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A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network

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ABSTRACT

Manual approaches to recognize cucumber diseases are often time-consuming, laborious and subjective. A deep convolutional neural network (DCNN) was proposed to conduct symptom-wise recognition of four cucumber diseases, i.e., anthracnose, downy mildew, powdery mildew, and target leaf spots. The symptom images were segmented from cucumber leaf images captured under field conditions. In order to decrease the chance of overfitting, data augmentation methods were utilized to enlarge the datasets formed by the segmented symptom images. With the augmented datasets containing 14,208 symptom images, the DCNN achieved good recognition results, with an accuracy of 93.4%. In order to compare the results of the DCNN, comparative experiments were conducted using conventional classifiers (Random Forest and Support Vector Machines), as well as AlexNet. Results showed that the DCNN was a robust tool for recognizing the cucumber diseases in field conditions.

1. Introduction

Plant disease is a common threat to yield and quality of global agricultural production and bears responsibility for a significant portion of production costs. It is reported that the loss caused by plant disease accounts for at least a 10% reduction in global food production (Mutka & Bart, 2015). Cucumber, one of the most common vegetables in China, is severely affected by various diseases, such as downy mildew and powdery mildew (Zhang et al., 2017b; Ma et al., 2017). The process of recognizing diseases is often time consuming, laborious and subjective. Most of disease damage evaluation and treatment are done by farmers in the field with the guidance of plant pathologists. Incorrect diagnosis and pesticide usage are very common. Therefore, a timely and accurate recognition method of cucumber diseases is in great demand.

With the development of computer vision and machine learning, progress has been achieved on recognition and diagnosis of plant diseases (Bai et al., 2017; Dorj et al., 2017; Mahlein, 2016; Ma et al., 2015; Mutka & Bart, 2015; Pethybridge & Nelson, 2015; Stewart & Mcdonald, 2014; Bock et al., 2009). Many recognition and diagnosis methods are proposed by following the pipelined procedures of image segmentation, feature extraction, and pattern recognition (Zhang et al., 2017a; Zhang et al., 2017b; Du et al., 2016). Recognition methods following the pipelined procedures have made some progress. But these methods are subject to two issues. First, the accuracy of these methods greatly depends on the extraction and selection of the visible disease features. Specifically, features of visible disease symptoms should be extracted accurately and proper features should be selected. Second, the methods following the pipelined procedures are relatively complicated. The presence of noises is largely unavoidable in disease images captured under field conditions, such as uneven illumination and clutter field background. This can severely decrease the quality of the features and affect the results of recognition. Therefore, many efforts are spent on eliminating the noises in the conventional methods to achieve robust results.

Convolutional neural network (CNN) is one of the best-performing methods for image recognition (Ghazi et al., 2017; Ding & Taylor, 2016; Grinblat et al., 2016; Krizhevsky et al., 2012). CNN can automatically learn appropriate features from training datasets instead of manual feature extraction. CNN has been proven to be a good option for plant disease recognition (Ferentinos, 2018; Mohanty et al., 2016). These applications of CNN based plant diseases diagnosis have been performed leaf-wise, assuming that the symptoms on a single leaf belong to one disease. However, multiple diseases may occur simultaneously in field conditions and symptoms of different diseases can be present on the same leaf. This may significantly influence the accuracy of the leaf-wise plant disease diagnosis (Barbedo, 2016; Bock et al., 2009). The

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symptom-wise plant disease recognition appears therefore to be a necessary supplement.

The objective of this paper was to apply state of the art deep learning techniques to the recognition of cucumber diseases using visible leaf symptom images. A deep convolutional neural network (DCNN) was utilized to conduct symptom-wise classification so that plant disease recognition can be achieved without the influence of multiple diseases symptoms presented on one leaf. An image dataset containing symptom images of four cucumber diseases, i.e., anthracnose, downy mildew, powdery mildew and target leaf spots, was constructed. Based on the dataset, the DCNN was trained to recognize cucumber diseases.

2. Material and methods

2.1. Image datasets

The dataset used for recognition was composed of symptom images of anthracnose (*Colletotrichum orbiculare*), downy mildew (*Pseudoperonospora cubensis*), powdery mildew (*Golovinomyces cichoracearum*) and target leaf spots (*Corynespora cassiicola*). Some disease images are shown in Fig. 1. Symptom images of anthracnose, target leaf spots, and part of downy mildew were segmented from images downloaded from the Internet (PlantVillage, https://plantvillage.org/. Forestry Images, https://www.forestryimages.org/). The remaining symptom images were segmented from images captured using a digital camera (Nikon Coolpix S3100) under field conditions at the Greenhouse No.5 of the Agricultural Scientific Innovation Base, Tianjin Academy of Agricultural Sciences, Tianjin, China. Images were obtained in a 2592 × 1944 pixel spatial resolution with flash always off and without optical or digital zoom. The images were captured between 8:00 and 17:00 on April 20, 2016. All the images were resized to 800 × 600 pixels prior to image analysis to reduce the computational cost and improve the image processing efficiency.

Symptom images were segmented using a disease symptom segmentation method which combined a comprehensive color feature with region growing. The comprehensive color feature (CCF) consists of three color components, Excess Red Index (ExR), H component of HSV color space and b* component of L*a*b* color space, which implements powerful discrimination of disease spots and clutter background. Then an interactive region growing method based on the color feature was used to achieve robust and fast symptom image segmentation (Fig. 2). For more details about the method, readers are referred to Ma et al., (2017). Since the disease symptoms were small in area, all symptom images were resized to 20 × 20 × 3 for the recognition. A dataset containing 1184 symptom images was constructed. The number of symptom images for the four cucumber diseases, i.e., anthracnose, downy mildew, powdery mildew and target leaf spots, was 229, 415, 332, and 208 respectively. The constructed dataset was then divided into training and test datasets in a ratio of 8:2 by randomly selecting images from the dataset. Of the symptom images in the training dataset, 80% was used for training and 20% was used for validation.

Data augmentation can help enlarge the datasets for recognition and decrease the chance of overfitting (Barré et al., 2017; Grinblat et al., 2016). Because the datasets in this paper were relatively small, data augmentation was performed on the original datasets. Many techniques can be used for data augmentation, such as PCA jittering, random crop, image rotation and affine transformations (Dyrmann et al., 2016; Krizhevsky et al., 2012). Given the small size of the input symptom images, the augmentation method in this paper adopted transformations that would not reduce the size of input images. The augmentation method in this paper was to rotate the original datasets by 90, 180 and 270 degrees and flip horizontally and vertically. This produced 12 augmented datasets.

2.2. The deep convolutional neural network

The MatConvNet (Vedaldi & Lenc, 2015), a MATLAB (MathWorks Inc., USA) toolbox, was used to implement the CNN. The architecture of the DCNN is depicted in Fig. 3. It can be seen that an architecture similar to Lenet5 (Lecun et al., 1998) was adopted because it was fast to deploy and powerful in small-scale image recognition tasks (Ding & Taylor, 2016). Starting with the input layer formed by the symptom images in RGB color space with a size of 20 × 20 × 3, the DCNN was composed of four modules. The first module consisted of a Convolutional Layer that had 20 filters with a size of 5 × 5, and a Max-pooling Layer with the filter that had a size of 2 × 2 and a stride of 2. The Max-pooling Layer was applied to perform downsampling operations, i.e. shrinking the feature maps along both width and height by a factor of two (Barré et al., 2017). The second module consisted of a Convolutional Layer that had 100 filters with a size of 3 × 3, and a Max-pooling Layer with the filter that had a size of 2 × 2 and a stride of 2. The third module consisted of a Convolutional Layer that had 1000 filters with a size of 3 × 3. The last module of the DCNN consisted of a Fully Connected Layer with 1500 neurons. The output layer had four neurons representing the four cucumber diseases, i.e. anthracnose, downy mildew, powdery mildew and target leaf spots. Given the output layer, SoftMax function was used to calculate the estimated probability of the four categories of cucumber diseases.

The DCNN was trained on a NVIDIA Quadro P4000 (8 GB memory) with CUDA 9.0. The stochastic gradient descent with momentum (SGDM) was used to optimize the network weights. The learning rate was initialized as 0.001 and dropped every 20 epochs by a drop factor of 0.1. The momentum was set to 0.9 and remained constant for the training processing. A mini-batch of 128 was used. The maximum number of epochs used for training was set to 800.

2.3. Evaluation of the DCNN

Conventional classifiers used for the comparative tests with the DCNN were Random Forests (RF) (Breiman, 2001), and Support Vector Machines (SVM) (Cortes & Vapnik, 1995). AlexNet (Krizhevsky et al., 2012) was also adopted for comparison by transfer learning. For the conventional classifiers that were compared to the DCNN, recognition was achieved by following the pipelined procedures. After symptom image segmentation, feature extraction was performed, extracting color and texture features to distinguish the symptoms caused by different diseases. The color features consisted of the mean and variance of the nine channels from three color spaces, including R, G, B from RGB color space, H, S, V, from HSV color space, and L, a*, b*, from CIEL*a*b*

(a) Anthracnose (b) Downy mildew (c) Powdery mildew (d) Target leaf spots

Fig. 1. Images of the four cucumber diseases.