Classification of Growth Conditions in Paprika Leaf Using Deep Neural Network and Hyperspectral Images

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***Abstract*— Recently, the analysis research of crop's growth condition is done with the use of hyperspectral image. However, there are many factors such as physical factors and complexity of data make the hyperspectral image analysis difficult. This study presents the classification method of crop's leaf growth condition using hyperspectral image(HSI) and Deep Neural Network(DNN). Major information of plants is acquired through hyperspectral image, and the preprocessing is followed for the information to be used for DNN learning. The preprocessing is used by cutting the data in small patch size and rotating it for the models to be operated effectively. In the experiment, paprika leaves are divided into four types of leaves and backgrounds such as normal and damaged by harmful insects, and the result of the experiment showed 90.9% of accuracy. The presented method has advantages that the data generation method does not affect DNN and can classify various growth conditions that are difficult in the existing RGB image**.

Keywords—hyperspectral image, deep neural network, growth condition, image classification, paprika

I. Introduction

Among the many factors which have a direct and indirect effect on the crop yield, it is very useful to monitor physical condition and detect diseases and pests because they can reduce damage due to diseases and effectively promote growth[1]. Especially, they have recently and widely been utilized including analyses on growth condition of plants, the detection of diseases and pests, modeling, etc. by using hyperspectral imaging(HSI)[1]. And as HSI can be utilized as input data of deep neural network(DNN), the supervised classifier which can automatically extract and learn the characteristics got to be composed[2].

For paprika, a representative crop of protected horticulture, there are diseases that the leaves are blighted when damage is serious because leaf blight that leaves and ends of fruits usually get dark and rotten and small and white spots appear on the surface of the leaves by harmful insects[3]. Eventually, symptoms of diseases usually appear on leaves and the early detection is very important to make paprika grow well.

In this paper, we try to suggest crop's growth condition classification method by using HSI and DNN. In the experiment, paprika leaves were classified into 4 kinds of normal and insect pest leaves, etc. and the background. And the result of the experiment showed the accuracy of 90.9%.

II. Growth Condition Classification Technique

This chapter suggests crop's growth condition classification method by using HSI and DNN. Figure 1 shows the overall procedure. Crop's growth condition includes a normal leaf, a young leaf, a diseased leaf, an insect pest leaf, and the background as 5 conditions. Here, a young leaf came out 20 days before there are leaves on the top of a crop. The leaf which came out after the day is classified into the normal leaf.

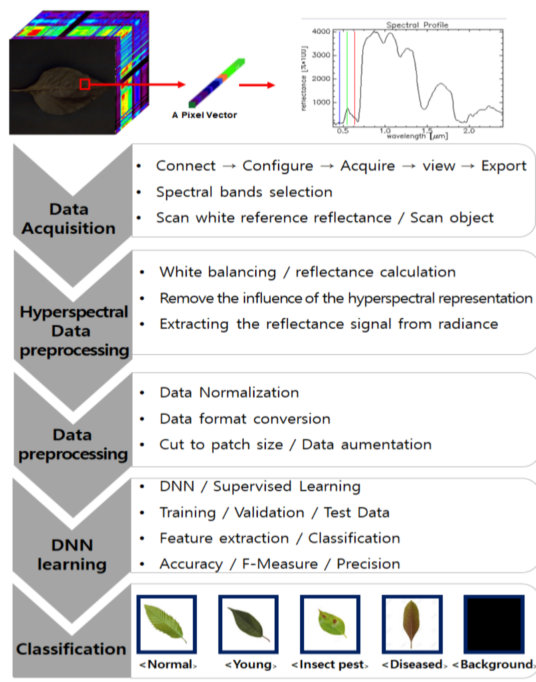

Fig. 1. Overall procedure of growth condition classification

A. Acquisition stage of HSI data

HSI of paprika leaves was done in a greenhouse located in Gunsan, Jeollabuk-do, Republic of Korea on September 2019. For the hyperspectral camera system, Snapscan VNIR(IMEC In c.) with a snapscan sensor was used and the data was obtained i n the room that 2 sets of halogen lamps (FOMEX H1000, Halo gen 650W) were installed.

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B. Data preprocessing stage for input of DNN

In order to classify leaves according to the conditions, the modification of VGG-16[4], a kind of DNN, is used. Generally, it is well known that deep learning basically requires large mounts of data. However, the data set can be insufficient because it takes a lot of time for HSI to be done and the equipment is very expensive. Therefore, the original images according to the growth conditions of Table 1 are not immediately used as the learning data in this paper and the data required for learning were secured by cutting them to be small patch sizes through the data preprocessing process.

TABLE I. NUMBER OF IMAGES FOR GROWTH CONDITIONS

Leaf condition	Number of images
Normal leaf	51
Young leaf	50
Diseased leaf	55
Insect pest leaf	50
Background	21
Total	227

The learning data are not insufficient because the patches including diseases and insect pests include data related to the small areas of the leaves. Therefore, for the diseased and insect pest leaves, the number of patches is increased by rotating the only areas with the disease and insect pest 15 degrees and extract them from the original images like Figure 2. The patches cut by rotating them can be treated as new patches because the shapes damaged by the disease and insect pest less depend on the rotation. Table 2 represents the number of patches used in DNN after the data preprocessing process.

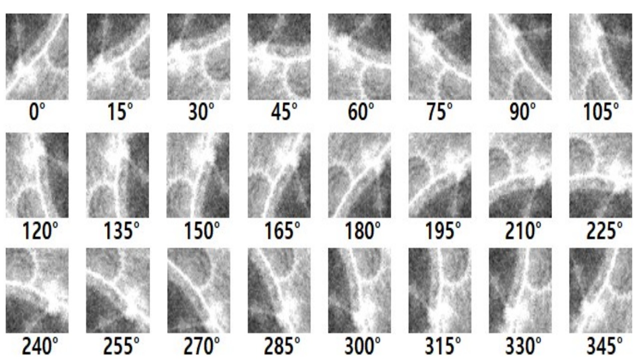

Fig. 2. Patches taken from the location of disease and their sampled images

TABLE II. NUMBER OF PATCHES USED FOR DNN

Usage	Number of patches
Training data	25,000 (5,000 per class)
Validation data	5,000 (1,000 per class)
Test data	5,000 (1,000 per class)
Total	35,000 (7,000 per class)

C. Classifier learning stage

The structure of DNN used in the model is the modification of VGG-16. It consists of 10 convolution layers, 4 max pooling layers, and 2 fully connected layers as shown in Figure 3. For the activation functions, ReLU is used in the hidden layer and soft-max is done in the output layer. Images are classified by using the parameters learned in the extraction stage with ReLU and soft-max.

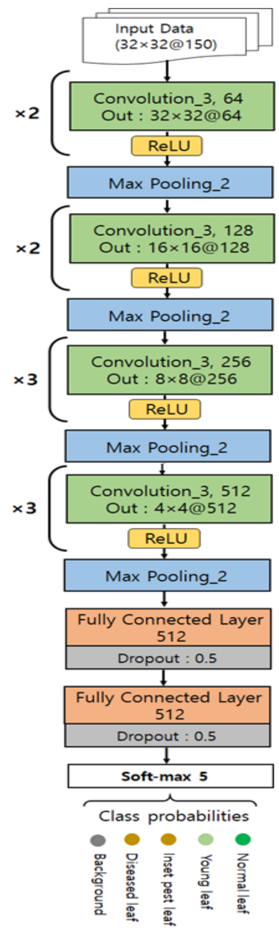

Fig. 3. Structure of DNN

III. EXPERIMENTAL RESULTS

A. Experimental environment

The deep learning environment for applying the crop growth status classification method is as follows. The CPU used Intel Xeon E5-2640 v4, and the GPU responsible for learning used Nvidia Geforce GTX 1080 Ti. It consists of 64GB of memory and uses Tensorflow-GPU, a deep learning framework that can be quickly implemented in the Windows 10 environment. We obtained hyperspectral images of the leaf conditions of 4 kinds with the method suggested in Figure 4. Each image has the sizes of 1280W × 800H × 150C and 585MB.

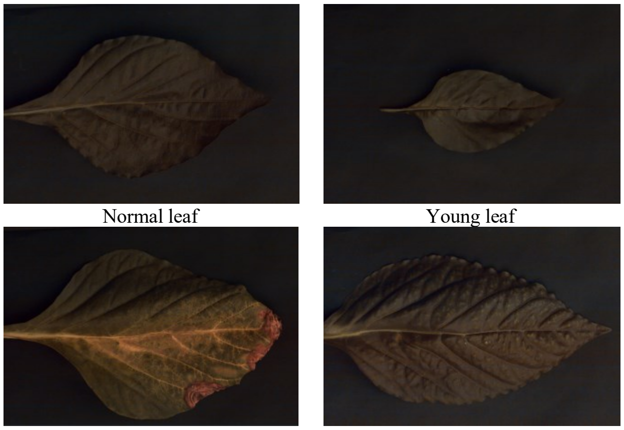

Fig. 4. Hyperspectral image based on leaf condition

B. *Results of classification results*

The training data set of DNN consists of 25,000 patches as indicated in Table 2. The drop out rate of the fully connected layer is 0.5 and the mini-batch size is 100.

TABLE III. ACCURACY OF TEST DATA FOR VARIOUS EXPERIMENTS

Classifier		Accuracy(%)
VGG-16 modified	ReLU	90.9
	PReLU($\alpha = 0.01$)	89.8
VGG-16[5]	ReLU	86.4
	PReLU($\alpha = 0.01$)	86.9
ConvNet[5] (13 Layers)	ReLU	82.3
	PReLU($\alpha = 0.01$)	81.7

Table 3 shows the result which learned 3 models by cutting images according to growth conditions of paprika leaves. For each model, ReLU and PReLU(α = 0.01) were used as the nonlinear activation functions and the VGG-16 modified shows the highest accuracy as 90.9%. For algorithmic performance, precision, recall, F-measure, and accuracy were evaluated based on the confusion matrix.

TABLE IV. CONFUSION MATRIXES OF CLASSIFICATION RESULTS

Actual / Predicted	Normal leaf	Young leaf	Diseased leaf	Insect pest leaf	Back ground
Normal leaf	755	126	104	15	0
Young leaf	96	613	281	6	4
Diseased leaf	10	15	9	895	71
Insect pest leaf	125	261	605	9	0
Background	0	0	0	0	1,000

Table 4 shows the classification result of the test patches by the confusion matrix to evaluate the algorithm. The results evaluated according to each indicator based on this are shown in Table 5. The evaluation indicators can be found that the accuracy is well classified in order of the diseased leaf, the normal leaf, the young leaf, and the insect pest leaf.

TABLE V. EVALUATION MATRIXES OF CLASSIFICATION RESULTS

E.I.[a] / L.C.[b]	Precision	Recall	F-measure	Accuracy
Normal leaf	76.6	75.5	76.0	90.5
Young leaf	60.4	61.3	60.8	84.2
Diseased leaf	96.8	89.5	93.0	97.3
Insect pest leaf	60.6	60.5	60.5	84.2
Background	93.0	100.0	96.4	98.5
Average	77.5	77.4	77.4	90.9

a. Evaluation Indexes

b. Leaf Condition

And the young and insect pest leaves were evaluated that the accuracy, precision, and recall are relatively lower than those of other conditions. It's because the two leave's spectral albedo is very similar with each other. And the method to increase recall must be used because damage to crops can be serious due to diseases as insects and pests cannot early be judged when the leaves damaged by insects are misclassified.

IV. CONCLUSION

In this paper, we suggested growth condition of paprika classification method by utilizing HSI and DNN and the results of the initial experiment by applying this to it. The experiment shows that the method to extract patches and create data does not a burden to DNN and well preserve data necessary for classifying paprika leaves growth conditions. And DNN can be found to classify leaves comparatively well under the condition of many spectrum bands with HSI.

The suggested method does not stay at classifying patches and can apply semantic segmentation which classifies each patch's classes by predicting its labels. And the classification models of crop's growth conditions can diagnose their conditions more accurately and quickly as the method is applied to crop's stem and fruits.

ACKNOWLEDGEMENTS

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