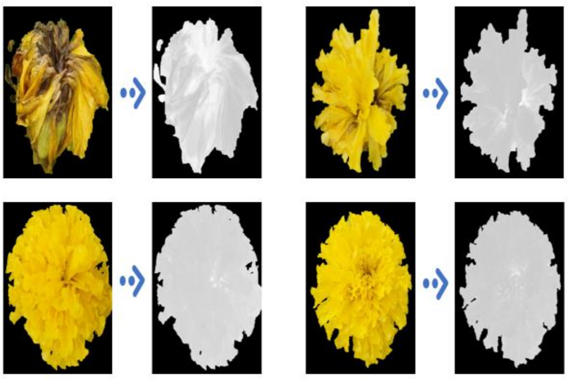


Fig. 3 The sample of output image after changing color-space

***e) Image Segmentation*:** In this process, the watershed technique is used to emphasize the black areas on the marigold flower (which is now converted to white color in the previous process) to be more prominent as an image segmentation approach. The watershed segmentation with distance transform between black and white pixels was calculated by Euclidean distance (D) as in (3) [17][18].

$$D([x_1, y_1],[x_2, y_2]) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (3)$$

Where $[x_1, y_1]$ is the coordinate pixel that distance determined to other pixels in coordinate $[x_2, y_2]$.

Thus, the white color ranges were segmented and converted to red color ranges, as shown in Fig. 4.

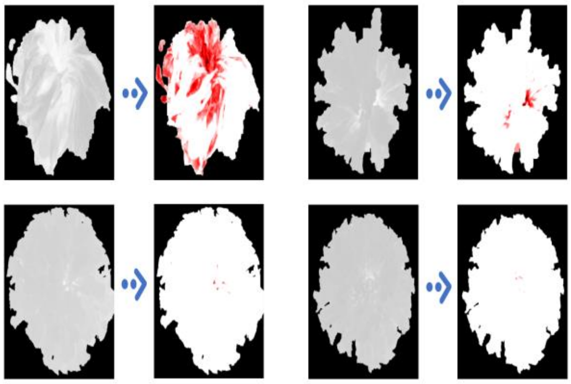


Fig. 4 The sample output image segmentation in red color

Therefore, the processing of multimodality imaging in this work was illustrated as in Fig. 5.

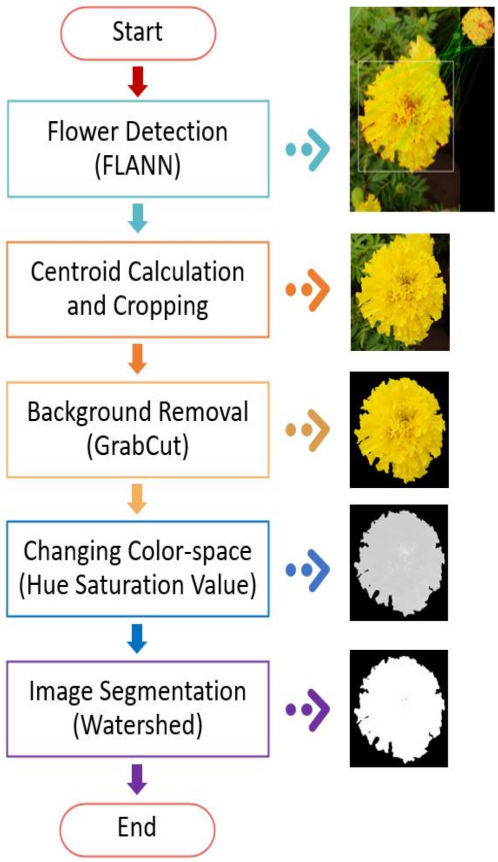


Fig. 5 The multimodal image processing for marigold disease prediction

C. Neural Network Modeling

There are three processes for deep learning modeling of marigold flower disease prediction as follows.

a) Dataset Preparation: According to multimodal image processing, there are four datasets, including RGB, RGB noBG, HSV, and Watershed datasets. Each dataset was separated into three sets: 65% for training the model, 15% for model validation, and 20% for model testing by randomizing images of infected and uninfected marigold flowers in a similar proportion. Therefore, each dataset was separated as in Table I.

TABLE I
THE FIXED NUMBER OF IMAGES WAS RANDOMLY GROUPED IN A DATASET

Image set	Number of Images		
	Uninfected	Infected	Total
Training set (65%)	806	637	1,443
Validation set (15%)	186	147	333
Testing set (20%)	248	196	444
Total	1,240	980	2,220

***b) Neural Network Modeling*:** The VGG16-based CNN architecture was applied in this work. The VGG16 architecture was designed by Simonyan and Zisserman [19]. There are sixteen layers with weights and Rectified Linear Unit (ReLU) activation function, including thirteen two-dimensional convolutions (Conv) layers, two fully connected (FC) layers (two dense layers), and a softmax layer which has two classes (uninfected and infected). Each convolution layer has a 3x3 filter of stride one and used the same padding size.

Furthermore, the VGG16 model consisting of five max polling layers of a 2x2 filter of stride two and a flatten layer. In this research, two dropout layers were added and set at 0.5, which was the optimum value for regularizing the neural network from the overfitting [20]. Moreover, the authors added a rescaling layer at the beginning of the model architecture for resizing the square image dataset to a dimension of 224x224 pixels before feeding it into the VGG16 model, as illustrated in Fig. 6. Therefore, the model architecture in this work has 134,268,738 trainable parameters.

The neural network modeling was trained for 500 epochs by applied the Adaptive Moment Estimation (Adam) optimizer with the learning rate at 0.0001, and the batch size was 128 to reduce the variance in parameter update. Besides, the early stopping was set to avoid overtraining in case of the long training.

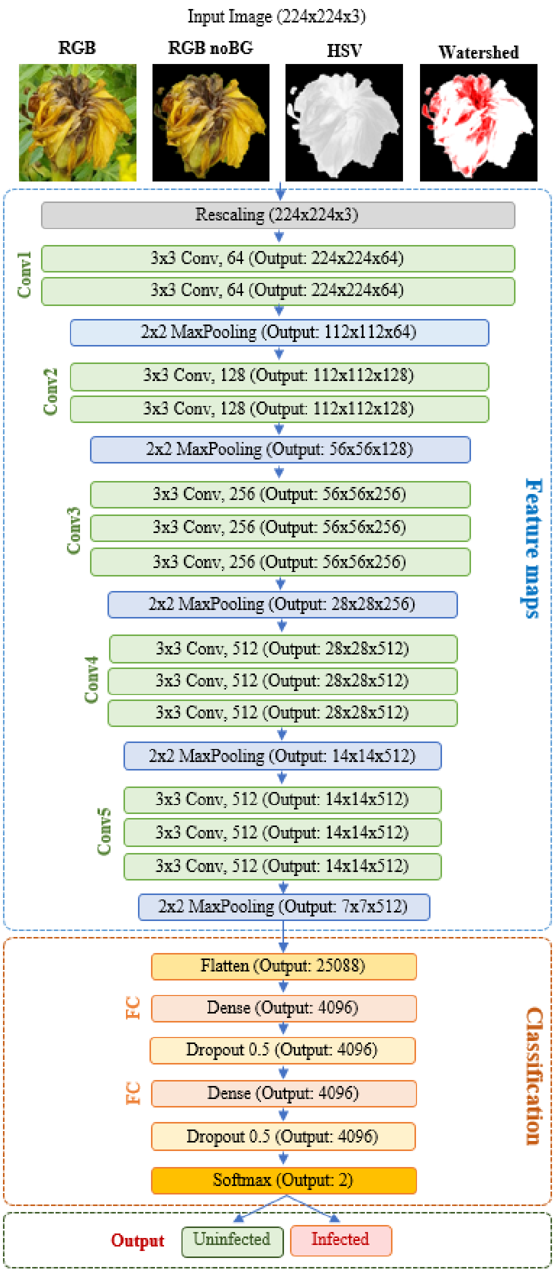


Fig. 6 The neural network modeling architecture

D. Model Effectiveness Evaluation

All four models from the datasets were training, validating, and testing during the neural network modeling. The binary cross-entropy or log loss (L) function was applied to validate the effectiveness of the models. It was calculated as in (4) [21].

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot \log(p(x_i)) + (1 - y_i) \cdot \log(1 - p(x_i))] \quad (4)$$

Where:
N refers to the total number of examples;
y_i refers to the truth value or target label of example i;
x_i refers to the input of example i;

p refers to the model output that predicted the softmax probability of example i.

Further, the model was testing the effectiveness by applied the accuracy, precision, sensitivity, and specificity that were calculated in (5) [22], (6) [23] [24], (7) [22], and (8) [25], respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

Where:

TP refers to the marigold flower that was uninfected, and the predicted class output was uninfected;

TN refers to the marigold flower that was infected, and the predicted class output was infected;

FP refers to the marigold flower that was infected, and the predicted class output was uninfected;

FN refers to the marigold flower that was uninfected, and the predicted class output was infected;

Therefore, the overall processes for marigold flower disease prediction were illustrated in Fig. 7.

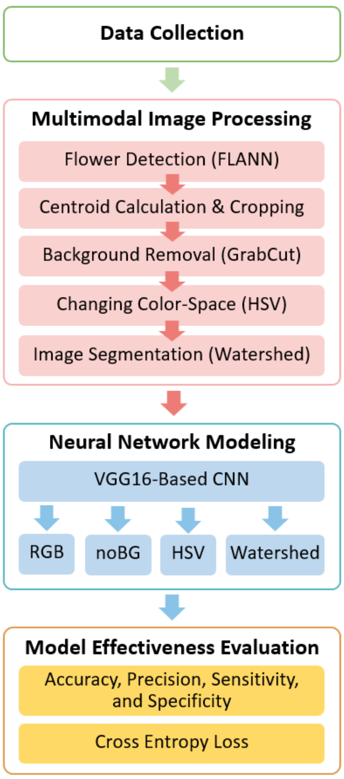


Fig. 7 The model framework of marigold flower disease prediction using deep neural network

III. RESULTS

The results of the effectiveness of the models which were generated from four datasets were shown as follows:

A. The Model Validation Result

The models were validated with accuracy and binary cross-entropy loss. The result showed that the model using the watershed dataset had the highest validation accuracy and validation loss compared to the other models. It gave the validation accuracy of 88.03%, with the validation loss was 4.21% after the 26th epochs of model training. The remaining model testing, including HSV, RGB noBG, and RGB datasets, gave the validation accuracy at 86.15%, 79.64%, and 69.59%, respectively. For the effectiveness of the model testing with the validation loss, the HSV, RGB noBG, and RGB datasets gave the loss values was 5.97%, 6.76%, and 9.95%, respectively. The comparison results of the model validation were shown in Fig. 8 and Fig. 9.

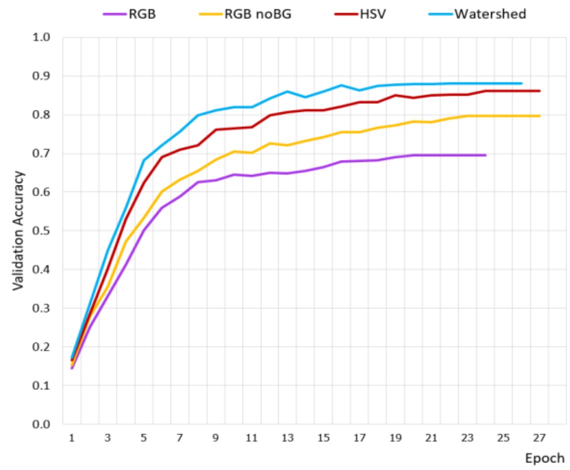


Fig. 8 The comparison results of the validation accuracy of the models

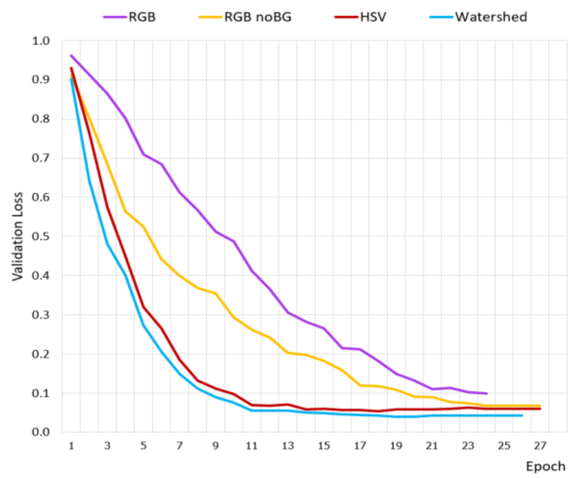
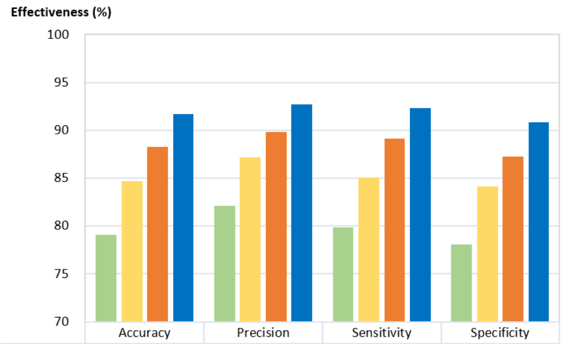


Fig. 9 The comparison results of the validation loss of the models

B. The Model Testing Result

The result showed that the multimodal image processing dataset which applied the watershed technique gave higher effectiveness of the model testing than other datasets. The watershed dataset gave the model testing accuracy of 91.67%, the precision of 92.71%, the sensitivity of 92.34%, and the specificity of 90.82%. Further, other datasets used to create the neural network model gave the accuracy of the model testing followed by 88.29%, 84.68%, and 79.05% for the HSV, RGB noBG, and RGB datasets. For the precision, sensitivity, and specificity were compared the effectiveness of the model testing as shown in Fig. 10.



	Accuracy	Precision	Sensitivity	Specificity
RGB	79.05	82.16	79.84	78.06
RGB noBG	84.68	87.19	85.08	84.18
HSV	88.29	89.84	89.11	87.24
Watershed	91.67	92.71	92.34	90.82

Fig. 10 The comparison results of the effectiveness of the model testing

IV. CONCLUSION

Marigold flowers are widely used in several fields such as religion, health, and livestock in many countries. However, before the harvesting process, farmers may suffer diseases on the marigold flowers that can result in farm damage. This research presented a technique for identifying marigold flowers whether they have the disease or not using VGG16-based CNN architecture, a deep learning technology combined with multimodal image processing. The flower region on the image was discovered by using the FLANN, centroids, and GrabCut algorithm. Four image datasets were processed, including the RGB, RGB without background (noBG), HSV, and watershed. The results showed that the image dataset which was processed the image segmentation using the watershed technique had the highest efficiency for CNN modeling. This model was validated by applying the binary cross-entropy loss and tested the model based on the accuracy, precision, sensitivity, and specificity. It gave the validation accuracy of 88.03% and the validation loss of 4.21%. In addition, this model testing gave the efficiency rating of the accuracy was 91.67%, the precision was 92.71%, the sensitivity was 92.34%, and the specificity was 90.82%. Therefore, it could be suggested that the CNN modeling with multimodal image processing was suitable for predicting the disease on the marigold flowers.

For further studies, the authors plan to develop the technique and the application for specifying each disease on the flower based on the internet of things technology that might help the farmers via smartphones or closed-circuit television (CCTV) in the real world.

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