Improvement of the Efficiency of Grape Leaf Disease Classification Using VGG12 with Wide Convolution Layer

Jiraporn Thomkaew*, Podjana Homhual, and Apichai Chanudom

Department of Innovation Management and Business Information, Faculty of Management Technology, Rajamangala University of Technology Srivijaya, Thailand
Email: jiraporn.th@rmutsv.ac.th (J.T.); podjana.h@rmutsv.ac.th (P.H.); apichai.c@rmutsv.ac.th (A.C.)
*Corresponding author

Manuscript received October 31, 2024; revised January 3, 2025; accepted April 15, 2025; published August 6, 2025.

***Abstract*—This article presents a model improvement to increase the efficiency of grape leaf disease classification using the VGG12 (Visual Geometry Group with 12 Layers) with Wide Layer model. It is a new model based on the concept of VGG16 (Visual Geometry Group with 16 Layers) and InceptionV3 Block. It aims to present a small convolutional neural network model. It reduces the number of parameters and computational costs but increases the efficiency of grape leaf disease classification. By reducing the number of layers of the VGG16 model from 16 to 12, horizontal feature maps are forwarded instead of hierarchical feature maps between the second to eighth layers. Feature maps are combined to forward the feature maps hierarchically to the next layer. In addition, the filter size was changed from 3×3 to 1×3 and 3×1 to reduce the number of parameters and help the model process faster. Multiple Dilated Convolution was used to obtain more feature maps and did not increase the parameters. The model's results were evaluated by experimenting with a four-class grape leaf dataset from the PlantVillage dataset, consisting of three classes of diseased grape leaves and one class of healthy grape leaves. The results showed that the proposed model gave an accuracy of 99.95% in classifying grape leaf disease and comparing the proposed model with the models ResNet50, VGG16, InceptionV3, DenseNet121, and MobileNetV2, whose classification accuracies were 64.14%, 91.16%, 97.92%, 97.71%, and 99.69%, respectively. It was found that the model proposed has the highest accuracy, and it uses 1,571,839 parameters.**

***Keywords*—VGG12 with wide convolution layer, VGG16, multiple dilated convolution, grape leaf disease classification**

I. Introduction

Agriculture has been a primary occupation of the Thai people for a long time. There is agriculture in terms of raising animals and growing crops. Each region of Thailand raises animals and grows different crops according to the country's climate and geography. Climate conditions are constantly changing rapidly, causing agricultural products to be damaged and produced not up to the production standards required by the market. Currently, the government supports and assists farmers by providing agricultural academics with academic knowledge about promoting the production of agricultural products to provide knowledge to farmers and find ways to prevent impacts that may occur on the products. However, because problems with various diseases of farming plants often happen quickly and have wide-ranging effects, farmers usually need to work on dealing with the issues, causing them to lose income due to damaged crops. Analyzing plant diseases using agricultural academics or people with expertise in plant diseases may take a long time, and errors may occur sometimes. This is because each type of plant has very similar physical characteristics. The disease characteristics of plants in the early stages of various diseases may have the same characteristics. Therefore, if the initial stage of the disease is incorrectly analyzed, it may significantly affect agricultural production. Researchers from many fields of knowledge develop research to solve problems for farmers as quickly as possible to prevent crop damage. New technology was introduced and came to be used more in agricultural work. Research is being developed to solve agricultural problems, focusing on precision and speed. Computer vision is one of the most popular modern technologies for solving agricultural problems. Computer vision is a technology that focuses on working with images, such as image recognition [1, 2], Image detection [3, 4], image classification [5, 6], and Forecasting [7], etc. Computer vision is a technology that uses models of deep neural networks that work similarly to the human brain. Working together in multiple layers, a model can learn, recognize, analyze, and classify data by providing a dataset for the model's learning. Today's work focuses mainly on image operations, so convolutional neural network models have been developed specifically for image operations. Therefore, researchers are increasingly applying computer vision technology for image recognition, detection, and classification, such as medical image classification [8–11], recognition of people from facial images [12–14], real-time object detection [15–17], plant leaf disease classification [18–20], etc.

The most common method of classifying leaf diseases is based on changes in leaf shape and color, which can sometimes cause errors in human classification of plant leaf diseases. Therefore, machine learning has been used to solve the problem of classifying plant diseases from images of plant leaves. Machine learning has continuously developed and is increasing in trend. Computer vision is used to learn and recognize pictures from the features of plant leaf images, such as the length, width, notches around, color, texture, etc. Researchers will need to have their own image feature extraction process for these features, while convolutional neural network models will automatically extract image features. The convolutional neural network models initially developed were large-scale models because developers focused on developing deep models that used multiple hidden layers, resulting in models with large sizes, using many parameters and requiring high computational costs, such as VGG16, VGG19, ResNet, DenseNet, etc. As a result, many researchers are currently trying to present lightweight convolutional neural network models, focusing on reducing the model size to use fewer parameters and reducing processing time and cost. The computations are reduced, and

DOI: 10.7763/IJCTE.2025.V17.1377

the model can be deployed on small mobile devices. But it still provides high data classification accuracy.

This study presents a lightweight convolutional neural network model for grape leaf disease classification. The proposed model is developed from the VGG16 artificial neural network model. VGG16, with a total of 16 layers, uses a 3×3 filter throughout the network, which gives the model approximately 138.4 million parameters. It takes a long time to process and uses high computational costs. Because this model is hierarchical, the image feature map is hierarchically forwarded from the first to the sixteenth layer. It takes a long process but still provides good data classification accuracy. Moreover, the InceptionV3 Block model concept with distributed image feature extraction is implemented simultaneously. That is after the model receives the input image. The image is forwarded to the convolution layer to extract sparse image features simultaneously from every convolutional layer. Therefore, it is possible to reduce the running time of the model. Therefore, the advantages of both models are combined by improving the VGG16 model to have 12 layers. Reducing the number of model layers makes it possible to reduce the model's parameters and processing time. Feature map forwarding from the second layer to the eighth layer is used horizontally instead of hierarchically as in the InceptionV3 Block model, and the filter size has been changed from 3×3 to 1×3 and 3×1. Experiments were conducted with the grape leaf dataset of the PlantVillage dataset from www.kaggle.com. It is a freely available standard data set for conducting computer vision research. It consists of 4 classes of diseased and healthy grape leaves, containing 4140 images.

The remainder of this paper is as follows: "Related Work" is presented in section II, "Materials and Methods" is given in section III, "Experimental Results and Discussions" is presented in section IV, and the "Conclusion" is presented in section V.

II. Literature Review

Nowadays, many researchers are developing research on plant disease classification and detection using offline and real-time plant leaf images. Most researchers focus on developing research on image processing to increase image quality and influence the performance of more accurate models. Improve the process by manually extracting image features to obtain exact, complete features and classify plant leaf diseases more accurately. This includes developing models to be more efficient and precise in disease classification by reducing the number of model parameters, processing time, and model size to be smaller. In this section, we present research articles related to plant leaf disease classification, such as research on image preprocessing, manual image feature extraction, and model development for leaf disease classification.

Image pre-processing is a procedure for enhancing image quality before image feature extraction and classification, as the research of Gayathri *et al.* in [21] presents the detection of diseased rice leaves using K-means clustering to segment images of diseased rice leaves before extracting image features. It uses hybrid features obtained by extracting image features from SIFT (Scale-Invariant Feature Transform), DWT (Discrete Wavelet Transform), and GLCM (Gray Level Co-occurrence Matrix). KNN (K-Nearest Neighbors), ANN (Artificial Neural Network), Bayesian, and multiclass SVM (Support Vector Machine) are used as image classifiers. The results showed that image segmentation of diseased rice leaves using K-means clustering before image feature extraction with SIFT, DWT, and GLCM combined with multiclass SVM classification had an accuracy of 98.63%. Zhang *et al.* in [22] presented leaf species identification using input image processing by converting RGB color images into grayscale and binary images using OTSU's thresholding and morphology methods using the HSI color model. It uses saturation values to allow for more accurate extraction of image surface features, and features from the shape of plant leaves are also used. Classify plant leaves using the Back Propagation Neural Network. Experiment with the Flavia leaf image and ICL leaf image datasets. The results show that Image processing before feature extraction and combining multiple features can achieve the highest accuracy of 94.22% on the Flavia dataset and 87.82% on the ICL dataset. In addition, Reddy *et al.* [23] present a method for classifying plant species by analyzing color images using a Convolutional Neural Network. Image quality is improved through image enhancement, denoising, segmentation, and binarization. Use features from morphological shape features and texture features. The proposed neural network consists of four convolutional layers followed by two fully connected layers, four max-pooling layers, and finally, a softmax layer to classify images. Experiments were performed on five datasets: Leaf snap, UCI leaf (University of California, Irvine), PlantVillage, Flavia, and Swedish. The experimental results show that the proposed CNN (Convolutional Neural Network) model can extract features better than manual feature extraction. It has better classification accuracy than conventional methods from experiments with Flavia, Swedish, UCI leaf, PlantVillage, and Leaf snap datasets. Accuracy values are 100%, 100%, 100%, 89.99%, and 97.99%, respectively. Therefore, image processing steps to increase image quality before feature extraction can improve the accuracy of plant leaf disease classification. In this work, we use image processing by removing the image's background. To reduce the problem of different light and shadows in the image, which the model classifies more accurately.

In addition to image processing, image feature extraction is another factor that will help the model classify plant leaf diseases more accurately. The research study found that the commonly used image feature extraction method is manual image feature extraction, which determines which properties to use from the image, such as color, shape, and texture features. For example, the research of Basavaiah *et al.* [24] presents the identification of tomato leaf diseases using a combination of color histograms, Hu Moments, Haralick, and Local Binary Pattern features. Classify images with Random Forests and decision trees. The experimental results show that data classification with a Random Forest has an accuracy of 94%, higher than classification with a decision tree with an accuracy of 90%. Kolivand *et al.* [25] presented leaf venation detection, a unique feature that can use only one feature to classify plant leaves. The highlight of the research is extracting leaf venation by converting the image to grayscale and using Canny edge detection for detecting leaf edges, which results in leaf venation, leaf boundary, and unwanted false curves. Then, delete the leaf edge to get the venation and curves of the leaves before separating the venation and curves. The next step is hue normalization image, and the last is image fusion. Experiments were performed on the Flavia and Acer datasets. The experimental results showed that the proposed method had 98.6% and 89.83% classification accuracy on the Flavia and Acer datasets. Another method is automatic image feature extraction. Most feature extraction methods use a convolutional neural network model when inputting images into the convolutional neural network model. The convolution model automatically learns and extracts image features and then passes the feature map to the next layer. Bisen in [26] presents automatic plant classification using deep convolutional neural networks, image processing to remove image noise, rotation, centering, resizing, normalization, rescaling, and data augmentation, and presents a model that is used for classifying plants by providing hidden layers for learning and extracting image features for classifying plants. Experimenting with the Flavia and Swedish leaf datasets, the results show that the proposed model can automatically classify plant species with an accuracy of 97%. Mezenner *et al.* [27] presented tomato leaf disease classification by extracting tomato leaf features with a CNN model and then classifying tomato leaf diseases with Support Vector Machines. The proposed model is developed based on the LeNet model, consisting of 3 convolutional layers after the convolutional layer, followed by Bachnormalization and MaxPooling, Flatten, and then extracting image features through the Dense layer to be used for tomato leaf disease classification with Support Vector Machines. Experiments were performed on the tomato leaf dataset. The results showed that the proposed model had a tomato leaf disease classification accuracy of 98.25%.

In addition, it was found that the relatively large model size limits leaf disease classification using convolutional neural networks. It uses a lot of resources and takes a long time to process. Therefore, there has been research on developing models for classifying plant leaf diseases, focusing on creating smaller models. It takes faster processing time but still provides high accuracy. Zhou *et al.* [28] present a hybrid deep learning model for tomato leaf disease identification by improving the residual dense network to Restructure Deep Residual Dense Network, in which the RDB is directly connected to all subsequent layers. The input image will be merged into the Res-Dense-Block (RDB), then combined with the improved RDB block with the Input layer in the residual concatenate tensor layer. Experiment with the tomato leaf dataset from the AI CHALLENGER dataset. The experimental results show that the proposed model has an accuracy of in classifying tomato leaf diseases of 95% and the highest accuracy when compared to other CNN models such as Deep CNN, ResNet50 and DenseNet121 have accuracies of 93.21%, 88.49%, 91.96%, respectively. Thangaraj *et al.* [29] presented a model to identify diseases of tomato leaves using a deep artificial neural network Modifed-Xception model. The proposed method uses transfer learning for weight transfer by dividing the model into two parts: feature extraction and classification. Feature extraction uses convolution layers, pooling layers, and Rectified linear unit activation functions, and MaxPooling is used to reduce the size of feature maps obtained from convolution layers. The classification step uses Global Average Pooling (GAP) instead of the fully connected layer in basis networks. It uses fine-tuning techniques to update the weights obtained from training the model with the tomato leaf dataset. Experiments were conducted with the tomato leaf dataset from the PlantVillage dataset. The results showed that using Adam and RMSprop optimizers had better accuracy than the SGD (Stochastic Gradient Descent) optimizer, with the Adam optimizer having the highest accuracy of 99.55%, followed by RMSprop at 99.01% and SGD at 81.77%, respectively. Thakur *et al.* [30] presented the VGG-ICNN (Visual Geometry Group with Inception-based Convolutional Neural Network) model for plant leaf disease identification. It combines the VGG16 model and GoogleNet Inception v7 block to reduce the network size but still has high classification efficiency. The proposed model consists of two convolution layers using filter size 64, a maxpooling layer, and two convolution layers using filter size 128 and a MaxPooling layer. Then, three Inceptionv7 blocks are added after the MaxPooling layer of VGG16. The Inceptionv7 block uses a filter size of 1024, uses a Global Average Pooling (GAP) layer instead of a flattening layer, then a fully connected layer, and uses the SoftMax activation function for data classification. The proposed model can reduce the number of parameters to about 6 million, comparable to lightweight CNN models. The model was evaluated by testing it on five datasets, including small data sets and large data sets such as PlantVillage Dataset, Embrapa Dataset, Apple Dataset, Maize Dataset, and Rice Dataset. The results showed that PlantVillage Dataset had the highest accuracy of 99.16%, followed by Rice, Apple, Embrapa, and Maize with an accuracy of 96.67%, 94.24%, 93.66%, and 91.36%, respectively. Hassan *et al.* [31] improved the architecture of the deep convolutional neural network model by improving convolutional layers with different model depths. They were replaced with a separable convolution layer in InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0 models. Transfer-learning and finetuning are used to improve the model performance. The proposed method can reduce the number of parameters and computational cost of the model and improve the classification efficiency. They were evaluated by experimentation with the PlantVillage dataset using different batch sizes and dropouts with image segmentation. The experimental results showed that the proposed method had classification accuracy values of 98.42%, 99.11%, 97.02%, and 99.56%, respectively. Wang *et al.* in [32] presented a lightweight neural network to reduce the number of parameters but still have high classification accuracy—model presentation Dense-MobileNet with the use of DenseNet Block and MobileNet. Improving MobileNet's convolutional layers to have dense connections, the proposed model can use the resulting feature maps of the previous convolutional layers to generate feature maps for the next layer. The filter size has been reduced, thus reducing the number of model parameters and computational costs. Experiment with Caltech-101 and Uebingen Animals datasets. The experimental results show that the proposed model uses fewer parameters and computation time than DenseNet121, MobileNet, and Dense1-MobileNet and had the highest classification accuracy of 77.8% for the Caltech-101 dataset and 92.1% for the Uebingen Animals dataset. Selvam *et al.* [6] presented a disease classification model of ladies' finger leaves using deep learning. The proposed model consists of 4 convolutional layers and two fully connected layers. The convolutional layer uses filter sizes 32, 64, 64, and 128 using kernel size 3×3, followed by the ReLU function. The convolutional layer is followed by a maxpooling layer with a stride equal to 1 pixel. Then, two fully connected layers are classified using the softmax function. Experiment with a manually collected ladies' finger leaf dataset from a farm in India. Image augmentation techniques were used for the experimental dataset. The results showed that the proposed model using a 70:30 data set split and Adam's optimizer had the disease classification accuracy of ladies' finger leaves, which was 96%. Yucel *et al.* [33] presented a CNN model for rice leaf disease classification. Feature extraction of rice leaf images is applied using the Efficientnetb0, Shufflenet, and Resnet101 models. It uses the transfer of 1000 image features from the model. Then, it combines the feature maps of each rice leaf image obtained from each model for 3000 features before classifying rice leaf disease using a Support Vector Machine (SVM). Combining the feature maps from the three models can increase the accuracy of rice leaf disease classification. Experiments were conducted with the rice leaf dataset from Kaggle. The results showed that the proposed model had an accuracy of 98% in rice leaf disease classification and had the highest accuracy when comparing rice leaf disease classification with the Resnet101, Darknet53, Alexnet, MobilenetV2, Googlenet, and Shufflenet models. Elfatimi *et al.* [34] presented a model for automatically classifying and identifying bean leaf diseases with high accuracy. The proposed model uses model training and transfer learning from MobileNetV2 using hyperparameters and the same optimizations as the MobileNet model, as well as experimenting with the bean leaf dataset from NaCRRI. The bean leaf disease classification results of the model architectures with different aspects were compared. Hyperparameters and optimizers such as Adagrad, NAdam, SGD, RMSprop, and Adam optimizer were used under the same conditions to evaluate the best bean leaf disease classification performance. Experimental results show that the proposed model achieves the highest accuracy when using the Adam optimizer. The optimizer uses a learning rate of 0.001 and a batch size 32. The accuracy of bean leaf disease classification was 98.50%. Vishnoi *et al.* [35] presented a model for apple leaf disease detection using a deep neural network that focused on designing the model architecture to be compact, reducing the number of parameters and computational cost to be able to use on small portable devices. Experiments were performed on the apple leaf dataset from the PlantVillage dataset. The experimental results of the proposed model were compared with VGG19, ResNet152, DenseNet201, MobileNetV2, ResNet50, VGG16, InceptionV3, Xception, and MobileNet. The results show that the proposed model uses the least number of parameters and has the smallest model size compared to the above CNN models. Moreover, it takes the least time for model training and testing but still has the highest accuracy for disease classification of apple leaves at 98%. Ahmed *et al.* [36] presented a lightweight and fast deep neural network model for tomato leaf disease classification. The proposed model works on MobileNetV2 architecture with pre-trained models and transfer learning to extract tomato leaf image features from 9 models, including DenseNet121, DenseNet201, EfficientNet-B0, MobileNet, MobileNetV2, NASNet-. Mobile, ResNet50, ResNet152V2 and VGG19. Then, the transfer learning from the MobileNetV2 model was chosen because it is small and has a high classification accuracy. Take the feature map obtained from the pre-training of the model through the fully connected layer, add dense blocks before classification, and then classify tomato leaf diseases with the Softmax function. They are experimenting with the tomato leaf dataset from PlantVillage Dataset. The experimental results showed that the proposed model had the highest tomato leaf disease classification accuracy, 99.30%. The proposed model has a small size of only 9.60 MB, and when evaluating the model with FLOPs, it was found to use only 4.87 FLOPs (Floating Point Operations Per Second). It can be concluded that the proposed model is small in size, can work quickly, has good accuracy, and can be used on small devices. Thomkaew *et al.* [37] presented the Modified Visual Geometry Group (VGG)-InceptionV3 model for tomato leaf disease classification. The proposed model is improved from the basis of the VGG16 and InceptionV3 models by improving the InceptionV3 block model by adding convolutional layers for receiving input images from 3 to 4 layers. The filter size has been resized from 3×3 to 1×3 and 3×1, which allows reducing the number of model parameters. The improved InceptionV3 block model is then applied to the VGG16 model by adding the improved InceptionV3 block model between the 4th and 5th layers of the VGG16 model and then reducing the number of layers of the VGG16 model. Layer by layer to evaluate the accuracy of disease classification of tomato leaves. Experiment with the tomato leaf dataset from the PlantVillage Dataset with ten classes. The experimental results show that the proposed method can reduce the number of model parameters. The processing time was reduced, but the model provided a high tomato leaf disease classification accuracy of 99.27%.

From related research, it was found that the application of image processing technology and deep learning for plant disease classification focuses on improving the quality of images, such as noise removal, image segmentation, and light and shadow adjustment, to increase the accuracy of feature extraction and disease classification. Research on manual feature extraction and automatic feature extraction with Convolutional Neural Networks (CNN) can reduce the complexity and increase the model's accuracy, including improving the CNN model to reduce the number of parameters and increase efficiency by using transfer learning and fine-tuning. In addition, lightweight CNN models that are small for use on small devices but still have high accuracy have been developed. Therefore, we present a VGG12 with Wide Convolution Layer in this work. The proposed model reduces the number of parameters and processing time but provides high accuracy in leaf disease classification.

III. Materials and Methods

In this section, we present the proposed model's workflow, which includes preparing the dataset for model testing, studying the VGG16 base model and then experimenting by reducing the number of layers of the VGG model from 16 to 12, designing the Wide Layer based on the InceptionV3 block, and including defining the parameters for evaluating the proposed model.

A. Dataset and Pre-processing

For our experiments, we used the plant leaf image dataset from the PlantVillage dataset [38], a public dataset that can be accessed at www.kaggle.com. Contains images of diseased and healthy leaves of 14 different plants: apple, blueberry, cherry, corn, grape, orange, peach, bell pepper, potato, raspberry, soybean, squash, strawberry, and tomato, a total of 38 classes, with a total of 54,304 images. The images have an RGB color model of size 256×256 pixels, with different backgrounds, lights, and shadows. Therefore, in this work, the background of the image was removed and the size of the image was resized to 224×224 pixels. An example image of a plant leaf is shown in Fig. 1 and details of the number of images of each class are shown in Table 1. The dataset was then divided into 70% model training dataset, 20% validation dataset, and 10% testing dataset.

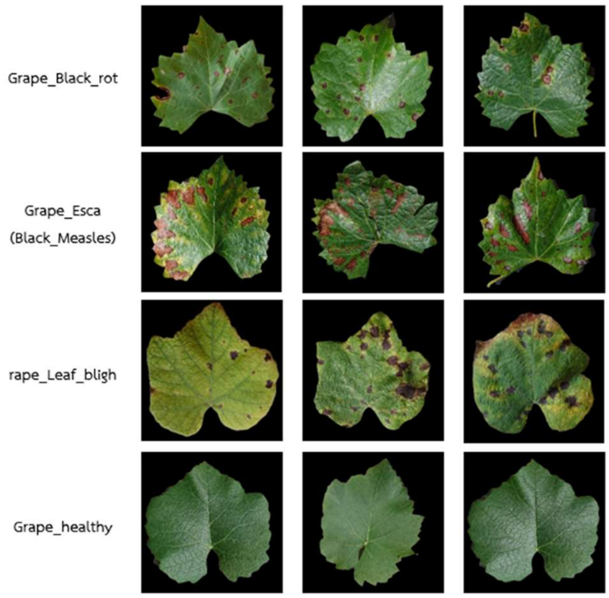

Fig. 1. Sample of plant leaves from the PlantVillage dataset.

Table 1. Describe the number of classes and images of the dataset

No. Class	Class	Number of Images
1	Grape Black rot	1,180
2	Grape Esca Black Measles	1,384
3	Grape healthy	500
4	Grape Leaf blight	1,076
	Total Images	4,140

B. VGG16

VGGNet was developed by Simonyan *et al.* [39] from the Visual Geometry Group, Department of Engineering Science, University of Oxford, which won the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in 2014. The idea of developing VGGNet is to increase the number of convolutional layers to make the network architecture deeper, such as VGG16 and VGG19 having 16 and 19 convolutional layers, respectively. This research uses the VGG16 model, which consists of an input image layer of 224×224 pixels, an RGB color image. Therefore, there are three channels in the input layer. This is followed by 13 convolutional layers with 64, 128, 256, and 512 filter sizes. A 2×2 Maxpooling is applied after the 2nd, 4th, 7th, 10th, and 13th convolutional layers. It uses a 3×3 kernel throughout the network. They were then followed by three fully connected layers and the Softmax function for image classification, as shown in Fig. 2. The VGG16 model uses approximately 138.4 million parameters. It is a large network, time-consuming, and computationally expensive. This research improves the architecture of the VGG16 model from 16 layers to 12 layers, consisting of a 224×224 pixel input image layer, followed by two convolution layers with filters size 64, two convolution layers with filters size 128, two convolution layers with filters size 256, two convolution layers with filters size 512, and one convolution layers with filters size 128. BatchNormalization and Maxpooling were applied after convolutional layers 2, 4, 6, 8, and 9, followed by three fully connected layers, each with four classes, and Softmax was used for grape leaf disease classification. Reducing the number of model layers reduced the number of parameters and processing time of the model but still provided good grape leaf disease classification accuracy.

C. InceptionV3

InceptionV3 was developed by researchers at Google by Szegedy *et al.* [40] 2015, they received first runner-up in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) 2015. The idea is to develop a smaller model with higher accuracy and classification efficiency by reducing the depth of the model to make it wider instead. That is, it uses the principle of parallel image feature extraction. Inception's first-generation architecture consists of three first-level convolutional layers using 1×1 filters and one Maxpooling layer. Then, based on three second-level convolutional layers, 1×1, 3×3, and 5×5 filters are applied, and the resulting feature maps are combined before being sent to the next model block. The architecture is shown in Fig. 3. Changing the filter size of the convolutional layer from 5×5 to 3×3 and 3×3 allows the model to reduce the number of parameters and processing time. This research uses a concept based on the InceptionV3 block model to improve the VGG16 model, allowing feature maps to be extracted and forwarded horizontally instead of hierarchically, including adjusting the filter size.

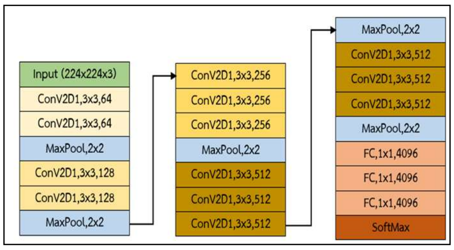

Fig. 2. Architecture of the VGG16 model.

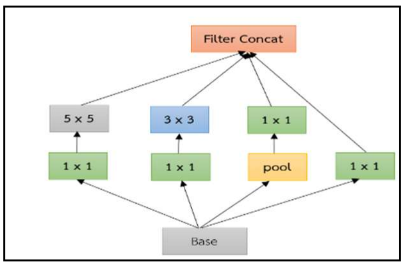

Fig. 3. Architecture of the InceptionV3 block.

D. Dilated Convolution

Dilated convolution is a technique that gives the model a wider image region for feature extraction and can cover all areas of the image. Expanding the model's view of the image can cover all areas of the image. Increasing the space between pixels while the filter is moving can sometimes result in some pixels on the image needing feature extraction. Dilated convolution is suitable for tasks that require capturing image features over a wide area, such as segmentation, object detection, and time-series analysis. Results in a more extensive feature map but keeps the number of model parameters the same. Increasing the hyperparameter null between filters so the gain rate determines how much space between filters can be adjusted. Using multi-level dilated convolution allows the model to extract image features at multiple levels [41]. This work defines the dilated convolution of the multilevel convolution layer. The first two convolution layers used one dilated convolution. The third and fourth convolution layers used two dilated convolutions. The fifth and sixth convolution layers used three dilated convolutions. The seventh and eighth convolution layers used two dilated convolutions, and the ninth convolution layer used three. Different dilated rates at different layer levels can help the model capture a broader range of images at various levels. However, using the reasonable dilated rate requires multiple experiments to find the best-dilated rate for each task to avoid oversizing, which will result in the model overlooking some aspects of the image and not capturing all the features of the image.

E. VGG12 with Wide Convolution Layer

This study focuses on improving the efficiency of grape leaf disease classification. It presents the VGG12 with Wide Convolution Layer model, developed from the basic model of VGG16 and the InceptionV3 block described in the previous section of this article. The proposed model is shown in Fig. 4. The proposed model consists of an input image layer with size 224×224 pixels, RGB color image, followed by two convolution layers with size 64, using filters of size 1×3 and 3×1, using one dilated convolution, two convolutional layers of size 128 using filters of size 1×3 and 3×1, using two dilated convolutions. Two convolutional layers of size 256 use filter sizes 1×3 and 3×1 using three dilated convolution, two convolutional layers of size 512 use 1×3 and 3×1 filters using two dilated convolution, and one convolution layer of size 128 uses a filter size 1×3, used three dilated convolutions. Three fully connected layers, each layer has four classes and grape leaf diseases are classified using the Softmax function.

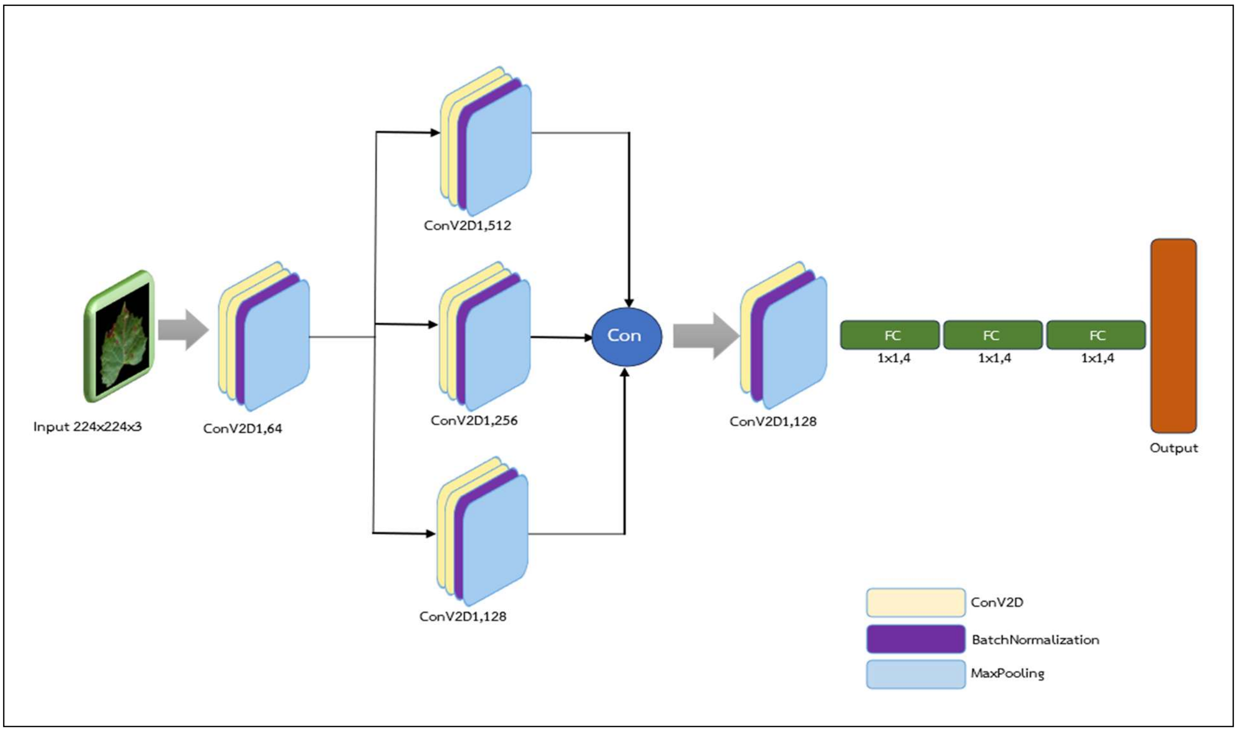

Fig. 4. The architecture of the VGG12 with wide convolution layer.

From Fig. 4, The proposed model has an input image layer and two convolutional layers of size 64 between the first and second layers; hierarchical feature map forwarding is used. Then, the feature map obtained from the second layer is forwarded to the third, fifth, and seventh convolutional layers in a horizontal forwarding instead of hierarchical. Forwarding feature maps from the third, fifth, and seventh layers to the fourth, sixth, and eighth layers uses hierarchical feature map forwarding. Then, the feature maps obtained from the fourth, sixth, and eighth convolutional layers are combined and forwarded to the ninth convolutional layer, the fully connected layer, and the output layer.

IV. Results and Discussion

This study presents the VGG12 model with Wide Convolution Layer, aiming to increase the efficiency of grape leaf disease classification with a small convolutional neural network, reducing the number of processing time, parameters, and machine resources for less processing required but still providing high accuracy in grape leaf disease classification. The model was developed from VGG16 because it is easy to design and has a hierarchical network, but it is a large network and takes a long time to work. Moreover, the advantage of the InceptionV3 block model is that horizontal feature extraction provides a complete feature map, reducing the model's processing time. The experiment uses Python digital programming language. The model is implemented on a computer with an NVIDIA GPU. 11th Gen Intel(R) Core(TM) i7-1165G7, 16.0 GB of RAM. For the experiment with the grape leaf image dataset from the PlantVillage dataset, the input image was an RGB color image. The image was processed by removing the background and resizing the image size to 224×224 pixels. The dataset was divided into training 70%, validation 20%, and testing 10%. Configure hyper-parameters for training the model and use Adam as the optimizer. Set the learning rate value to 0.001. The batch size equals 64, and the experiment will have 50 epochs.

The proposed model was evaluated by reducing the number of layers of the VGG16 model by one layer at a time to compare the optimal number of layers based on the accuracy of grape leaf disease classification, processing time, and the number of parameters used. The experiment found that the number of layers of the model was 16, with a high accuracy of 99.79%, but it took a long time. And a large number of parameters. Reducing the number of layers to fifteen minimizes the time and number of model parameters but also reduces accuracy. The number of layers with the highest accuracy in classifying grape leaf disease was 12 layers with an accuracy of 99.95%, processing time 50 seconds/step, using 1,571,839 parameters. When the number of layers is reduced from 11 layers to 9 layers, it can be seen that the processing time and number of parameters are reduced. Similarly, the accuracy of data classification decreased gradually as well. Therefore, this research chose to use a model with a number of layers equal to 12 layers, and when considering the accuracy of classifying grape leaf diseases according to various classes, shown with a Confusion Matrix, as shown in Table 2. The results of the experiment are shown in Table 3. It was found that the proposed model was able to classify diseases grape leaves have an accuracy of 100% for three classes and an accuracy of 99.68% for 1 class.

From Table 3, it was found that when the number of layers is reduced, the number of parameters and processing time are reduced as well. If the model is very deep, it will result in too many parameters, which will cause overfitting because the model remembers too much data from learning. At the same time, if the model uses too few parameters, it will result in the model receiving insufficient features for learning and classifying data, decreasing the accuracy of data classification. Therefore, this research reduced the number of layers and parameters, which is the most suitable at 12 layers and 1,571,839 parameters. The proposed model has accuracy and loss values during training and validation as shown in Figs. 5 and 6.

Table 2. Confusion matrix

Classes		0	1	2	3	Accuracy (%)
Grape Black rot	**0**	271	0	0	0	100
Grape Esca Black Measles	**1**	1	310	0	0	99.68
Grape Leaf blight	**2**	0	0	250	0	100
Grape healthy	**3**	0	0	0	130	100

From Table 2, it was found that the proposed model could classify grape leaf diseases correctly 100% in the classes Grape Black rot, Grape healthy, and Grape Leaf blight, while the Grape Esca Black Measles class had an accuracy of 99.68%. It misclassified Grape Esca Black Measles to Grape Black rot because these two grape leaf diseases have similar initial characteristics and color of diseased leaves, so the model misclassified grape leaf diseases by 0.32%.

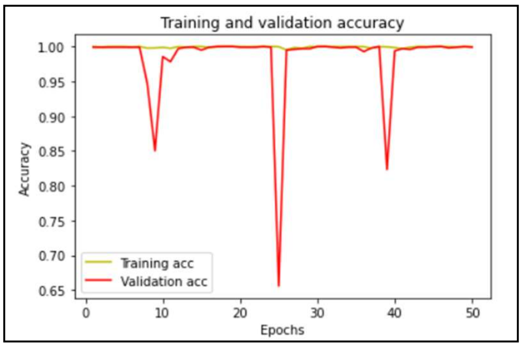

Fig. 5. Compares the accuracy values during training and validation of the proposed model.

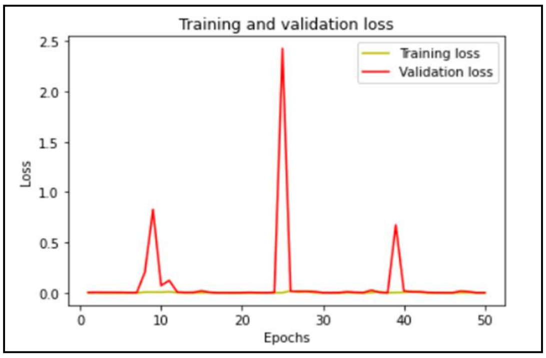

Fig. 6. Compares the loss values during training and validation of the proposed model.

From Figs. 5 and 6, the proposed model has accuracy and loss values during training and validation for grape leaf disease classification. It has high accuracy in both training and validation datasets, which are overall close to 1.0 (100%) for accuracy and close to 0 for loss, indicating good performance of the model, except for some points that may need to be considered for further improvement to reduce the fluctuation in accuracy of the validation set.

Table 3. Comparison results of reducing the number of layers of the proposed model

Number of Layers	Accuracy (%)	Loss	Times	F1	Parameters
16	99.79	0.0413	135	99.81	3,898,144
15	91.89	0.0301	106	87.66	3,109,152
14	95.90	0.0096	88	95.89	2,320,160
13	99.69	0.0690	81	99.71	2,217,248
12	**99.95**	**0.0011**	**50**	**99.91**	**1,571,839**
11	98.96	0.0364	50	98.85	639,264
10	98.38	0.0303	46	99.3	536,352
9	97.71	0.0306	27	97.89	338,464

Table 4. Comparison of the accuracy values of grape leaf disease classification using the proposed model with state-of-the-art convolutional neural network models

Model	Accuracy (%)	Times	Parameter
ResNet50	64.14	25	23,595,908
VGG16	91.16	54	14,716,740
Inception-V3	97.92	24	21,810,980
DenseNet121	97.71	29	7,041,604
MobileNetV2	99.69	14	2,263,108
Proposed Model	**99.95**	**50**	**1,571,839**

The experiment found that the proposed model has a grape leaf disease classification accuracy of 99.95% and can reduce the number of parameters of the VGG16 model from 138.4 million parameters to 1,571,839 parameters. The processing time is 50 seconds/step. Compare the accuracy of grape leaf disease classification using the proposed model with state-of-the-art convolutional neural network models, including ResNet50, VGG16, InceptionV3, DenseNet121, and MobileNetV2, as shown in Table 4. It was found that the proposed model had the highest accuracy in classifying grape leaf disease, and the processing time of the proposed model showed that the proposed model took less time to process than the VGG16 but took more processing time than ResNet50, InceptionV3, DenseNet121, and MobileNetV2 models. Therefore, if both aspects are considered together, it is found that the proposed model still gives the best performance. Although it takes longer than other models, it has the highest accuracy and is still within acceptable limits.

In addition, the experimental results were evaluated on Potato, Apple, Corn, Grape, Tomato, and PlantVillage leaf datasets to assess the proposed model's performance, as shown in Table 5.

Table 5. Comparison of the accuracy of the proposed model with multiple datasets

Data set	Number of Classes	Number of Images	Accuracy (%)	Time
Potato	3	2,500	99.83	36
Apple	4	3,396	100	24
Corn	4	3,852	99.23	29
Grape	4	4,139	99.95	54
Tomato	10	18,159	99.35	195
PlantVillage	38	54,304	99.44	380

From Table 5, the proposed model was evaluated on multiple datasets, each differing in the number of classes and images, which reflects varying levels of complexity in leaf disease classification. These include smaller datasets such as Potato, Apple, Corn, and Grape, as well as larger datasets like Tomato and the full PlantVillage dataset. The experimental results demonstrate that the proposed model consistently achieved high classification accuracy exceeding 99% across all datasets. It was observed that the processing time increases as the number of classes and total images increases. This suggests that while the model maintains strong classification performance regardless of dataset size, more complex or larger datasets may require additional computation time.

V. Conclusion

This article focuses on improving the efficiency of grape leaf disease classification by introducing the VGG12 model with Wide Convolution Layer as a new convolutional neural network model. This study focuses on presenting a smaller model, reducing the number of parameters and processing time of the model, but still providing high accuracy in grape leaf disease classification. The proposed model improves on the VGG16 and InceptionV3 block models by reducing the number of layers of VGG16 to 12 layers and improving the feature map forwarding between the second and eighth layers. It is horizontal instead of hierarchical. It uses the InceptionV3 block model concept, and feature maps are combined at the concatenation layer before being sent to the ninth layer. Horizontal forwarding of feature maps between layers makes the model more general and able to extract more complete image features. The model's processing time can be reduced with the horizontal transmission of feature maps. Changing the filter size from 3×3 to 3×1 and 1×3 allows the number of model parameters to be reduced, and using multi-level dilated convolution can expand the filter without increasing the number of parameters, but improving feature extraction. We evaluated the model by conducting experiments on grape leaf disease classification using the PlantVillage dataset. The proposed model achieved the highest classification accuracy of 99.95%, meaning that it correctly identified diseased and healthy grape leaf images with near-perfect precision. Additionally, the model demonstrated reduced processing time compared to deeper architectures. Due to its high accuracy and lightweight design, the proposed model is suitable for deployment on small, resource-constrained devices, such as smartphones or portable agricultural equipment.

To support the statistical reliability of this result, we performed a two-sample proportion z-test to determine whether the differences in classification accuracies between the proposed model and the other models are statistically significant. The null hypothesis (H) assumes equal proportions of accuracies, while the alternative hypothesis (H_a) suggests a significant difference. We used a test dataset size of 414 images for all models. The statistical test results are summarized in Table 6.

Table 6. Results of the two-sample proportion z-tests comparing the proposed model with the other state-of-the-art models

Compared Model	Accuracy (%)	z-score	*p*-value	Significant Difference ($p < 0.05$)
ResNet50	64.14	27.51	< 0.0001	Yes
VGG16	91.16	6.41	< 0.0001	Yes
InceptionV3	97.92	2.51	0.012	Yes
DenseNet121	97.71	2.73	0.0063	Yes
MobileNetV2	99.69	0.98	0.327	No

Table 6 presents the results of two-sample proportion z-tests comparing the proposed model with several state-of-the-art models. The proposed model shows statistically significant improvements in classification accuracy over ResNet50, VGG16, InceptionV3, and DenseNet121 at a significance level of $\alpha = 0.05$.

However, the accuracy difference between the proposed model (99.95%) and MobileNetV2 (99.69%) is not statistically significant ($p = 0.327$). This indicates that, from a statistical standpoint, both models perform similarly in terms of classification accuracy. Despite the lack of statistical significance, the proposed model's higher accuracy—even a 0.26% improvement—can translate to meaningful practical benefits in large-scale agricultural applications. For example, in a system classifying 100,000 images, this small improvement could result in 260 more correctly classified cases, potentially preventing misdiagnoses and reducing financial losses for farmers. Therefore, while the proposed model may not statistically outperform MobileNetV2, it offers deterministic advantages in accuracy and is better suited for scenarios where even minor classification improvements have tangible impact.

However, the proposed model still has certain limitations. Although it achieved a classification accuracy of 99.95% on the PlantVillage dataset—where environmental factors such as lighting, background, and leaf positioning are controlled—it has not yet been tested under real-world conditions, where such variables cannot be managed. Additionally, while the model demonstrates high accuracy, its processing time remains longer compared to other models such as ResNet50, InceptionV3, DenseNet121, and MobileNetV2. Therefore, future work should focus on testing the model in uncontrolled, real-world environments and optimizing its architecture to reduce processing time while maintaining or improving accuracy.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Jiraporn Thomkaew led the research and designed the experimental model. Podjana Homhual collected the experimental dataset, and Apichai Chanudom analyzed and evaluated the experimental results. The final draft has been approved by all authors.

Acknowledgment

The author wishes to thank the Faculty of Management Technology, Rajamangala University of Technology Srivijaya, for allowing the author to develop the research until it was completed.

References

[1] J. Chen, W. Chen, A. Zeb, S. Yang, and D. Zhang, "Lightweight inception networks for the recognition and detection of rice plant diseases," *IEEE Sensors Journal*, vol. 22, no. 14, pp. 14628–14638, July. 2022. doi: 10.1109/JSEN.2022.3182304

[2] M. Masood, M. Nawaz, T. Nazir, A. Javed, R. Alkanhel, H. Elmannai, S. Dhahbi, and S. Bourouis, "MaizeNet: A deep learning approach for effective recognition of maize plant leaf diseases," *IEEE Access*, vol. 11, pp. 52862–52876, 2023. doi: 10.1109/ACCESS.2023.3280260

[3] K. Roy, S. S. Chaudhuri, J. Frnda, S. Bandopadhyay, I. J. Ray, S. Banerjee, and J. Nedoma, "Detection of tomato leaf diseases for agro-based industries using novel pca deepnet," *IEEE Access*, vol. 11, pp. 14983–15001, 2023. doi: 10.1109/ACCESS.2023.3244499

[4] Z. Xiao, Y. Shi, G. Zhu, J. Xiong, and J. Wu, "Leaf disease detection based on lightweight deep residual network and attention mechanism," *IEEE Access*, vol. 11, pp. 48248–48258, 2023. doi: 10.1109/ACCESS.2023.3272985

[5] P. Kaur, S. Harnal, R. Tiwari, S. Upadhyay, S. Bhatia, A. Mashat, and A. M. Alabdali, "Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction," *Sensors*, vol. 22, p. 575, 2022. doi.org/10.3390/s22020575

[6] L. Selvam and P. Kavitha, "Classification of ladies finger plant leaf using deep learning," *Journal of Ambient Intelligence and Humanized Computing*, 2020. doi.org/10.1007/s12652-020-02671-y

[7] K. Phoksawat, E. Phoksawat, and B. Chanakot, "Forecasting smoked rubber sheets price based on a deep learning model with long short-term memory," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 1, pp. 688–696, Feb. 2023. doi: 10.11591/ijece.v13i1.pp688-696

[8] S. Deepak and P. M. Ameer, "Automated categorization of brain tumor from MRI using CNN features and SVM," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 8357–8369, 2021. doi.org/10.1007/s12652-020-02568-w

[9] R. Sivanandan and J. Jayakumari, "A new CNN architecture for efficient classification of ultrasound breast tumor images with activation map clustering based prediction validation," *Medical & Biological Engineering & Computing*, vol. 59, pp. 957–968, 2021. doi.org/10.1007/s11517-021-02357-3

[10] H. Che, L. G. Brown, D. J. Foran, J. L. Nosher, and I. Hacihaliloglu, "Liver disease classification from ultrasound using multi-scale CNN," *International Journal of Computer Assisted Radiology and Surgery*, vol. 16, pp. 1537–1548, 2021. doi.org/10.1007/s11548-021-02414-0

[11] A. M. Ibraheem, K. H. Rahouma, and H. F. A. Hamed, "3PCNNB-Net: Three parallel cnn branches for breast cancer classification through histopathological images," *Journal of Medical and Biological Engineering*, vol. 41, pp. 494–503, 2021. doi.org/10.1007/s40846-021-00620-4.

[12] N. Zhou, R. Liang, and W. Shi, "A lightweight convolutional neural network for real-time facial expression detection," *IEEE Access*, vol. 9, pp. 5573–5584, 2021. doi: 10.1109/ACCESS.2020.3046715

[13] B. Kocacinar, B. Tas, F. P. Akbulut, C. Catal, and D. Mishra, "A real-time CNN-based lightweight mobile masked face recognition system," *IEEE Access*, vol. 10, pp. 63496–63507, 2022. doi: 10.1109/ACCESS.2022.3182055

[14] H. Qi, C. Wu, Y. Shi, X. Qi, K. Duan, and X. Wang, "A real-time face detection method based on blink detection," *IEEE Access*, vol. 11, pp. 28180–28189, 2023. doi: 10.1109/ACCESS.2023.3257986

[15] J. Liu and X. Wang, "Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model," *Plant Methods*, vol. 16, p. 83, 2020. doi.org/10.1186/s13007-020-00624-2

[16] X. Wang, J. Liu, and X. Zhu, "Early real-time detection algorithm of tomato diseases and pests in the natural environment," *Plant Methods*, vol. 17, p. 43, 2021. doi.org/10.1186/s13007-021-00745-2

[17] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," *IEEE Access*, vol. 7, pp. 59069–59080, 2019. doi: 10.1109/ACCESS.2019.2914929

[18] J. He, T. Liu, L. Li, Y. Hu, and G. Zhou, "MFaster R-CNN for maize leaf diseases detection based on machine vision," *Arabian Journal for Science and Engineering*, vol. 48, 2023. doi.org/10.1007/s13369-022-06851-0

[19] R. Yakkundimath, G. Saunshi, B. Anami, and S. Palaiah, "Classification of rice diseases using convolutional neural network models," *J. Inst. Eng. India Ser. B*, vol. 103, 2022. doi.org/10.1007/s40031-021-00704-4

[20] M. Prabu and B. J. Chelliah, "Mango leaf disease identification and classification using a CNN architecture optimized by crossover-based levy flight distribution algorithm," *Neural Comput & Applic*, vol. 34, 2022. doi.org/10.1007/s00521-021-06726-9

[21] D.T. Gayathri and P. Neelamegam, "Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu," *Cluster Computing*, vol. 22, pp. S13415–S13428, 2019. doi.org/10.1007/s10586-018-1949-x

[22] L. Zhang, Y. Zheng, G. Zhong, and Q. Wang, "Research on leaf species identification based on principal component and linear discriminant analysis," *Cluster Computing*, vol. 22, pp. S7795–S7804, 2019. doi.org/10.1007/s10586-017-1439-6

[23] S. R. G. Reddy, G. P. S. Varma, and R. L. Davuluri, "Optimized convolutional neural network model for plant species identification from leaf images using computer vision," *International Journal of Speech Technology*, vol. 26, pp. 23–50, 2023. doi.org/10.1007/s10772-021-09843-x

[24] J. Basavaiah and A. A. Arlene, "Tomato leaf disease classification using multiple feature extraction techniques," *Wireless Personal Communications*, vol. 115, pp. 633–651, 2020. doi.org/10.1007/s11277-020-07590-x

[25] H. Kolivand, B. M. Fern, T. Saba, M. S. M. Rahim, and A. Rehman, "A new leaf venation detection technique for plant species classification," *Arabian Journal for Science and Engineering*, vol. 44, pp. 3315–3327, 2019. doi.org/10.1007/s13369-018-3504-8
[26] D. Bisen, "Deep convolutional neural network based plant species recognition through features of leaf," *Multimedia Tools and Applications*, vol. 80, pp. 6443–6456, 2021. doi.org/10.1007/s11042-020-10038-w
[27] A. Mezenner, H. Nemmour, Y. Chibani, and A. Hafiane, "Tomato plant leaf disease classification based on cnn features and support vector machines," in *Proc. 2nd International Conference on Advanced Electrical Engineering (ICAEE)*, Constantine, Algeria, 2022, pp. 1–5. doi: 10.1109/ICAEE53772.2022.9962070
[28] C. Zhou, Z. Zhang, S. Zhou, J. Xing, Q. Wu, and J. Song, "Grape leaf spot identification under limited samples by fine grained-GAN," *IEEE Access*, vol. 9, pp. 100480–100489, 2021. doi: 10.1109/ACCESS.2021.3097050
[29] R. Thangaraj, S. Anandamurugan, and V. K. Kaliappan, "Automated tomato leaf disease classification using transfer learning-based deep convolution neural network," *Journal of Plant Diseases and Protection,* vol. 128, pp. 73–86, 2021. doi.org/10.1007/s41348-020-00403-0
[30] P. S. Thakur, T. Sheorey, and A. Ojha, "VGG-ICNN: A lightweight CNN model for crop disease identification," *Multimedia Tools and Applications*, vol. 82, pp. 497–520, 2023. doi.org/10.1007/s11042-022-13144-z
[31] S. M. Hassan, A. K. Maji, M. Jasinski, Z. Leonowicz, and E. Jasinska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics*, vol. 10, p. 1388, 2021. doi.org/10.3390/electronics10121388
[32] W. Wang, Y. Li, T. Zou, X. Wang, J. You, and Y. Luo, "A novel image classification approach via dense-mobilenet models," *Mobile Information Systems*, vol. 2020, 2020. doi.org/10.1155/2020/7602384
[33] N. Yucel and M. Yildirim, "Automated deep feature fusion based approach for the classification of multiclass rice diseases," *Iran Journal of Computer Science*, 2023. doi.org/10.1007/s42044-023-00152-x
[34] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans leaf diseases classification using mobilenet models," *IEEE Access*, vol. 10, pp. 9471–9482, 2022. doi: 10.1109/ACCESS.2022.3142817
[35] V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan, and A. A. Khan, "Detection of apple plant diseases using leaf images through convolutional neural network," *IEEE Access*, vol. 11, pp. 6594–6609, 2023. doi: 10.1109/ACCESS.2022.3232917
[36] S. Ahmed, M. B. Hasan, T. Ahmed, R. K. Sony, and M. H. Kabir, "Less is more: Lighter and faster deep neural architecture for tomato leaf disease classification," *IEEE Access*, vol. 10, pp. 68868–68884, 2022. doi.org/10.1109/ACCESS.2022.3187203
[37] J. Thomkaew and S. Intakosum, "Improvement classification approach in tomato leaf disease using modified visual geometry group (vgg)-inceptionv3," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 13, no. 12, 2022. http://dx.doi.org/10.14569/IJACSA.2022.0131244
[38] D. P. Hughes and M. Salathe, "An open access repository of images on plant health to enable the development of mobile disease diagnostics", arXiv Print, arXiv:1511.08060, 2015. doi: 10.48550/arXiv.1511.08060
[39] K. Simonyan and A. Zisserman, "Very deep convolutional neural networks for large-scale image recognition," in *Proc. ICLR 2015*, 2015, pp. 1–14.
[40] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," arXiv Print, arXiv: 1512.00567v3, 2015. doi: 10.48550/arXiv.1512.00567
[41] S. A. Agnes, J. Anitha, and S. I. A. Pandian, "Classification of mammogram images using multiscale all convolutional neural network (MA-CNN)", *J. Med. Syst.*, vol. 44, no. 30, 2020.