Region of Interest Selection on Plant Disease

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Abstract. Plant diseases is one of the most influential factors in agricultural production. It can affect product quality, quantity, or yield of crops. Diagnosis of plant diseases is made mainly based on the experience of farmers. This work is done based on the naked eye. It is often misleading, time-consuming, and laborious. Machine learning methods based on leaf images have been proposed to improve disease identification. Transfer learning is accepted and proven to be effective. In this paper, we used the transfer learning method to classify apple tree diseases. The research data were used from the Fine-Grained Visual Categorization (FGVC7) Kaggle PLANT PATHOLOGY 2020, expert-annotated to create a pilot dataset for apple scab, cedar apple rust, multiple diseases, and healthy leaves. The InceptionV3 architecture trained with the Adam optimizer attained the highest validation accuracy.

Keywords: Plant disease · Classification · Transfer learning

1 Introduction

Plant diseases [1] is one of the most influential factors in agricultural production. It can affect product quality, quantity, or yield of crops. Diagnosis is the first step in the study of any disease. A rapid and accurate diagnosis of the disease is required before appropriate control measures can be instituted. Unfortunately, diagnosis of plant diseases is made mainly based on the experience of farmers. This is very time-consuming and error-prone. Moreover, due to significant crop numbers, complex disease symptoms, the farmer's experience should lead to undesirable treatment results [1]. Methods have been developed to assist

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in plant disease identification. Laboratory-based techniques have been developed and established over the past decades. The techniques commonly used to detect plant diseases are ELISA and PCR [2]. The segmentation and classification of leaf images with a complicated background using deep learning are studied [3]. The results show that the average Misclassification Error (ME) of 80 test images using Mask R-CNN is 1.15%. The average accuracy value for the leaf classification of 150 test images using VGG16 is up to 91.5%. The authors [4] introduces Few-Shot Learning (FSL) algorithms for plant leaf classification using deep learning with small datasets. FSL using Siamese networks and Triplet loss was used and compared to classical fine-tuning transfer learning. The authors [5] propose an automatic detection framework based on deep learning is investigated for apple leaves disease classification. A combination of parameters like learning rate, batch size, and optimizer is analyzed, and the best combination of ResNetV2 with Adam optimizer provided the best classification accuracy of 94%.

In plants, some common diseases are brown and yellow spots, early and late scorch. Identifying the disease correctly when it first appeared is an essential step in effective disease management. Inaccurate diagnosis and treatment can lead to excessive or insufficient chemical use, increased production costs, or potentially significant disease outbreaks [6]. In recent years, digital imaging and machine learning have shown tremendous potential to speed up diagnosing plant diseases [7]. Therefore, the automatic classification of plant diseases is an important research topic in agriculture. It helps to detect diseases at a very early stage.

Transfer learning [8] is an advantageous approach to building strong taxonomy networks using little data. Using transfer learning to adapt existing neural models for visual categorization tasks in image classification and many other domains has been successful [9]. In this paper, we propose a new approach to classify plant disease based on transfer learning. To help enhance the classification results, we have looked at two segmentation approaches: Region Of Interest (ROI) selection uses Canny edge detection [10] and watershed transformation [11]. Then, we performed transfer learning with six pre-trained models VGG16 [12], VGG19 [12], DenseNet [13], InceptionV3 [14], Resnet50 [15] and InceptionResNetV2 [16] to develop a leaf classifier. With this method, plant diseases can be identified at an early stage, and pest and infection control tools can be used to solve pest problems while minimizing risks to plants, people, and the environment.

The remainder is organized as follows: Sect. 2 introduces the plant disease. Section 3 introduces the proposed method for plant disease classification with transfer learning. Section 4 we give a short description of the dataset, tools, and our experimental results. Finally, we conclude in Sect. 5 and point out future work directions.

2 Plant Disease

Plant disease [1] is the deterioration of a plant's normal state. Plant diseases develop due to a timely combination of the same factors that lead to plant diseases: susceptible host plants, toxic pathogens, and favorable environmental conditions over a relatively long time. Humans can inadvertently help initiate and develop disease through some of their activities by planting or pruning trees in wet weather.

Plant diseases are a normal part of nature and are one of many ecological factors that help keep hundreds of thousands of plant and animal species living in balance. Plant cells contain special signaling pathways that enhance their defenses against insects, animals and pathogens.

Fig. 1. Images from the Apple scab

Plant diseases affect the survival, adequate growth, and yield of all crops and thus affect one or more of the basic prerequisites for a healthy, safe human life. Plant diseases can be classified according to the nature of their main pathogens, infectious or non-infectious.

Fig. 2. Images from the Apple rust

Apple, Malus Domestica, is a species of deciduous tree in the family Rosaceae, grown for its fruit, called an apple. The apple is one of the most commonly grown fruits in the world, having around (pome) shape and a variety of colors from green to red. When grown from seed, apple trees can take six to ten years to mature and bear fruit. The leaves of the plant are oval, the length can be up to 13 cm, the width is 7 cm. Some diseases on Apple leaf: Apple Scab[1] Fig. 1, Apple Rust[2] Fig. 2, Powdery Mildew[3] (Fig. 3), Multiple diseases (Fig. 4) denotes the plant is suffering both scab and rust.

Fig. 3. Images from the Apple Powdery mildew.

Plant disease causes great economic loss to farmers worldwide. The Food and Agriculture Organization estimates that pests are responsible for about 25% of crop losses[4]. Diagnosis is the process of identifying the plant disease. A good diagnostician must go through many iterations of the scientific method,

Fig. 4. Images from the Apple multiple diseases.

[1] https://www.thespruce.com/apple-scab-disease-4845572.
[2] https://extension.psu.edu/apple-diseases-rust.
[3] https://extension.psu.edu/apple-disease-powdery-mildew.
[4] https://en.wikipedia.org/wiki/Plant_pathology/.

Table 1. Comparison of the characteristics of the Apple disease.

Disease	Symptoms	Pathogen	Survival and spread	Influence
Scab	- First appears as, small pale yellow dots on the upper surface - Finally, tiny, black, fruiting bodies become visible - Black, scabby lesions on leaves and fruit	fungus Venturia inaequalis	The pathogen survives through perithecia in the soil debris	- Severely affected leaves may turn yellow and drop - The apples are so blemished
Rust	- Appear on the upper surface of apple leaves shortly after bloom - Small, pale yellow spots appear on the upper surface of leaves - Lesions on apple leaves, telial gall on cedar	fungus Gymnosporangium juniperi-virginianae	If a spore lands on a susceptible apple leaf and environmental conditions are favorable infection can occur in as little as four hours	- Infected leaves may remain on the plant or may become yellow and fall - Rust in leaves and fruit will not cause other infections in the plant
Powdery Mildew	- 3–4 day delay in the opening of infected buds - Become covered with a white to light gray powder	fungus Podosphaera leucotricha	- The fungus overwinters in fallen, infected leaves. Spores blow up onto healthy leaves to infect them	- It's unlikely to kill your plant, but it will sap its strength - Reduce the size of the entire shoot

through observations of plants, the environment, and information from growers. Incorrectly identifying diseases and pathogens, disease control measures can be a waste of time and money and can lead to crop damage (Table 1).

3 Plant Disease Classification

Apple rust, apple scab, and multiple diseases may affect the plant. Manual inspection is sluggish, vulnerable to mistakes, and requires a lot of human resources and time. The method proposes for plant disease classification can achieve high classification accuracy, outperforming humans in many cases.

We have used the concept of transfer learning for classification. With transfer learning, instead of starting the learning process from scratch, you start from patterns that have been learned when solving a different problem. In image classification, transfer learning is often manifested through the use of pre-trained models. The model of plant disease classification using transfer learning consists of three phases: image pre-processing, image segmentation and classification. Figure 5 shows the proposed system that is used in this study.

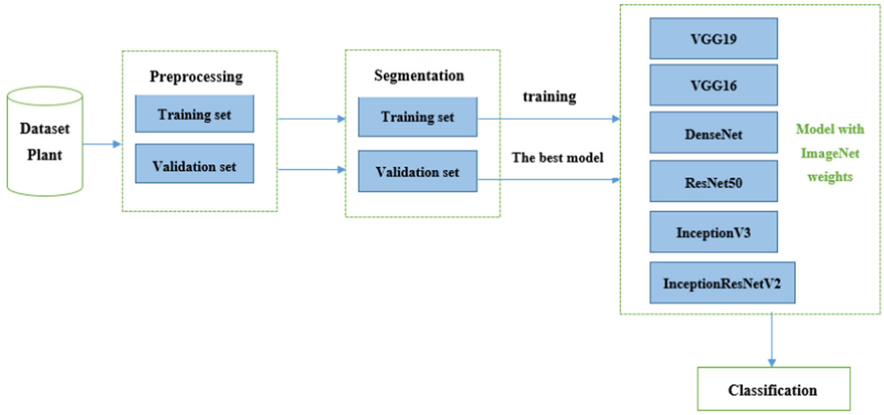

Fig. 5. The proposed method for plant classification with transfer learning technique.

3.1 Pre-processing

Image pre-processing [17] is an important step in image analysis. The aim of image preprocessing is to improve contrast. Pre-processing can include simple operations image cropping, contrast improvement, dimensionality reduction.

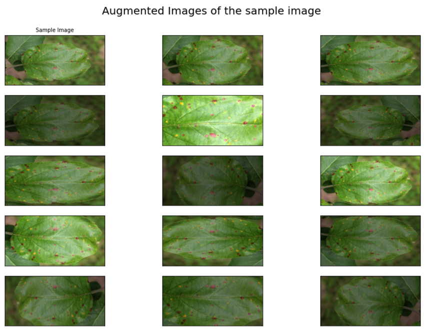

Fig. 6. Data augmentation.

The data contains many images of healthy and infected leaves. The input images in the dataset were downscaled to 512 × 512 pixels resolution from the original size. As a result, the Plant Pathology 2020 dataset has an unbalance distribution of samples among the four classes. Image data augmentation [18] is a technique used to extend the size of the training dataset. In our training set, we have applied many geometric transformations to the increased data. We use vertical flipping and horizontal flipping, random zoom, and images with different brightness levels. Image data augmentation techniques are shown in Fig. 6.

3.2 Segmentation

Segmentation [19] is a step in image analysis to subdivide an image into meaningful regions. Image segmentation can help enhance the classification results. We need to separate the diseased leaves from the unnecessary background. We have looked at two segmentation approaches.

We use the Region Of Interest (ROI) selection, to detect the edges of the leaf, ROI selection using watershed transformation. Method Canny edge detection will only work if the target leaf is in the middle area and the image is of good quality. Results are shown in Fig. 7.

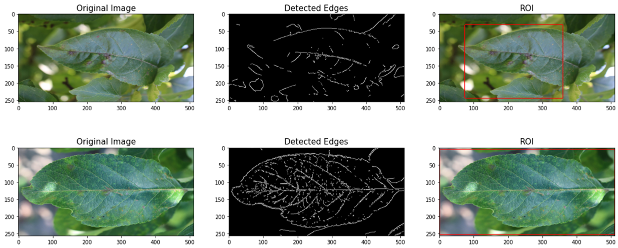

Fig. 7. ROI selection used Canny edge detection.

For many images, the ROI selection method does not give accurate results. Therefore, we try another method to determine the ROI according to the shape of the target leaf.

Watershed transformation is one of the most reliable methods for automatic and unsupervised segmentation is watershed transformation. This technique has been successfully applied to solve a variety of difficult image segmentation problems. The basic idea is to treat the image as a topographic surface, the gray level of the pixels in the image corresponds to the local minimum, elevation, and it influence areas defined as watersheds. The purpose of the watershed transformation is to define hydrolysis lines on the topographic surface. Results are shown in Fig. 8.

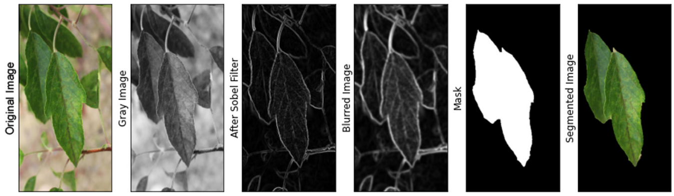

Fig. 8. ROI selection using watershed transformation.

3.3 Classification

Transfer learning is a type of machine learning technique, in which the pre-trained models [20] are reused to leverage their weights to introduce them as the initialization of a new CNN model for a different purpose. In this paper, we use pre-trained neural network models in the ImageNet dataset[5] such as VGG16, VGG19, DenseNet, InceptionV3, Resnet50 and InceptionResNetV2.

With transfer learning, we use pre-trained models and fine-tuning them to our problem. We use features learned from the ImageNet dataset by eliminating the final classifier and combining them with logistic regression as a general classifier predicting our class labels in the new domain.

4 Experiment

In this section, our method's performance is evaluated on a data of plant disease from the Kaggle PLANT PATHOLOGY 2020 competition. This work is presented as follows: Sect. 4.1 description the experimental data. Then, the tools used for the experiment are presented in Sect. 4.2. Finally, we formulate experimental scenarios and some remarks of results in Sects. 4.3 and 4.10, respectively.

4.1 Data Used

The data were used from the FGVC7 Kaggle PLANT PATHOLOGY 2020 competition [6]. The data included 1821 labeled training images of apple tree leaves. There are 516 images of healthy leaves, 91 images of multiple diseases, 622 images of apple rust, and 592 images apple scab.

The distribution of the four classes is shown in Fig. 9. The column chart shows that the "Multiple diseases" layer makes up only a tiny fraction of the entire dataset. On the other hand, the "Rust" layer took the most quantity, the "Scab" layer was the second most, and the "Healthy" layer took the third place.

4.2 Tools

Our method has been implemented with Python[6]. Keras and Tensorflow are used to deploy deep learning models. Numpy is used to perform basic math. For the prior training, we used ImageNet weights for each model. The input shape of the leaf image is $512 \times 512 \times 3$. We will use TPU for training for grading purposes. The escribed model was trained for 40 epochs, using Adam optimizer while minimizing categorical cross-entropy loss.

[5] https://papers.nips.cc/paper/2012/hash/c399862d3b9d6b76c8436e924a68c45b-Abstract.html.
[6] https://www.python.org/.

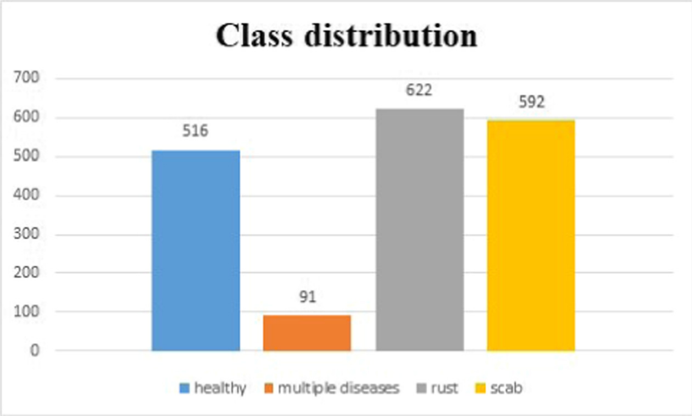

Fig. 9. Plant disease distribution.

4.3 Model Used

This study used 1,548 training images and 273 validation images of disease and healthy leaves (ratio into 85:15). Each of these experiments runs for 40 epochs. We performed transfer learning with six models InceptionV3, DenseNet, InceptionResNetV2, ResNet50, VGG16 and VGG19.

4.4 Scenario 1: Transfer Learning with InceptionV3

The pre-trained InceptionV3 model is used. InceptionV3 model used 21,776,548 trainable parameters and 34,432 non-trainable parameters of InceptionV3 layers. The initialized weights of ImageNet are used for each layer. The weight value was updated using Adam Optimizer for each epoch. The last layer is used for the classification with softmax as the activation function. The loss function used is categorical cross-entropy.

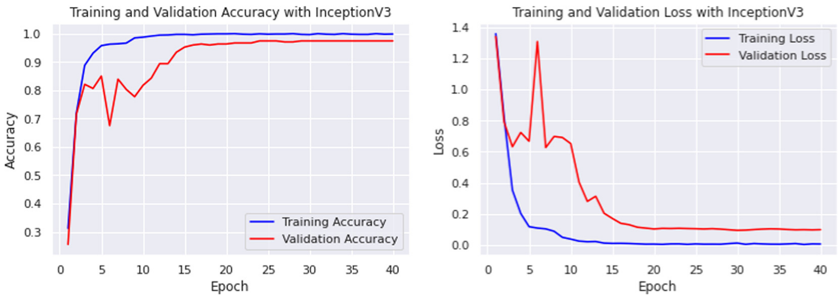

Fig. 10. Plant disease classification performance in training and validation phases of the InceptionV3 model.

Figure 10 shows the training process of the InceptionV3 model. The accuracy improves quickly from 0.2555 in epoch 1 to 0.9745 and stabilizes after 40 epochs. From the above plots, we can see that the losses decrease and accuracies increase. The training accuracy of 0.9976 was obtained, while a validation accuracy of 0.9745 was achieved.

4.5 Scenario 2: Transfer Learning with DenseNet

With the number of epochs as scenario 1, we experiment with DenseNet model. The DenseNet model utilized 18,100,612 trainable layers parameter and 229,056 non-trainable parameters of DenseNet layers. The training accuracy of 0.9965 was obtained, while a validation accuracy of 0.9635 was achieved.

The training process of the DenseNet model is shown in Fig. 11. The accuracy improves quickly from 0.0657 in epoch 1 to 0.9635 and stabilizes after 35 epochs.

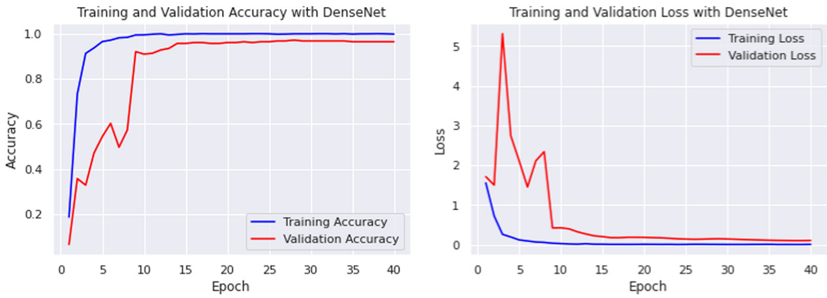

Fig. 11. Accuracy and Loss with DenseNet.

4.6 Scenario 3: Transfer Learning with InceptionResnetV2

The InceptionResnetV2 model is experimented. InceptionResnetV2 model used 54,282,340 trainable layers parameter and 60,544 non-trainable parameters of InceptionResnetV2 layers. With the number of epochs is 40, the results of the Validation phase reach 0.9672 accuracies.

Figure 12 shows the training process of the InceptionResnetV2 model. The validation loss is reduced from 1.3154 at the first epoch to 0.1286 at epoch is 40.

4.7 Scenario 4: Transfer Learning with Resnet50

The Resnet50 model is used with weights are loaded into the network with no top layer. The Resnet50 model utilized 18,100,612 trainable layers parameters and 229,056 non-trainable parameters of Resnet50 layers.

The Accuracy and Loss of the Resnet50 model is shown in Fig. 13. The training accuracy of 0.9967 was obtained, while a validation accuracy of 0.9635 was achieved. The validation loss is reduced from 1.6323 to 0.1922 at epoch 40.

Fig. 12. Accuracy and Loss with InceptionResnet.

Fig. 13. Accuracy and Loss with Resnet50.

4.8 Scenario 5: Transfer Learning with VGG16

The VGG16 model operates with 14,716,740 trainable layers parameters. We used just 40 epochs, the VGG16 model achieving a probability validation accuracy of 0.9453. The training loss is 0.1466 and the validation loss is 0.2028. The Accuracy and Loss vs epoch with the VGG16 model is shown in Fig. 14.

4.9 Scenario 6: Transfer Learning with VGG19

The VGG19 model used 20,026,436 trainable layers parameters. Model is trained using the training dataset with a limit of 40 epochs. The results of the validation phase reach an accuracy of 0.9161.

The loss reduce quickly from 1.2072 in epoch 1 to 0.2028 after 40 epochs. The training process of the VGG19 model is shown in Fig. 15.

For input data disease, samples of apple rust, apple scab, multiple diseases and healthy leaves are considered. Segmented images can be classified into different plant diseases. Figure 16 shows the input and output image where the input image is an apple leaf with rust disease and output image shows the classification of disease "rust" using selection watershed transformation. The results of the experiment scenarios were provided in the following Table 2.

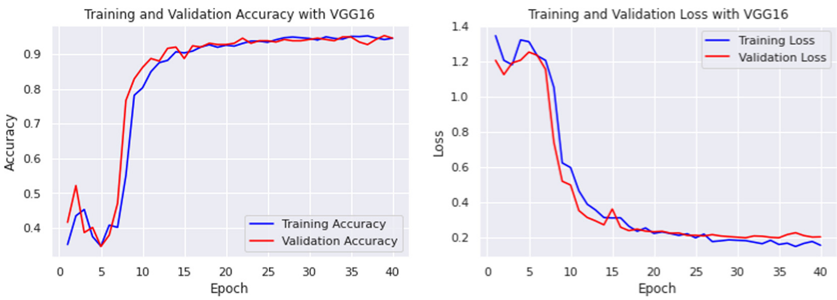

Fig. 14. Accuracy and Loss with VGG16.

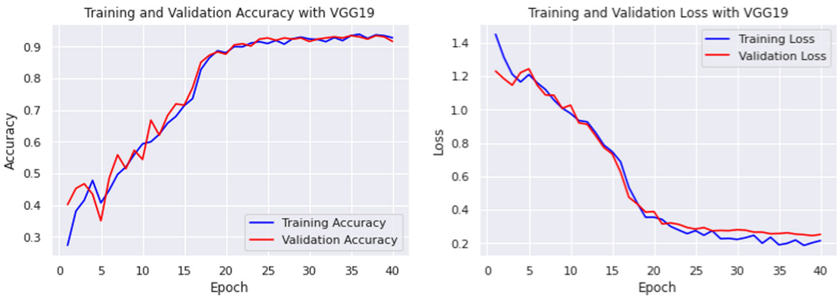

Fig. 15. Accuracy and Loss with VGG19.

Fig. 16. Input image of "apple rust" and output disease is "apple rust".

Table 2. Experimental results.

Model	Trainable params	Accuracy train	Accuracy val
InceptionV3	21.776.548	0.9976	**0.9745**
DenseNet	18.100.612	0.9965	0.9635
InceptionResnetV2	54.282.340	0.9994	0.9672
Resnet50	23.527.556	0.9967	0.9635
VGG16	14.716.740	0.9485	0.9453
VGG19	20.026.436	0.9328	0.9161

4.10 Discussion

Six pre-trained models are performed with transfer learning technique and achieved an accuracy of over 90%, with InceptionV3 reaching the highest accuracy.

From Table 2, the accuracy of the InceptionV3 model is the highest at 0.9745. InceptionResnetV2 model obtained the second-highest validation accuracy probability of 0.9672. VGG19 ranks behind all five pre-trained models, achieving a probability validation accuracy of 0.9161.

Compare the performance of the proposed method with published results. The accuracy of our training model gives better results, as shown in Table 3.

Table 3. Comparison with published results.

Model	Accuracy
ResNetV2 [5]	0.947
Deep learning [3]	0.915
Proposed Model	**0.9745**

5 Conclusion

Plant disease causes significant damage to the agricultural industry. Plant disease identification and classification play an important role in disease detection, mitigation, and management. This study introduces an approach using transfer learning method for the classification of plant diseases. The proposed model is ensemble of six CNN architectures (VGG16 [12], VGG19 [12], DenseNet [13], InceptionV3 [14], Resnet50 [15] and InceptionResNetV2 [16]). The system was experimental on the Kaggle PLANT PATHOLOGY 2020 dataset and had an accuracy of 97.45%. Besides, The method can save compute time and resources and successfully learn a new task. In the future, more data at different stages of different diseases will be collected and classified.

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