Basic Study of Automated Diagnosis of Viral Plant Diseases Using Convolutional Neural Networks

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Abstract. Detecting plant diseases is usually difficult without an experts' knowledge. Therefore, fast and accurate automated diagnostic methods are highly desired in agricultural fields. Several studies on automated plant disease diagnosis have been conducted using machine learning methods. However, with these methods, it can be difficult to detect regions of interest, (ROIs) and to design and implement efficient parameters. In this study, we present a novel plant disease detection system based on convolutional neural networks (CNN). Using only training images, CNN can automatically acquire the requisite features for classification, and achieve high classification performance. We used a total of 800 cucumber leaf images to train CNN using our innovative techniques. Under the 4-fold cross-validation strategy, the proposed CNN-based system (which also extends the training dataset by generating additional images) achieves an average accuracy of 94.9 % in classifying cucumbers into two typical disease classes and a non-diseased class.

1 Introduction

Plant diseases have a devastating effect on agricultural products. The monetary loss caused by plant diseases is estimated to be $30–50 billion annually [1]. Viral plant diseases in particular cause significant damage to agriculture. Because there is no treatment for these diseases, infected plants must be removed as quickly as possible to avoid secondary infection; thus, early detection is required. As a result, the number of diagnostic requests to prefectural agricultural agencies in Japan has been increasing. In general, plant diagnosis by experts is expensive, and viral plant diseases are occasionally missed or misdiagnosed because their symptoms are difficult to identify. Thus, plant pathologists have shared their knowledge with farmers through farming communities [2].

To improve diagnostic results, several studies on machine learning-based automated plant diagnosis have been conducted [3–7]. Huang proposed a recognition method based on a multi-layer perceptron to identify bacterial soft rot,

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bacterial brown spot and Phytophthora black rot appearing on orchids, and reported an average classification accuracy of 89.6 % [4]. Phadikar et al. proposed a system based on self-organized maps; it achieved over 70 % accuracy in distinguishing between rice blast and brown spot appearing on rice leaves [5]. Zhang et al. utilized a support vector machine for distinguishing downy mildew, brown spot, and angular leaf spot on cucumbers, and attained an accuracy of 83.3 % [6]. Xu et al. analyzed nutrient deficiency in tomatoes by means of k-nearest neighbor clustering based on leaf color and texture. They detected nitrogen and potassium deficiencies with probabilities of 90 % and 85 %, respectively [7]. However, these methods are faced with several difficulties, involving the detection of regions of interest (ROIs) for subsequent processing, the design and implementation of efficient diagnosis parameters, and so on. Accordingly, it is quite difficult to apply these techniques to other purposes (i.e. detecting other diseases or detecting diseases on different plants).

On the other hand, convolutional neural networks (CNNs) are widely percieved as one of the most promising classification techniques among machine learning fields. The most attractive advantage of CNN is their ability to acquire requisite features for the classification from the images automatically during their learning processes. Recently, CNN have demonstrated excellent performance in large scale general image classification tasks [8], traffic sign recognition [9], leaf classification [10], and so on.

In this paper, we introduce an innovative technique to enhance the learning ability of a CNN training schema, and propose an automated plant disease diagnosis system based on these enhancements. In this study, we develop a plant disease diagnosis system that uses leaf images to detect two harmful viral infections that afflict cucumber plants (MYSV: melon yellow spot virus, and ZYMV: zucchini yellow mosaic virus). We designed our system to receive, as input, a leaf image from the plant to be investigated, and to yield a diagnostic result as output for practical use. Because CNNs are highly expected to acquire "features of the disease" automatically, our system is designed to perform accurate recognition without troublesome pre-processing or parameter design. We expect that farmers will be able to detect early-stage infections by using our system in conjunction with a common digital camera.

2 Plant Disease Detection System

2.1 Material and Pre-processing

Images of cucumber leaves were supplied by Saitama Prefectural Agriculture and Forestry Research Center, Japan. The dataset consists of 800 cucumber leaf images (300 with MYSV, 200 with ZYMV, and 300 non-diseased); the leaves are situated in the center of the images. OLYMPUS 5P560UZ and SONY DSV-RX100 color digital cameras were used for capturing leaf images with resolutions of 2048×1536 and 2736×1824 pixels, respectively. All pre-processing procedures are shown in Fig. 1.

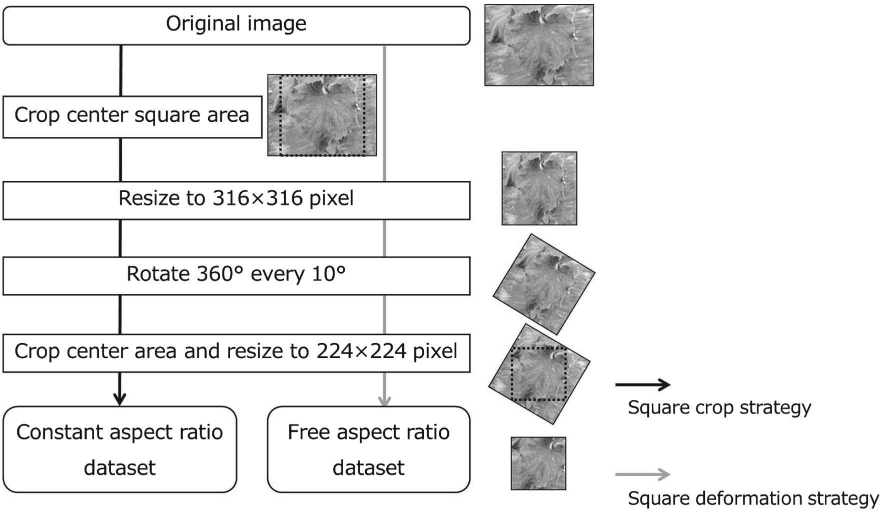


Fig. 1. Schematics of pre-processing.

We designed our system to accept images from various types of digital cameras, to accommodate images captured in different sizes and aspect ratios. In our tests, we used two pre-processing strategies, namely (1) square crop, and (2) square deformation. In the (1) square crop strategy, we select a square region from the center of the photographed image. Thus, the side regions of the images are removed, because we assume that leaf images will be photographed with the area of interest situated in the center. In the (2) square deformation strategy, we forcibly deform the photographed image into a 1:1 aspect ratio with bi-linear interpolation. These pre-processing strategies created two types of datasets: the "constant aspect ratio dataset" and "free aspect ratio dataset", respectively. Subsequently, each leaf image in the training dataset was artificially extended 36 times by rotating the image with 10 degree increments. This rotation process helps CNN to acquire various types of local features, because CNN learn them using convolutional integration. Therefore, we expect this rotation process to help improve classification performance. Finally, we resized these images into 224×224 pixels using bi-linear interpolation.

2.2 Architecture

Our CNN-based plant disease detection system, which uses the Caffe framework [11], includes convolution layers (Conv), pooling layers (Pool), and local contrast normalization layers (Norm). Each neuron in our network is activated by a rectified linear unit (ReLU) function [12]. An illustration and details of our CNN architecture are shown in Fig. 2 and Table 1. In Fig. 2, we omitted "Pool" and "Norm" to enhance clarity.

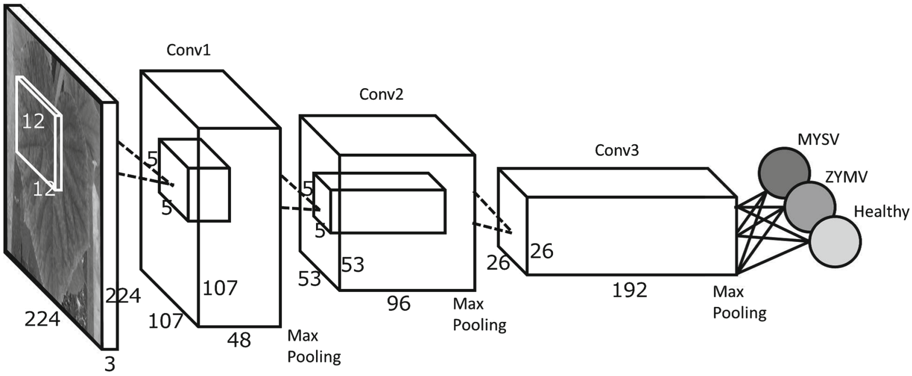


Fig. 2. Illustration of our CNN architecture.

Table 1. Details of our CNN architecture.

Layer name	Function	Weight filter sizes	Output tensor†	Notes
Input	-		$3 \times 224 \times 224$	
Conv1	Convolution	12×12	$3 \times 107 \times 107$	stride = 2, bias = 0
Pool1	Max Pooling	3×3	$48 \times 53 \times 53$	stride = 2
Norm1	Normalization	5×5	$48 \times 53 \times 53$	
Conv2	Convolution	5×5	$96 \times 53 \times 53$	stride=2, bias = 1
Pool2	Max Pooling	3×3	$96 \times 26 \times 26$	stride = 2
Norm2	Normalization	5×5	$96 \times 26 \times 26$	
Conv3	Convolution	5×5	$192 \times 24 \times 24$	stride = 2, bias = 0
Pool3	Max Pooling	3×3	$192 \times 12 \times 12$	stride = 2
Norm3	Normalization	5×5	$192 \times 12 \times 12$	
Dense	Full Connection		$3 \times 1 \times 1$	bias = 0

† : # of color channels (or # of feature maps) × width of the map × height of the map

The convolution layer convolves the input image (or the output of the previous layer) with tunable weight filters (i.e. kernel), in order to extract local features. By applying various types of weight filters, CNN acquire shift invariant and scale invariant local features from the input. The pooling layer summarizes the output of the previous layer and acquires the object's translation invariance. In our system, we applied max-pooling in each pooling layer. The local contrast normalization layer subtracts the means of neighborhood pixels from the target pixels and divides the subtracted pixels by the standard deviations of the neighborhood pixels. This layer enables the system to compensate for variations among images captured under different conditions.

3 Experiments

We performed three experiments for each dataset to estimate the effectiveness of our method. Experimental conditions are shown in Table 2. Experiment-1 uses the normal CNN model for the classification (as a performance baseline). Experiment-2's training epoch is adjusted with our proposed method (Experiment-3). Experiment-3 tests our proposed method. Note again that the proposed method rotates the input image every 10 degrees, to generate a total of 36 training images. All of these experiments were evaluated under the 4-fold cross-validation strategy.

Table 2. Experimental conditions.

	rotation	# of training epochs
Experiment-1	no	40
Experiment-2	no	1440(40×36)
Experiment-3(proposed)	yes	40

Tables 3 and 4 summarizes the system's classification performance when differentiating between plant diseases with the constant aspect ratio and free aspect ratio datasets.

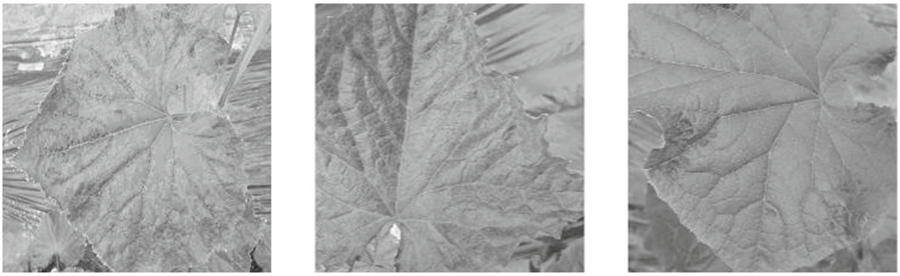
Table 3. Differentiation results (Constant aspects ratio dataset).

	Accuracy(%)	Sensitivity for MYSV (%)	Sensitivity for ZYMV (%)	Specificity (%)
Experiment-1	78.5	74.0	76.0	84.7
Experiment-2	83.1	82.7	76.5	88.0
Experiment-3(proposed)	**94.9**	**96.3**	**89.5**	**97.0**

Table 4. Differentiation results (Free aspects ratio dataset).

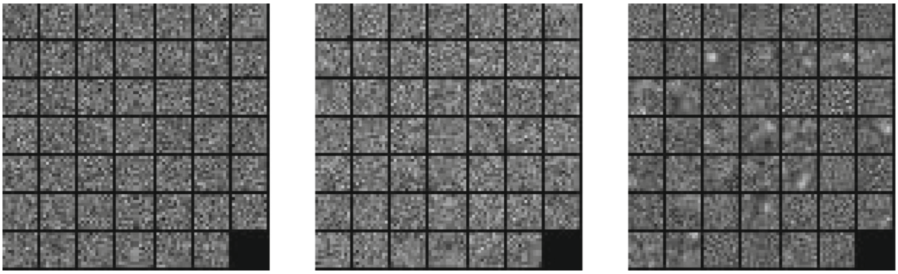
	Accuracy(%)	Sensitivity for MYSV (%)	Sensitivity for ZYMV (%)	Specificity(%)
Experiment-1	77.0	73.0	74.5	82.7
Experiment-2	80.5	78.6	77.5	84.3
Experiment-3(proposed)	**92.5**	**95.3**	**87.0**	**92.0**

Figure 3 shows examples of correctly classified leaf images (a:MYSV, b:ZYMV and c:Non-diseased) from the constant aspect ratio dataset. Figure 4 shows weight filters obtained by the first convolution layer in Experiments-1, 2 and 3.



(a) (b) (c)

Fig. 3. An example of (a) MYSV, (b) ZYMV, (c) Normal leaves.



(a) (b) (c)

Fig. 4. Weights of kernel obtained in (a) Experiment-1, (b) Experiment-2, (c) Experiment-3.

4 Discussion

The results in Tables 3 and 4 show that CNN could solve difficult differentiation problems without segmenting the ROI (i.e. leaf areas) or extracting the requisite features. For both datasets, the proposed method (Experiment-3) achieved the best performance. From these results, we confirmed that expanding the dataset by rotating the images contributed significantly to enhancing the system's differentiation ability. Furthermore, the rotation created a larger variety of weight maps (Fig. 4(c)) than ordinal cases (Fig. 4(a) and (b)). On the other hand, we can also see the results from the constant aspect ratio dataset showed superior performance compared to the results from the other dataset, while the differences were limited. These facts imply that, as expected, CNN acquired various types of local features as a result of the rotation process. We can conclude that CNN learned effective features of plant diseases that are robust to geometrical distortions; in addition, we conclude that it not necessary to consider the aspect ratio of the camera, because of the effectiveness of the data expansion process.

We note that our dataset was obtained from a single source, and that the disease types were limited in this study. In practical use, there will be undesired effects appearing in the images, such as sunlight, drooping, and others effects caused by various situations. We will continue to improve our system, to enable it to distinguish a greater variety of diseases under various photographic conditions.

5 Conclusion

In this study, we proposed a novel detection system for viral plant disease using CNN and confirmed its effectiveness. We also confirmed that our strategy for training the CNN significantly improved its classification accuracy. We expect that this will free the system's users from paying a extra attention to the details of the photographic conditions. We will develop our next system in near future. We expect that our future system will make a significant contribution to the agricultural field.

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