Crops Disease Diagnosing using Image-based Deep Learning Mechanism

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***Abstract*— To increase the crop productivity environmental factors or product resource, such as temperature, humidity, labor and electrical costs are important. However, above all, crop disease is the crucial factor and causes 20-30% reduction of the productivity in case of its infection. Thus, the disease of the crop is much more important factor affecting the productivity of the crops. Therefore, the farmer concentrates on the cause of the disease in the crops during its growth, but it is not easy to recognize the disease on the spot. Until now, they just relied on the opinion of the experts or their own experiences when the disease is doubtful. However, it triggers a decrease in productivity as no taking appropriate action and time. In this paper, to address this problem we provide the mechanism, which dynamically analyses the images of the disease. The analysis result is immediately sent to the farmer required the decision and then feedback from the farmer is reflected to the model. The mechanism performs the diagnosing of the disease, especially for the strawberry fruits and leaves, with data set of images using deep learning. Thus, it encourages increasing of the productivity through the fast recognition of disease and the consequent action.**

***Keywords*— Deep Learning, Image-based, Crops, Strawberry disease, CNN, diagnosing.**

I. Introduction

Recently technologies are converged in various industry fields each other. For example, using ICT (Information and Communication Technologies) in agriculture boosts the productivity of the crop. That is, smart farming combined application of ICT solutions employed the equipment such as environmental devices, i.e. IoT (Internet of Things) sensors, cameras, drones, robots, and so on, delivers more productive farming. Thus, it provides the convenience to farmers who can automatically control, for example, their greenhouse's inside facilities, side window or ceiling window at the long distance. In addition, it helps farmers make a decision to manage or operate their farms. Thus, they can increase the productivity and improve economic returns as they use those ICT solutions.

To increase the crop productivity environmental factors or product resource, such as temperature, humidity, labor and electrical costs are important. However, above all, crop disease is the crucial factor and causes 20-30% reduction of the productivity in case of its infection. Diseases in crops cause major production and economic losses in agricultural industry worldwide. To keep sustainable agriculture, the monitoring of health of crops and detection of diseases are more important. Furthermore, if the disease detection is quickly informed, it can make easy the control of disease and can improve productivity [3].

Considering it, the disease of crop is the important factor affecting the productivity of the crop. Therefore, the famer concentrates on the cause of the disease in crop during its growth, but it is not easy to recognize the disease on the spot. Until now, they just relied on the opinion of the experts or their own experiences when the disease is doubtful. However, it triggers a decrease in productivity as no taking appropriate action and time.

In the aspect about the crop disease, the smart farming can also provide more benefits for the recognition of the disease and offering the related information compared to conventional decision-making method. For theses, nowadays much more intelligent techniques are emerged. Currently, according as the data such as text, images, and videos is getting huge, deep learning approach is growing trends. Large amount of data gives better analysis results, i.e., can identify the disease well.

In this paper, we address the mechanism to diagnose the disease when the famer sends the strawberry leaf, fruit images taken by smartphone to the analysis engine system. For that, we present an approach based on CNN (convolution neural network) to classify the healthy and disease strawberry images. CNN is to gain the accuracy of classification of the disease, get the promising results, avoid the handcraft features and stand on self-taught features reducing [4]. We also use TensorFlow and Keras to build the neural networks of the model and train, evaluate the data set.

For the immediate recognition of the diseases, we provide the mechanism, which dynamically analyses the images of the disease. The analysis result is just sent to the farmer required the decision and then feedback from the farmer is reflected to the model. The mechanism performs the diagnosing of the disease with dataset of images using deep learning. Thus, it encourage increasing of the productivity through the fast recognition of disease and the consequent action.

According to kind of crops, it is important what part of the plant such as fruit, leave or stem have to be classified. Therefore, we researched their characteristics and then performs data aggregation and deep learning and handles its result to classify the strawberry disease. We have intentionally caused the disease of the strawberry using test bed to have much more images and have took the picture of the disease strawberry for training the model and testing using the images.

The feedback from the farmers about the result of the required disease image will improve the classification model. As a result, the proposed whole mechanism can dynamically analyses the images of the disease at farm spot receiving the disease image from the famer and they can easily access the diagnosing system by smartphone application.

We describe the related work and the proposed system construction for disease classification in Section II and Section III respectively. Disease identification steps are described in Section IV. Experimental results are also described in Section V. At last, we make the conclusions in Section VI.

II. Related Work

There were many previous works about deep learning. However, these studies just mentioned that the dataset is fixing at the beginning of model training and evaluation. After testing the required image currently the result is provided but it is not fed back to improve the model in real-time.

Sharadab et al [1] mentioned about deep learning to detect image-based plant disease. They also used CNN to train the model and public data set of 54,306 images of diseased and healthy plant leaves. The model is to identify 14 crop species and 26 diseases. They just focused on comparison of progression of mean F1 score across all experiments, grouped by train-test set splits.

Scientists from EPFL and Penn State University have trained a deep-learning neural network that can accurately diagnose crop diseases by "seeing" and analyzing normal photographs of individual plants. The algorithm, which is part of the PlantVillage project, represents the first successful proof of concept for disease diagnosis through smartphone photos, and will be used to build an app for farmers [5].

Jihen Amara [6] also introduced the mechanism to identify and to classify the diseases of banana leaves using the deep learning technology. In addition, they conducted a set of experiments using the data set, which is offering from the PlantVillage project [7] including real dataset of banana disease. However, they do not provide a mechanism that offers the feedback of the result to improve dynamically the model

III. Proposed System Architecture

To address the proposed disease diagnosing of the crops, we construct the system architecture to classify and identify strawberry diseases automatically with two main components as shown in Fig. 1. First, data aggregation module receives images for training and testing, preprocesses the received images to translate into binary data and refines it. Those aggregating images are generally acquired from strawberry greenhouses of the test bed induced the diseases by standard digital camera or smartphone, while they are acquired from strawberry greenhouses of the farmer who required the disease identification by his smartphone.

Secondly, the disease learning and testing engine constructs the model and performs the disease identification using the data from data aggregation module, which is stored in the big data hadoop cluster consisted of name and data nodes.

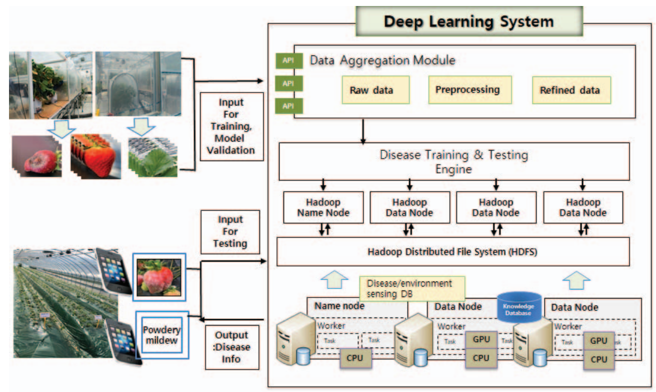


Figure 1. Proposed system architecture

We have the dataset, which is separated into training, validation and testing set and each set has its own data set of parts of strawberry plant. Dataset of parts of strawberry plant includes healthy and four types of disease images to identify. For our experiments, we used various data set of color-based images for model training and testing images of healthy, infected leaf or fruit part of strawberry. Fig. 2 shows the test bed including chambers to obtain data set for the training. Especially, chambers are to have infected fruits, leaves images. We make chambers so to cause intentionally the disease that to get the infected fruit and leaf images. After cultivating the fungus, we used it on leaves and fruits in the chamber to cause the disease. The chamber has many environmental sensors and appliances such as humidifier, heater and so on to cause the disease from healthy leaves and fruits.

(a) Chambers to cause the disease

(b) Cultivating the fungus (c) Inside of the chamber

Figure 2. Test bed to obtain the healthy and disease strawberry images

IV. Disease Identification Procedures

Data including images are getting much larger the analysis using deep learning is getting more popular lately. CNN for deep learning are well known for analyzing visual imagery and can easily extract appropriate features from with multi-layer hierarchy. It is also able to perform the identification and classification of the required objects easily with just minimal preprocessing. In addition, CNN is to get the promising results, avoid the handcraft features and stand on self-taught features reducing. Therefore, we used CNN to gain the accuracy of classification of the disease.

Fig. 3 shows identification steps of strawberry diseases including CNN, which consists of an input layer, several hidden layers and output layer. The hidden layers include 5 convolution layers, 5 pooling layers and 2 fully connected layers. The learning rate is 0.1. For the model construction, first, data are aggregated for training, which are converted an image into a binary byte file and distorted as image preprocessing. Then it is defined to extract features from each input image through several convolution and pooling layers. Subsequently, to classify the diseases defining of hypothesis and cost function are followed by using the fully connected layers. At last, to classify the diseases the softmax activation function is computed and it is previously determined. The rectified nonlinear activation function (ReLU) as activation function is performed after every convolution.

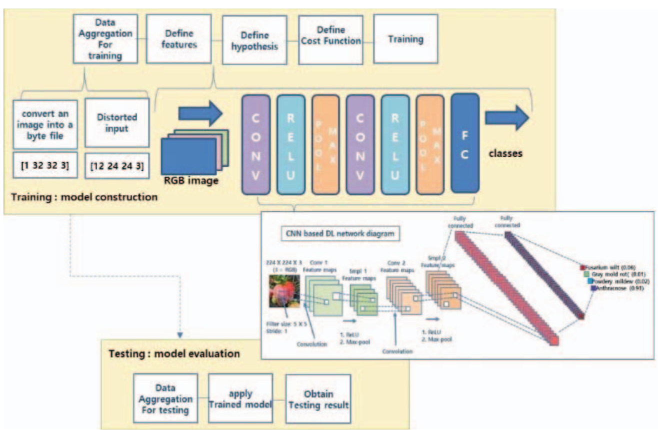


Figure 3. Identification steps of strawberry diseases

In addition, for the model evaluation, data aggregation is performed the same as the model construction. Application of training model is also conducted and the testing result is finally obtained.

V. Experimental Results

We limit our experiment to target classification of fruits and leaves of healthy and disease strawberries such as powdery mildew, anthracnose, fusarium wilt, and gray mold rot. Powdery mildew of them, for example, is considering a moderate disease that can affect fruit, leaves and flowers [2]. This disease produces white patches of web-like growth that develop on both the lower and upper leaf surface. In this paper, we just focus on fruits and leaves of the strawberry and use the images as shown in Table 1. Table 1 shows a set of experiments using the data set, the number of images with which we tried many cases and the results of the training used it. Actually, we could not get enough images early at the beginning of the experiment because it was difficult to get them around us easily. Therefore, we intentionally caused the diseases and then got the images. As shown in it, there is a gradual increase in the number of images.

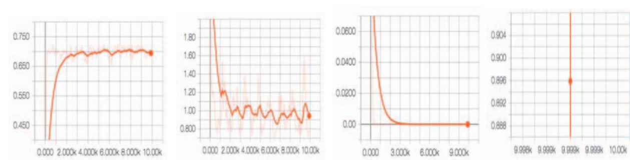
We have built the system with several convolutional and two fully connected networks for recognizing the diseased strawberry leaves. Our model performs up to 94% accuracy at beginning of the experiments on a CPU. We have resized the images to 227x227 or 224x224 pixels and trained our model with objective function, which represents the result of the total loss about 0.7 for 10.00k times based on kernel size 15x15 and stride size 5x5, as shown in Fig. 4.

TABLE I. A SET OF EXPERIMENTS USING THE DATA SET

	Training Dataset		Testing Dataset		The total number of images	Training Loss	Training accuracy
	Healthy Images	Disease Images	Healthy Images	Disease Images			
Fruit : Powdery mildew	158	147	158	147	610	0.7	0.94
Fruit : Powdery mildew	135	345	158	147	785	0.78	0.90
Leaf : Anthracnos	1188	178	361	96	1823	0.73	0.833
Leaf : Fusarium wilt	1188	284	361	76	1909	0.77	0.866
Leaf : Powdery mildew	1188	1164	361	264	3085	0.02	0.99
Leaf : Powdery mildew, Fusarium wilt	1189	1165, 285	362	265, 77	3343	0.28	0.97
Fruit : Powdery mildew, Gray mold rot	1788	2316, 3277	455	566, 765	9167	0.61	0.92

The learning rate is as shown Fig. 4 and Fig. 4 shows the how the degree of sparsity is in fully connected layer features.

(a) Resized strawberry photos



(b) Sparsity (c) Total loss (d) Learning rate (e) Accuracy

Figure 4. Resized strawberry photos and graphs of experimental results

Fig. 5 shows a few correct labels at random which represents the result of the total loss about 0.1 and accuracy 0.98 of training for epoch 10 using healthy 1189, and powdery mildew 1165, and fusarium wilt 285 leaf images

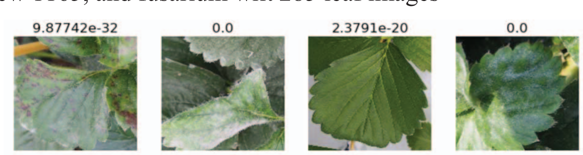
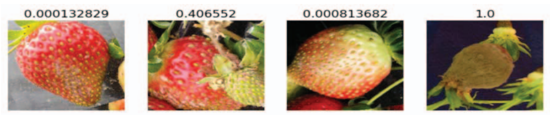


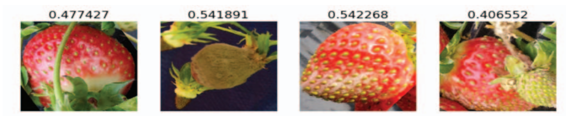
Figure 5. A few correct labels and photos of leaf disease experimental result

Fig. 6 shows a few correct, incorrect and the most uncertain labels at random which represents the result of the total loss about 0.61 and accuracy 0.92 of training for epoch 1 using healthy 1788, and powdery mildew 2316, and gray mold rot 3277 fruit images

(a) A few correct labels at random



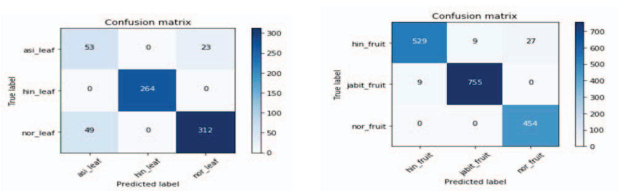
(b) A few incorrect labels at random



(c) The most uncertain labels (ie those with probability closest to 0.5)

Figure 6. Labels and photos of disease fruit experimental result

Fig. 7 shows the confusion matrix to represent the graphical view, which is the common way to analyze the result of a classification model using test dataset of leaf and fruit disease experiments as mentioned above



(a) For leaf disease experiment (b) For fruit disease experiment

Figure 7. Confusion matrix for testing experimental results

We built the neural networks of the model and trained, evaluated the data set with TensorFlow at the beginning of the experiments. To ease and simplify the construction of networks we then adopted VGG16 model with Keras. As shown in Table 1, the number of images among the healthy and disease classes to compare each other is not similar. It means that we cannot get better accuracy. Therefore, we try to get more images to improve the accuracy nowadays.

VI. CONCLUSIONS

In this paper, we addressed the mechanism to diagnose the strawberry disease when the famer sends the strawberry leaf or fruit image taken by smartphone to the analysis engine system. We have built the system with several convolutional and fully connected networks for recognizing the diseased strawberry fruits.

Our model performs up to 92% accuracy for classification of healthy, powdery mildew, and gray mold rot fruit images on a CPU. The model is initially running now on a CPU, as the beginning period of our project and limits the experiment to target classification of healthy and several disease strawberries. In the near future, we will extend our experiment with much more images and aim at many types of diseases, their many parts and the analysis environments to a GPU.

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