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EARLY DETECTION OF STRAWBERRY DISEASES AND PESTS USING DEEP LEARNING

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Abstract. *This paper presents a deep learning-based classification model for identifying strawberry leaf pest infection in order to be able to identify and cope with the symptoms of pests and diseases at an early stage. The strawberry leaf image data was acquired during the growth period. Due to the insufficient amount of data provided, leaf image data was added through web crawling using the Python library and open data provided by AI Hub. The added data was converted to the same image size to build a dataset, and training dataset and test dataset were defined using pseudo-labeling for stable learning. We applied RegNet and EfficientNet as CNN (Convolution Neural Network)-based image network models for repetitive learning and derived prediction accuracy through ensemble learning. The proposed model helps to identify and deal with pests on strawberry leaves in the growing season at an early stage. Therefore, it is expected to lead the increase in production of the agricultural industry and strengthen competitiveness.*

Keywords: Strawberry leaf pest, Deep learning, Ensemble learning, EfficientNet, RegNet

1. **Introduction.** Recently, the era of image data in various fields has come due to the remarkable development of image processing and machine learning technology. Four types of deep learning models (VGG16, Xception, ResNet50, and MobileNet) have been mainly used to reduce overfitting. However, they have shown disappointing accuracy in model performance.

In this paper, we apply EfficientNet, which has recently shown strong performance in image data analysis, to the image data of strawberry leaves in order to detect diseases and pests. We propose a method to reduce errors and improve accuracy by using RegNet in the ensemble method together with EfficientNet. Through the ensemble method, we were able to propose a model with higher accuracy in analyzing plant image data. The deep learning model proposed in this paper helps to identify pests on strawberry leaves and cope with at an early stage. Therefore, it is expected to contribute to the increase in strawberry yield and strengthen the competitiveness of the agricultural industry.

There have been lots of image classification studies on tomato leaves, and image data classification studies using EfficientNet have been performed in a variety of areas. Yu et al. suggested a method for diagnosing crop diseases in advance by comparing and analyzing techniques based on camera sensing [1]. Kim collected tomato leaf data and analyzed the characteristics by comparing and classifying them with a total of four models including EfficientNet [2]. Chung and Tai proposed a method for effectively classifying images by optimally matching the width, depth, and resolution of fruit image data [3]. Han et al. proposed a method of classifying mushroom image data based on EfficientNet to prevent misconceptions about poisonous mushrooms and to implement a service [4]. Atila

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et al. built a PlantVillage dataset containing 55,448 images of 39 classes, and it was confirmed that EfficientNet B5 and B4 model showed better performance than other models [5]. Radosavovic et al. introduced the RegNet model as a new network design model, and the RegNet model showed up to five times faster speeds in GPU than EfficientNet in comparable training settings and failure conditions [6]. Kim imaged a malicious code file and applied it to the EfficientNet model and suggested a method for dividing it by type [7]. Ji used the EfficientNet model to learn image data and predicted the characteristics of difficult-to-distinguish images with very high accuracy [8]. Kim and Choi proposed a pest classification method using the superpixel technique and CNN, and built a model that is practically applicable in the real environment, although it is slightly degraded in terms of performance [9]. Kang et al. used the EfficientNet model to detect cracks in wooden cultural assets and confirmed that it has superior performance to other models [10].

There have been a few existing studies related to strawberry pests. Dong et al. used AlexNet as a model for recognizing images of strawberry disease and pests, and showed good performance and improved image utilization [11]. Xiao et al. showed high accuracy and efficient training time using ResNet model despite training 1306 image data with low epoch [12]. Unlike the previous studies, we applied a new CNN-image network model (RegNet and EfficientNet) as a difference from the existing research, and conducted learning training using pseudo-labeling technology.

The importance of the horticultural crop market in agriculture is growing over time. Among them, strawberries are the largest crops in the market among horticultural crops, and at the same time have high added value. Nevertheless, strawberries are vulnerable to pests, and if not prevented, they can cause great losses not only to the farmers who produce them, but also to the agricultural economy. Consequently, it is required to develop a system model for promptly and accurately confirming the diagnosis of various pests of strawberries.

We used strawberry leaf data acquired during the growth period and crawled disease leaf data additionally. However, due to the lack of leaf image data, it was difficult to proceed with the study. Therefore, rather than substituting into the existing model, data reinforcement was performed. We propose a method to reduce the error in accuracy and further improve performance through ensemble learning.

This paper is structured as follows. Section 2 describes the overall process composed of data collection, dataset creation, CNN model learning and ensemble learning. Section 3 presents and describes the framework to be proposed. Section 4 shows the experimental process and the results of the experiment. Finally, Section 5 offers conclusions of this study.

2. Methods of Processing.

2.1. Data collection. We were provided with strawberry leaf data for this study. However, the number of image datasets was not that large for the deep learning-based study. Therefore, we collected additional data using the Python library – Beautifulsoup, which enables easy data collection from HTML information. In addition, it is possible to parse and collect data of similar classification. Furthermore, more data has been downloaded and open data provided by AI HUB has been added to the dataset for the study.

Figure 1 shows two types of dataset used in this study. The normal image dataset shows healthy strawberry leaves, and the disease image dataset shows strawberry leaf images infected with pests.

2.2. Dataset creation. We need to convert the collected data into an appropriate dataset. Table 1 shows the array shape of the training dataset and test dataset used in this study. The number of the training datasets is 1200, and the number of the test

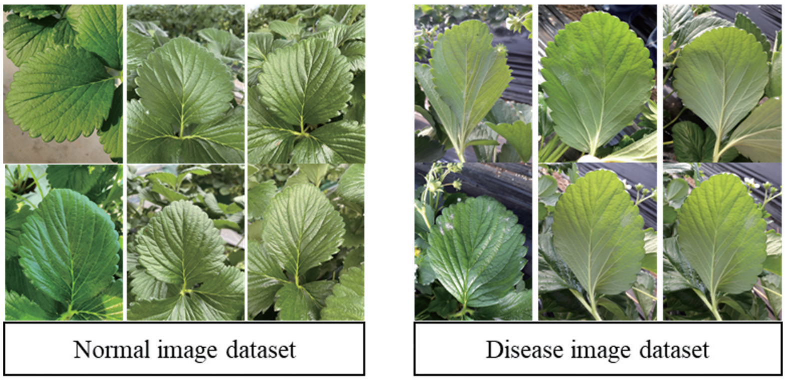

Figure 1. Strawberry leaf image dataset

Table 1. Array shape of training and test dataset

	Training dataset	Test dataset
Image array shape	$(1200, 1024, 1024, 3)$	$(300, 1024, 1024, 3)$
Label array shape	$(1200, 2)$	$(300, 2)$

datasets is 300. Images of channel 3 with a resolution of $1024 * 1024$ are used and each image data has a one-hot encoded label with one of two labels: 'normal' and 'disease'.

The resolution of the original image is large, which can cause bottlenecks when image loading. If that happens, the entire system will be limited in performance or capacity due to image elements. To avoid such a bottleneck, resizing the image dataset to an appropriate size $1024 * 1024$ was applied.

The pseudo-labeling method was adopted for more stable data learning. The pseudo-labeling refers to the artificial label created by the model and is mainly used to train the model. Since the class with the highest prediction probability is selected as a pseudo label, more stable data learning is possible.

2.3. **CNN model learning.** Previous studies have confirmed the proper use of the model for image processing and high accuracy in the pre-processing stage [13]. Therefore, we decided to use the EfficientNet model and the RegNet model in this study.

EfficientNet is a popular CNN-based ImageNet model that achieved SOTA (State-of-the-art) on several image-based tasks in 2019. EfficientNet performs model scaling in an innovative way, achieving excellent accuracy with far fewer parameters. It achieves the same, if not more accurate, than ResNet and DenseNet with shallower architectures. Currently, many image data studies utilize EfficientNet to achieve high accuracy. In this study, we used the EfficientNet-B3 model. Considering the model size, we decided that the B3 model would be sufficient.

RegNet is a model developed by FaceBook AI Research, FAIR team in 2020. The new 'low-dimensional design space' RegNet builds simple, fast and versatile networks. In comparable training settings and flops, we found that the RegNet model outperformed the EfficientNet model and was up to five times faster on the GPU. In this study, we used the RegNetY-064 model. Using the Pytorch image models library, we trained the model using RegNet, which has strength in generalization performance, as the base model. In this study, pseudo-labeling was repeatedly performed based on RegNetY-064.

2.4. **Ensemble learning.** We created a model directory and received RegNet and EfficientNet to build code for prediction and ensemble. In addition, a data frame for learning was created by adding the pseudo-labeling. The pseudo-labeling was performed repeatedly a total of five times.

In this paper, we applied ensemble learning combining RegNet and EfficientNet. Ensemble learning is a technique that uses multiple machine learning models to find the optimal solution. It uses multiple models to train on data and average the prediction results of all models. Ensemble learning includes means of several prediction vectors to reduce errors and improve accuracy.

For the experiment, we train RegNet model and EfficientNet model by dividing the training data by five folds as shown in Figure 2. For each fold, RegNet model calls the checkpoint of the model with the lowest loss and ensembles a total of five models. In the test data, if the predicted value through the softmax for each class is 0.8 or more, pseudo-labeling is performed and added to the train data. The final data to which pseudo-labeling data is added is divided into five folds and trained, and each model is trained. Finally, we combined two models of five-fold ensemble learning (RegNet and EfficientNet) that were learned with the pseudo-labeling set through RegNet.

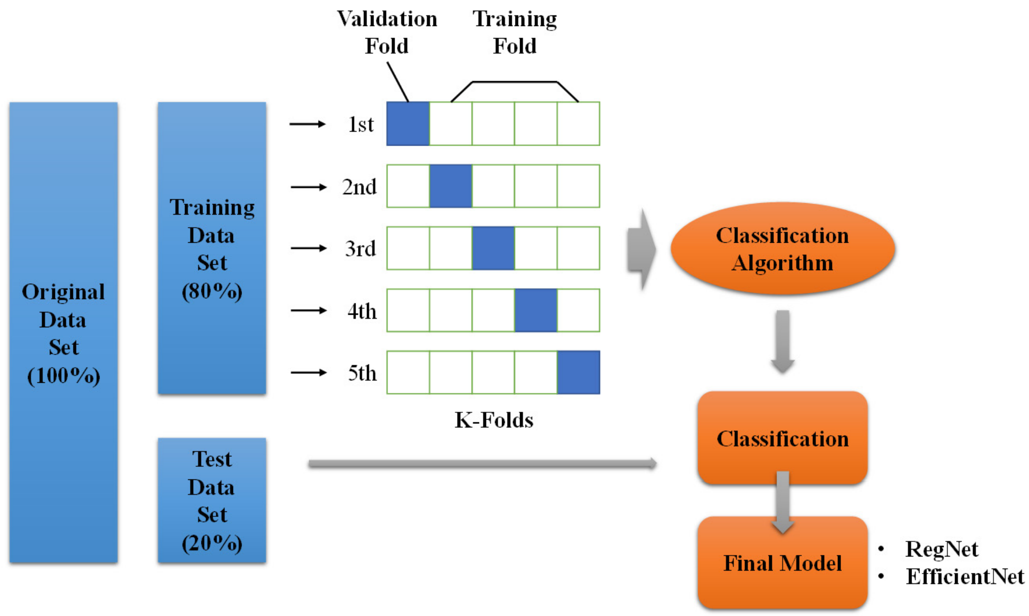

FIGURE 2. Five-fold ensemble learning

3. **Overall Framework.** The overall framework of system is shown in Figure 3. First, the strawberry leaf data acquired by the project team and additional image data augmented through web crawling and open data sharing. Then, the dataset is divided into the training data and test data. RegNet is used as the central model, and results are derived through EfficientNet and ensemble learning in the main function through training function and validation steps of the model.

4. **Implementation Results.** The total process of our study and implementation results are described in this section. At first, pseudo-labeling was performed on the test dataset for efficient model training. Figure 4 shows the implementation method of pseudo-labeling used in this study. After pseudo-labeling, the model was trained by adding it to the training dataset. We performed pseudo-labeling a total of six times. The first pseudo-labeling was performed using a 'RegNet five-fold ensemble' that has undergone an optimization process. Afterwards, a total of five pseudo label set updates were performed in the same model configuration. Two models of five-fold ensemble (RegNet and EfficientNet) trained with pseudo label set through RegNet were constructed and compared. As a result, it was confirmed that the 'EfficientNet five-fold ensemble' model showed the best performance.

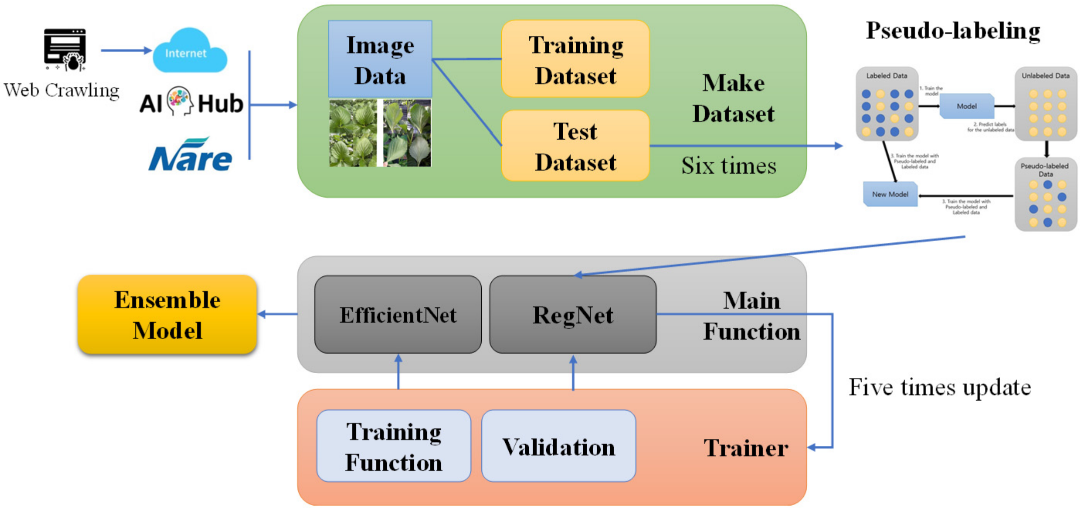

FIGURE 3. Overall framework of the proposed system

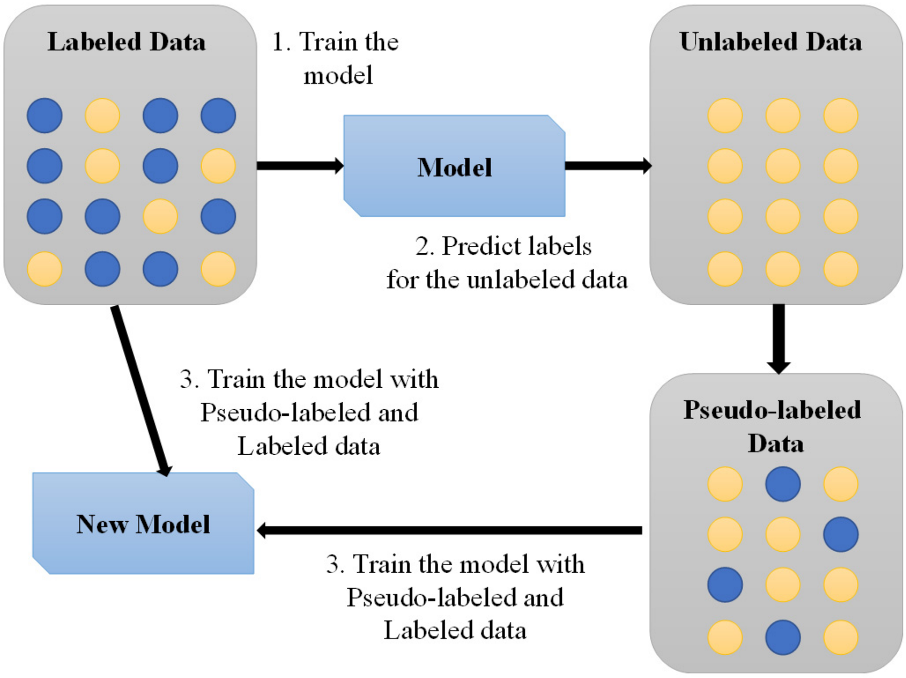

FIGURE 4. Pseudo-labeling learning

The codes used in this study were written based on Akash Haridas and Tarun Paparaju's codes from Kaggle – <Plant Pathology 2020 – FGVC7>, and mons2us code from DACON – <The 2nd Computer Vision Learning Contest>. We created a class for training and validation of the model. We set hyper-parameters to ensure correct training without overfitting, as demonstrated in other studies [14]. The ratio of training data and validation data was set to 8 : 2, and 1200 images were used to train the CNN model. Unfortunately, overfitting continued to occur during training. Therefore, we continued to modify the number of epochs and proceeded with the training. Table 2 shows hyper-parameters of the training model.

The accuracy of the experimentation results was 0.9980 and the F1 score was 0.9885. Figure 5 shows the learning curve for the classification model. Along with learning rate variation curve, the loss function values and accuracy are shown for each training and verification data set. As you can see in the graph, it shows high accuracy even at low epoch.

TABLE 2. Hyper-parameters of the training model

K-fold	5
Optimizer	Lamb
Scheduler	cycle
Epochs	2
Batch size	8
Weight decay	1e-3

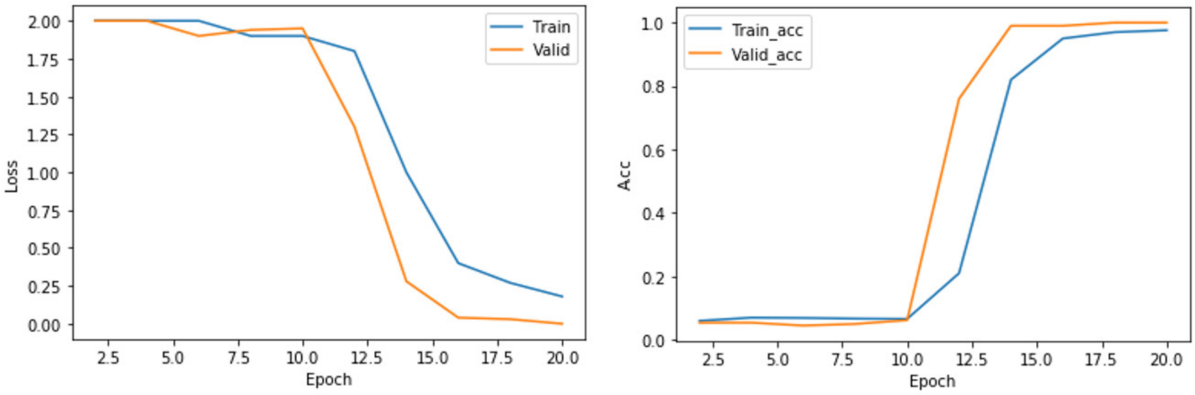

FIGURE 5. Learning curve of training model

5. **Conclusions.** This study proposed a deep learning-based classification model for identifying strawberry leaf pest infection to identify and cope with the symptoms of pests and diseases at an early stage. We proposed the preprocessing method and stable learning methods through the pseudo-labeling. Based on RegNet, the pseudo-labeling was performed repeatedly, and five-fold ensemble learning combining RegNet and EfficientNet learned with the pseudo-labeling set through RegNet.

Several pre-trained models such as RegNet and EfficientNet can be used to classify leaf diseases with high accuracy. Ensemble learning allows powerful verification technologies to propose more accurate and robust models. In terms of industry, we believe that it will be of great help to the agricultural industry as it can lead to an increase in production by early detection and response to diseases of crops.

There have been many classification studies using leaf data of other leaves (e.g., tomato), but only a few pest classification studies using strawberry leaves. Although, it is difficult to compare the performance with the existing research, the characteristics of this study can be summarized as follows. First, the original data were sufficiently secured and used without using data augmentation. Second, we refined the dataset through pseudo-labeling, applied it to the CNN-image network models, and derived the optimal results through ensemble learning. Third, relatively high accuracy results can be obtained with a small number of epochs by applying pseudo-labeling and efficient CNN-image network models.

Future research includes application of a variety of image processing and augmentation methods such as depth estimation and flipping in order to create models and compare the results. In addition, further research is needed to distinguish the types and severity of strawberry pests.

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