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Detection of Plant Disease with Leaf Images Using Deep Learning Based Generative Model

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ABSTRACT: Plant diseases are detected using deep learning based generative model which uses the pre trained images of both healthy and unhealthy leaves to segregate separately. The method of using high resolution technique helps in increasing the accuracy of detection of disease. This method is said to be effective compared to deep convolutional methods and gives the accuracy of about 99 percent.

KEYWORDS: GAN, Leaf, Plant Disease Detection, Super resolution.

I. INTRODUCTION

Plant disease detection and identification tasks have changed greatly from traditional methods to methods induced by Artificial Intelligence and machine learning. Deep learning was used for image-based plant disease detection. There are many overview papers on the applications of GANs, including image synthesis, semantic image editing, style transfer, image super-resolution and classification, these papers also point to remaining challenges in theory and application of GANs. As a new method to expand data set, GAN can generate high-quality images, it is very useful for image processing. An image superresolution (ISR) method has been proposed using generative adversarial networks (GANs) which can increase the resolution of a low-resolution image by 16 times to generate a high-resolution super-resolved (SR) image. Therefore, GAN can be used not only to improve model performance but also to provide endless suitable data.

Paper is organized as follows. Section II material and methods involved in this process. The principle of DGAN is given in Section III. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. MATERIAL AND METHODS

PlantVillage (www.plantvillage.org) is an open database for plant disease diagnosis that includes images of diseased and healthy leaves of various plants. In this paper, 31361 leaf images collected from PlantVillage were used as the experimental data, including healthy leaves from 5 different species and unhealthy tomato leaves affected by 10 diseases

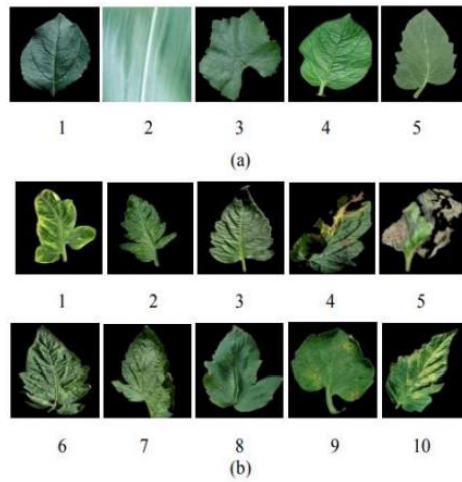


Fig. 1. Leaf samples from healthy plants and diseased tomato plants. (a) Samples of healthy plant leaves. From 1 to 5 are the leaves of apple, corn, grape, potato and tomato, based on the order in Table 1 (b) Samples of unhealthy tomato leaves. One leaf for each disease, based on the order in Table 2, the last one 10 is a healthy tomato leaf

To generate high-resolution images with clear and detailed information, this paper combines WGAN and SRGAN. The method can be broken down into two stages, as shown in Fig 2 (a) and (b). Fig 2(a) shows the generation of healthy leaves. Fig 2(b) shows the generation of unhealthy leaves, by using the WGAN trained in Fig 2(a) as the pretrained model combined with SRGAN. In the first stage, the structure of the generating network and discriminating network is consistent with that of WGAN. The purpose is to obtain 64*64 images with clear and detailed information. In the second stage, the generating network and discriminating network are consistent with that of SRGAN. The purpose is to reconstruct the 64*64 images and then obtain 256*256 high-resolution images with more detailed information. We needed to pretrain the model and then use the parameter values of the pretrained model as the initial value for the model parameters.

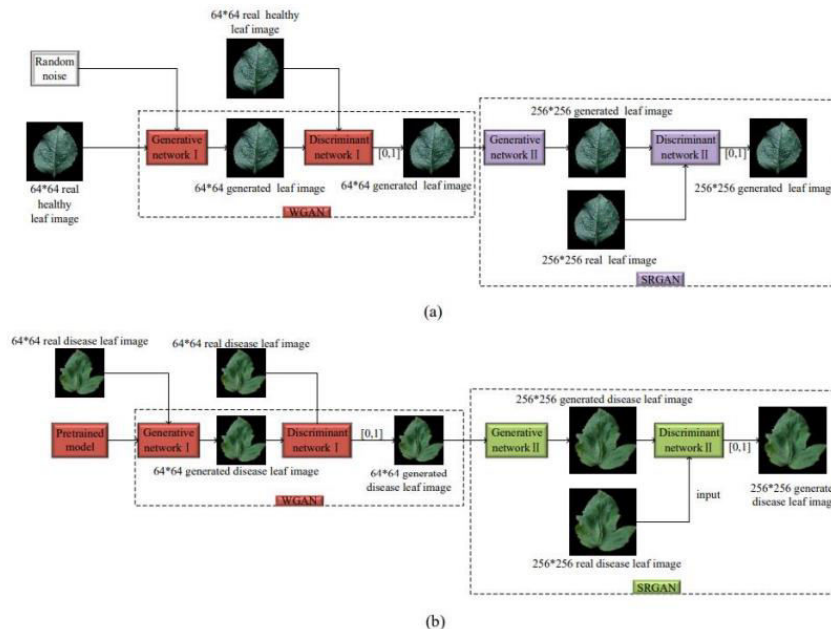


Fig. 2. DoubleGAN structural block diagram. (a) Generation process of healthy leaves (b) Generation process of diseased leaves

Some important aspects of this process are: a) The real 256*256 image was downsampled, and the corresponding low-resolution 64*64 image was obtained as the input of the generation network. The generation of the first high-resolution images by super-resolution reconstruction was obtained through forward propagation. b) Back-propagation was used to update the network parameters, which allowed the network to reach the global optimal solution. c) When the discriminating network was trained, the discriminating loss was used to calculate the probability that the image

generated by the discriminating network came from the natural image domain. If the difference between the obtained probability value and the actual value is smaller, the trained discriminating network is better, and a better discriminating network model was obtained after back-propagation. d) When the generated network was trained, its loss function increased the feature loss compared with that from the traditional GAN, which made up for the lack of high-frequency details in the original mean square error (MSE) loss-generated image. The greater the loss was, the greater the difference between the reconstructed high resolution image and the real image. After the loss value was obtained, the network parameters were updated through back-propagation to optimize the network model. The same training carried out for the next batch of images until the global optimal solution was obtained, which made the model converge.

III. THE PRINCIPLE

During training, the WGAN in stage I and the SRGAN in stage II were trained separately. After the model training was completed, random noise was used as the input, and the generated network parts in stage I and stage II were extracted separately and then connected serially. First, the generator was pretrained, and the parameters obtained were used as the initial weight of the generator when the SRGAN was trained. DGAN divides the building task into two stages. The first stage generates images with a size of 64*64. The second stage generates images with a size of 256*256. It can be seen that pretraining can quickly reduce the error between the generated image and the actual image in a short time. The super resolution results generated by the generator after training are shown in Fig 4.

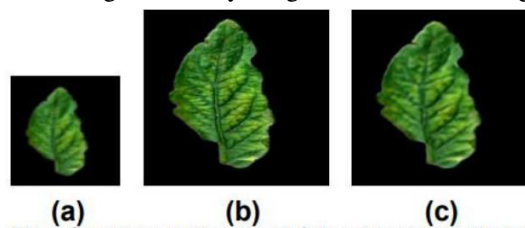


Fig. 4. Superresolution results. (a) Subsampled image, (b) generated high-resolution image, (c) actual high-resolution image

IV. RESULTS

We used the existing generation network DCGAN to generate 256 * 256 images, which were compared with the original images and the images generated by DoubleGAN. The images of unhealthy leaves were used as training data to expand the unbalanced data set. Then, three classical networks, VGG16, ResNet50 and DenseNet121, were used to classify and verify the data set before and after expansion, which proved that the diseased plant leaf image generated by DGAN was very similar to the actual image.

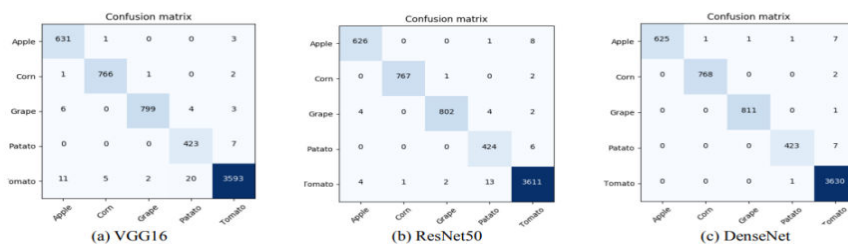


Fig. 7. classification results of the original plant leaf images data set

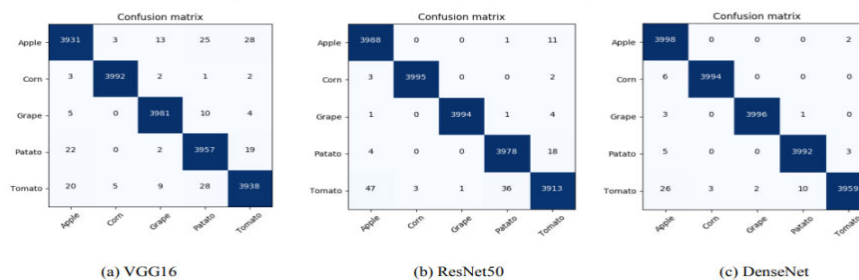


Fig.9. Classification results of the plant leaf images data set expanded by DoubleGAN



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Diease	DoubleGAN expansion		
	VGG16	ResNet50	DenseNet121
Bacterial spot	93.93	96.83	99.25
Early blight	78.71	95.24	98.88
Late blight	96.55	99.44	100.00
Leaf mold	88.52	97.85	99.81
Partial leaf spot	84.41	97.67	99.44
Two-spotted spider mites	92.06	97.39	99.44
Target spot	85.34	95.05	98.04
Mosaic virus	97.48	99.35	100.00
Yellow leaf curl virus	88.33	97.67	98.23
Healthy	98.04	99.53	100.00

V. CONCLUSION AND REFERENCES

This paper was undertaken to design DGAN for generating plant leaves in order to expand the data set and evaluate the utility of generated leaves by classification accuracy. The results have shown that the classification accuracy for the dataset expanded with DoubleGAN is higher than that for the original dataset.

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