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A Novel Method of Plant Leaf Disease Detection Based on Deep Learning and Convolutional Neural Network

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Abstract—**This study has developed a new plant disease detection approach by combining four CNN models. The experiment used an open source database of 36258 images classified in 10 plant species and 61 classes of healthy and disease plant leaves. 36258 images were divided into two datasets with 31718 images for the training set and 4540 images for the validation set. Four CNN models including Inception, Resnet, Inception Resnet, and Densenet were deployed and the results of CNN models were processed by a stacking method. The use of the stacking method achieved an 87% accuracy rate, which is a significant improvement compared to the result of using a single CNN model. The relatively high accuracy rate indicates that using a combination of CNN models by a stacking method could be an appropriate approach that can be extended to practical cultivation conditions as an advanced plant disease warning tool.**

Keywords- Plant Disease; Deep Learning; Transfer Learning; Inception Network; Residual Network (ResNet); DenseNet

I. INTRODUCTION

The ability to diagnose and control plant diseases helps to avoid crop losses. According to Strange RN and Scott PR, plant disease is a significant threat to global food security, resulting in 10-16% losses in the worldwide harvest of crops annually[1, 2]. It is easier to control plant diseases at their early stages. However, farmers commonly fail to detect emerging pathological infections since early changes are generally unobvious. Such failure to detect would cause significant crop losses, which leads to reduced plant yield and economic consequences [3].

Even though the threat posed by plant diseases is killing for crop yields, it is a waste to involve too much human effort in plant disease detection. It would take a great deal of time in learning diagnosis skills and standards and would require hundreds of hours of practice to improve accuracy. Therefore, a machine would help in this case.

Before a machine is introduced to detect plant infections, plant disease diagnosis heavily depends on expert agronomists or phytopathologists. They designed a criteria checklist based on research and plants observation in the field, to treat the disease before it went out of control. However, due to the great variety of infectious symptoms and huge differences in the same symptom among diverse species, even experts with professional optical equipment could fail to identify early-stage diseases [4]. Thus, the theory-based method is found incomparable in its efficiency and accuracy with a well-trained machine.

Researchers have developed different detection systems, targeting different plant diseases and species. For example, common digital image processing techniques were used to observe and analyze the features of leaves. Artificial Neural Networks (ANN) and Support Vector Machines (SVM) will then diagnose leaf features to identify infection [5]. Artificial Neural Networks is an information processing paradigm inspired by how biological nervous systems function [5]. Each time stimulated by electronic lines or computer programs, ANN will function as designed [5]. Due to its ability to accurately identify plant diseases in a much shorter time frame, ANN could contribute significantly to managing agricultural and forestry production.

ANN is composed of layers of artificial neurons. Each artificial neuron is a functional unit, receiving inputs and producing outputs accordingly. Each input has a weight. The output is a scalar number calculated from multiplying input weights with inputs and adding an overall bias. Each scalar number will then be processed in an activation function, such as sigmoid, relu, and tanh, to turn each neuron into a form of non-linear function. Therefore, each layer in ANN consists of multiple non-linear functions. Outside each layer is a vector, which is taken as the input for the next layer. Gradient descent updates the weights and bias in ANN, leading the ANN model to achieve its optimal state [6].

Recently, convolutional neural networks (CNNs), one specific type of ANN, have been applied to the classification of various plant diseases and made successful achievements [7]. But research still needs to be done to reduce training time, speed up convergence rate, and promote the final classification accuracy [8].

The current research aims to study a new plant disease detection approach by combining four CNN models including Inception, Resnet, Inception Resnet, and Densenet. The researcher trained and evaluated multiple CNN architecture models, resourcing from plenty of images of leaves at different infection stages. The combining of CNN models was found to well generate an automated plant disease detection system.

II. DATASET

Datasets are necessary for all research stages, both during the training phase and the phase evaluating the performance of recognition algorithms. The proposed system was trained and assessed on the open-source dataset from AI-Challenger. 36258 leave images were collected and grouped into 10 different plant species. Under each species, images of healthy and various disease plant leaves were classified, and finally 61 classes of images were grouped (Table 1). Healthy leaf samples added to each species group were used to distinguish between healthy and infected leaves. The system included two datasets including training set and validation set, with 31718 images for the training set and 4540 images for the validation set.

Table 1. Class Description

Species	Label id	Label name	Species	Label id	Label name
Apple	**0**	**Apple healthy**		**31**	**Pepper scab general**
	1	**Apple scab general**		**32**	**Pepper scab serious**
	2	**Apple scab serious**	**Potato**	**33**	**Potato healthy**
	3	**Apple frogeye spot**		**34**	**Potato early blight fungus general**
	4	**Cedar apple rust general**		**35**	**Potato early blight fungus serious**
	5	**Cedar apple rust serious**		**36**	**Potato late blight fungus general**
Cherry	**6**	**Cherry healthy**		**37**	**Potato late blight fungus serious**
	7	**Cherry powdery mildew general**	**Strawberry**	**38**	**Strawberry healthy**
	8	**Cherry powdery mildew serious**		**39**	**Strawberry scorch general**
Corn	**9**	**Corn healthy**		**40**	**Strawberry scorch serious**
	10	**Cercospora zeaemaydis tebon and daniels general**	**Tomato**	**41**	**Tomato healthy**
	11	**Cercospora zeaemaydis tebon and daniels serious**		**42**	**Tomato powdery mildew general**
	12	**Puccinia polysora general**		**43**	**Tomato powdery mildew serious**
	13	**Puccinia polysora serious**		**44**	**Tomato bacterial spot bacteria general**
	14	**Corn curyularia leaf spot fungus general**		**45**	**Tomato bacterial spot bacteria serious**
	15	**Corn curyularia leaf spot fungus serious**		**46**	**Tomato early blight fungus general**
	16	**Maize dwarf mosaic virus**		**47**	**Tomato early blight fungus serious**
Grape	**17**	**Grape healthy**		**48**	**Tomato late blight water mold general**
	18	**Grape black rot fungus general**		**49**	**Tomato late blight water mold serious**
	19	**Grape black rot fungus serious**		**50**	**Tomato leaf mold fungus general**
	20	**Grape black measles fungus general**		**51**	**Tomato leaf mold fungus serious**
	21	**Grape black measles fungus serious**		**52**	**Tomato target spot bacteria general**
	22	**Grape leaf blight fungus general**		**53**	**Tomato target spot bacteria serious**
	23	**Grape leaf blight fungus serious**		**54**	**Tomato septoria leaf spot fungus general**
Citrus	**24**	**Citrus healthy**		**55**	**Tomato septoria leaf spot fungus serious**
	25	**Citrus greening June general**		**56**	**Tomato spider mite damage general**
	26	**Citrus greening June serious**		**57**	**Tomato spider mite damage serious**
Peach	**27**	**Peach healthy**		**58**	**Tomato YLCV virus general**
	28	**Peach bacterial spot general**		**59**	**Tomato YLCV virus serious**
	29	**Peach bacterial spot serious**		**60**	**Tomato tomv**
Pepper	**30**	**Pepper healthy**			

III. METHOD

A. *Enrich DataSet with Data Augmentation*

Before starting to introduce the images to the model, the researcher conducted an exploratory data analysis. In statistics, exploratory data analysis (EDA) is an approach to analyze data sets for summarizing main characteristics, often with visual methods. The visualization of the data distribution indicating that the training dataset has a severe problem with class imbalance. Therefore, the researcher used an up-sampling method. To fix the number of images in the classes that appear the most, the researcher copied images in the rest classes, processed them with augmentation, and then added them to the dataset. The process was repeated until the number of images in each class was equal.

The primary three purposes of augmentations are to 1) increase the volume of data set, 2) slightly distort the image, and 3) reduce the over-fitting in the training session. In machine learning and statistics, overfitting occurs when statistical models describe random noise or errors instead of potential relationships [9]. The images were randomly processed with horizontal flip, vertical flip, random degree rotation, and brightness and contrast tuning.

B. *Convolution Neural Network*

In recent years, tremendous success has been witnessed in the field of visual imagery analysis. In 2014, a CNN structure, Inception, created by Google, won the champion in the classification of daily objects [10]. In the following year, an entirely different CNN structure, ResNet, beat Inception and won [11]. Inspired by the conception of Inception and ResNet, a new model called Inception ResNet was invented, with better performance than Inception or ResNet. Later in 2017, a Densely Connected Convolutional Network, which was also inspired by the notion of ResNet was published. [12] Multiple states of CNN architectures were hence explored. This research will create a plant disease diagnosis system based on the understanding of preceding structures of CNN models.

1) *Inception Network*

The Inceptions paper focuses on a new type of construction module for deep networks, which is now called "Inception module". At its core, this module comes from the intersection of two ideas.

The first insight relates to the manipulation of layers. Instead of only using one distinct kernel size at each layer, Inception Net uses the inception modules which compute multi-kernel sizes transformation on the same feature map in parallel and concatenate their result to one output [13].

The second insight relates to the problem which comes after applying the inception module. Since the inception module concatenates the output of using different kernel sizes, the concatenation results with a much thicker feature map (channel increases), and this results with using more parameters in the next layer to do the convolution. A 1x1 kernel is applied in the inception module before each multi-sized kernel, this can help to reduce the channel size of the feature maps, hence, fewer parameters are needed when doing the convolution [10].

2) Residual Network (ResNet)

The ResNet structure is invented to solve the degradation problem. According to Kaiming He and his partners' paper, it points out that building a deeper neural network by stacking layers of identity mapping on the trained shallower network would produce a result which should be exactly the same as the trained shallower network since the layer stacked are identity map [11]. In reality, because of the difficulty of training, an extremely deep network will cause degradation problem and the result is not as accurate as a relatively shallow network. However, the ResNet can solve this problem, the deeper the residual network is, the better the training set performances.

The rationale of ResNet is to build multiple residual blocks and stack them together. Each of the residual blocks of ResNet consists of a series of layers and a shortcut connection that connects the input and output of the module. Then it performs an addition act between input and output. If the input and output sizes are different, then zero padding or projection (by 1×1 convolution) can be used to get the matching size [11].

3) Inception Combine ResNet

Inspired by the residual network, the idea of residual blocks is applied in the Inception Network in which each residual block comprises a series of layers of inception module and a shortcut connection between the input and output [14].

4) Densely Connected Convolutional Networks (DenseNet)

The underlying logic of DenseNet is consistent with ResNet, but it establishes a solid connection between all the front and back layers. Another feature of DenseNet is feature reuse - using its connections to the channel. These features allow DenseNet to achieve better performance than ResNet but with fewer parameters and computational costs [12].

C. *Transfer Learning and Stacking Method*

Inspired by the foregoing four different model structures, this paper exploited four fine-tuned models and process a fine-tuning step to make models fit the goal. The training datasets were randomly split into multiple batches which the batch size was set to 16. These batches were fed into the model with a stochastic order, and once all batches were fed means one epoch was finished. Each model was trained for 20 epochs, an evaluation was made after one epoch training and the model was saved when there was an improvement occurs in score loss. Once all models were trained, a stacking method was applied by using the output of four different models. For each photo of plant leaves fed into the model, the output was a 61-dimensions vector in which each element represented probable corresponding class that the leaf belonged to. By feeding the output of 4 different models into a simple ANN model, it generated a new vector which consisted 61 elements. The final predict result would be the class which had the greatest value in the corresponding value in the new vector.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

The four proposed CNN-based models were trained for approximately 20 epochs as the loss curve converged around the x-axis (Fig. 1). Accuracy and loss score of the network were recorded in every batch. The total training time for all models was around 96 hours due to the large amount of training data. In training the forgoing four models, the training parameters were shown in Table 2. An SGD optimizer was exploited during the training step which the learning rate was initially set to 0.001 and momentum set to 0.9. Every 50 batches training step the loss score was assessed whether it had a significant reduction, and the learning rate would be reduced by a factor of 0.9 once the loss score failed to reduce for 50 batches.

Table 2. Training Parameters

Parameter	Value
Epochs	20
Batch size	16
Momentum	0.9
Weight decay	0.001
Learning rate	0.001-0.00001

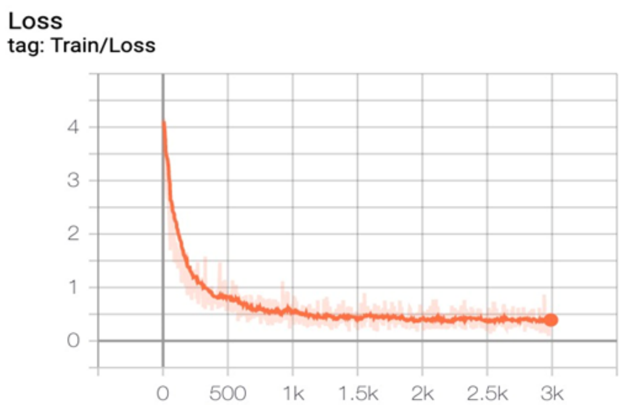

Fig. 1. Change of Loss Score for one of the Models

Table 3. Records of Accuracy for Each Model

Model Structures	Test Accuracy	Epochs	Times(s/epoch)
ResNet	0.8278	20	7214
Inception Net	0.8222	20	7300
DenseNet	0.8344	20	7132
Inception ResNet	0.8407	20	7280

After the 20 epochs training for each model, validation was made to all models and the accuracy rates were recorded in Table 3. All of the four models produced high accuracy after training for only 20 epochs; the data augmentation process and fine-tuned four CNN-based models both accounted for the system's high efficiency. Moreover, the use of the stacking method also improves the prediction accuracy for approximately 3 percent. This indicates the powerfulness of the stacking can be, and it summarizes the result of four models and draws conclusion from it which effectively improves the predict accuracy on the test data.

V. CONCLUSION

Although plenty of prior research has developed plant disease detecting systems using various computer vision techniques, CNN yields better performance. This research applied four preceding models including Inception, Resnet, Inception Resnet, and Densenet, and added a voting mechanism to detect 61 classes of healthy and disease plant leaves. The use of the stacking method achieved an 87% accuracy rate. Compared with another research which also used combined CNN modules to detect 10 plant diseases, and achieved an accuracy of 91.7% on the test data set [7], this research has combined different CNN models and detected more plant diseases (61 diseases).

The four models together improved the outcome of the training process. Thus, a trained machine, with relatively high accuracy and speed in plant diagnosis, has the potential to assist the economy in agriculture. If the technology can be widely applied, it will prevent plant diseases in the early stages and free farmers and experts from observing plants in fields. Even though the model's evaluation of the validation set has achieved exceptional performance, it is not yet prepared for practical use due to its high demand for computational power. Future research should focus on decreasing the number of parameters but maintaining accuracy. Also, future research should explore how to increase the volume of the database, for expanding the diversity of species that can be diagnosed through the machine system. Furthermore, the system is restricted to diagnose ongoing disease but is unable to foresee the potential of being infected. Therefore, the further step is to explore how to estimate the probability a plant would get infected or even predict the disease type the plant might develop.

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