A Cascaded Structure of pre-trained Convolutional Neural Network for Weed Classification

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Abstract. This study proposes a cascaded structure of a pre-trained convolutional neural network (CNN) for the classification of weeds. The method, known as transfer learning, involves dividing pre-trained CNN models that have been successful in image classification into models that classify families and species of plants. To evaluate this technique, the authors collected 60,506 datasets for 40 species from 5 selected families of exotic weeds and used domestic plant and weed experts to classify them. In their cascaded structure experiment, they then used DenseNet and EfficientNet models, which had previously shown promising results in single CNN transfer learning experiments. The results showed that the DenseNet-based cascaded structure model had 96.057% accuracy in classifying exotic weeds, which was 0.671% higher than the DenseNet transfer learning model and also reduced the model size by 18.7%. Similarly, the EfficientNet-based cascaded structure model had 96.24% accuracy and reduced model size by 18.3%. The authors suggest that this cascaded structure method can be effective for hierarchical datasets such as exotic weeds.

Keywords: Image Classification, Deep Learning, Lightweight model.

1 Introduction

Exotic weeds refer to plants that have intentionally or unintentionally left their place of origin, spread to other lands, and settled there, mainly due to the movement of humans, animals, and means of transportation. Recently, interest in the ecological characteristics and management methods of foreign weeds has increased as the spread of foreign plants and their impact on the ecosystem has become serious. Compared to other native weeds, foreign weeds expand their habitat faster and have the characteristics of adapting well to very diverse environmental conditions. Foreign weeds invading a certain area inevitably lead to changes in the entire ecosystem, mainly in the structure of vegetation communities. It causes changes in flora, changes in flora, etc., and ultimately leads to a

This research was supported by the BK21 FOUR Program(Fostering Outstanding Universities for Research, 5199991714138) funded by the Ministry of Education(MOE, Korea) and National Research Foundation of Korea(NRF)

decrease in species diversity. Foreign w Through various routes, foreign weeds enter agricultural lands such as rice fields, fields, and orchards ocular; they rapidly adapt to the agricultural land environment, which is rich in nutrients and richer in nutrients than the original ecosystem, and is less competitive, and reproduce in large quantities to fight native weeds through various routes. It has a superior position compared to [1].

There are many cases in which there is no special method for controlling foreign weeds, which cause more damage than native weeds, and in some cases, the situation is aggravated by incorrect control. In the case of weeds that grow naturally in Korea, it is possible to identify them accurately, and commercially available herbicides can be sufficiently effective, but in the case of foreign weeds, it is difficult to identify them accurately. There is no clear effect after treatment [2]. Therefore, accurately identifying foreign weeds is crucial to present accurate control methods. To this end, this paper proposes a CNN cascaded structure for classifying foreign weeds in a hierarchical structure through an effective pre-trained CNN model.

2 Related works

This study focuses on utilizing deep learning techniques to classify weeds. The aim is to extract plant features using convolutional neural networks (CNN) and develop a smartphone application system [3]. The study utilized a technique of inputting overlapping patches without image segmentation. Previous research [4, 5] in this field has yielded high accuracy rates, such as 93.8% using a deep learning-based weed classification model and 86.2% using a ResNet model with 10,413 plants of 22 species. However, these models cannot incorporate actual weed data or a comprehensive array of weed species present in cultivated fields. This study aims to address these limitations by utilizing a different approach for weed classification.

Previous studies have utilized convolutional neural network (CNN) model ensemble methods for weed classification, such as AgroAVNET, a CNN model that combines the strengths of AlexNet and VGG. This model achieved 93.64% accuracy in a study that classified 4,200 plants of 12 species [6]. Another study using five foreign weed datasets from Chonnam National University achieved a maximum accuracy of 98.77% through a Late Fusion method, which ensembles up to 5 models for 21 species [7]. However, it is noted that the use of multiple deep learning models may require a large number of parameters and significant training time.

Previous studies have employed a Hierarchical Approach with a Convolutional Neural Network (CNN) to classify foreign weeds [8]. This approach utilizes a cascaded structure of a recently advanced pre-trained CNN model, which enables the classification of foreign weeds with improved accuracy and fewer parameters. This approach also suggests methods to decrease the learning time.

3 Pre-trained CNN cascaded structure for exotic weed classification

3.1 CNN cascaded structure

This paper proposes a CNN cascaded structure model for classifying foreign weeds. This model employs a hierarchical approach that classifies data based on plant taxonomic characteristics, such as families and species. The proposed model has a cascaded structure, which includes a CNN model for classifying families and separate CNN models for classifying species. This approach allows for more accurate classification using a smaller number of parameters than a single CNN model. This is achieved by tailoring small CNN models to specific families and species rather than using a single, general model.

The image recognition problem can be mathematically viewed as conditional Bayesian Probability, where an input (a given foreign weed data image or a feature vector obtained from foreign weed data) X_i, a correct answer class Y_i, and a correct answer F_i be a family, $i = 1, \ldots, N$ denotes a training data sample. All correct classes are composed of one-hot encoding vectors, $Y_i \in \{0, 1\}^M$ and $F_i \in \{0, 1\}^K$ is vector of correct answer classes and families, respectively. With this basic notation, we can define three kinds of learning models:

$$P_w(\hat{Y} \mid X) \tag{1}$$

$$P_w(\hat{Y}, \hat{F} \mid X) \tag{2}$$

$$P_w(\hat{Y} \mid \hat{F}, X) \tag{3}$$

The learning model of equation (1) is a conventional classifier that predicts a class, the learning model of equation (2) is a global classifier that predicts a family and a class by joint probability, and equation (3) is a cascaded local classifier that predicts classes conditionally on the family. In the present study, we employ a learning model in which the weights are updated by a training algorithm such as back-propagation. Given an input feature vector, the model predicts a class and the family of the given input. The objective function is the categorical cross-entropy for both maximizing the likelihood of family and class prediction.

As illustrated in Figure 1, the proposed method for classifying foreign weed species employs a pre-trained convolutional neural network (CNN) model that first categorizes the samples into five families and then subsequently classifies them into 40 species using the results of the initial family classification. The architecture of this cascaded CNN model is designed to improve the classification performance by reducing the number of species to be classified. Specifically, it is demonstrated that by utilizing a cascaded pre-trained CNN structure that classifies an average of 8 classes, superior classification results are obtained compared to classifying all 40 species with a single pre-trained CNN model. Furthermore, it is worth noting that in previous studies, constructing a CNN cascaded structure required the design of models optimized for each family and species, which resulted in varying classification performance depending on the researcher's knowledge and experience. However, in this study, a pre-trained CNN model is utilized, enabling the selection of an appropriate model regardless of the researcher's expertise, leading to higher classification accuracy with fewer parameters and less training time.

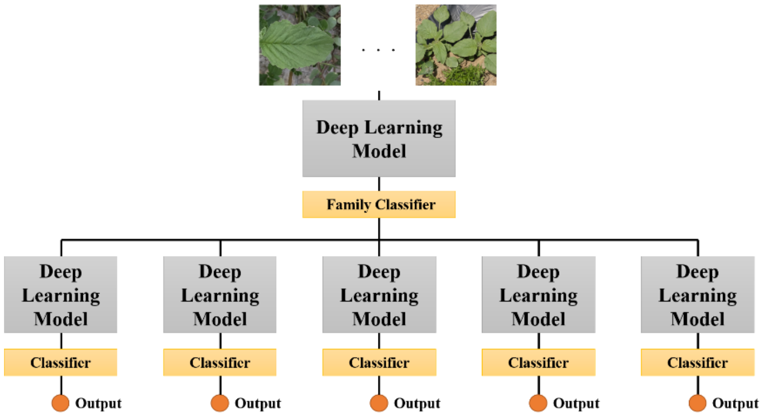

Fig. 1. Simple CNN cascaded structure.

3.2 Chonnam National University exotic weed dataset

Fig. 2. Samples after cropping by parts using a cropping tool.

Table 1. 5 families and 40 classes of original datasets

Dataset	Training	Validation	Testing	Total
Amount	50,802	16,940	16,958	84,700

The Chonnam National University foreign weed dataset was developed by a collaborative effort between Chonnam National University located in Gwangju, Korea, and six institutions supervised by the Rural Development Administration, namely the National Institute of Agricultural Sciences, Chungnam National University, Shinyeong

University, Hankyong University, and Sungkyunkwan University. The dataset comprises a total of 40 species, including seven species of Amaraceae from the National Institute of Crop Science, six species of Ginsengaceae from Chungnam National University, seven species of Meongajuaceae from Shinyeong University, six species of Convolvulaceae from Hankyong University, and 14 species of Asteraceae from Sungkyunkwan University. The dataset was collected by photographing foreign weeds with a smartphone camera and a high-resolution digital camera while traveling all over the country, and the final data was established through inspection of the collected dataset in collaboration with the National Institute of Crop Science.

The Chonnam National University foreign weed dataset, as depicted in Fig. 2, has been developed to identify the characteristics of foreign weeds. The dataset was compiled by extracting samples of leaves, flowers, fruits, and outposts, and the composition of the entire dataset is presented in Table 1.

4 Experiments and Results

In this experiment, the deep learning model was implemented with PyTorch version 1.12.0 of the Python language, and the experiment was performed using Intel(R) Core(TM) i9-7900X CPU 3.30GHz CPU, 128GByte DDR4 RAM, NVIDIA TITAN V with 12GByte built-in RAM.

4.1 CNN Transfer Learning for exotic weed classification

To apply a single CNN model to the proposed cascaded pre-trained CNN structure for foreign weed classification, a selection of pre-trained CNN models was evaluated, including AlexNet, VGGNet, GoogleNet, ResNet, DenseNet, MobileNetV2, SqueezeNet, ShuffleNet2, and EfficientNet, all of which were trained on the ImageNet dataset. These pre-trained CNN models were then evaluated through transfer learning using the 40 foreign weed datasets from Chonnam National University.

Table 2. Performance and model complexity of the pre-trained single model

pretraining model	Model Size (MB)	classification accuracy
AlexNet	57.2	0.86720
VGG	128	0.88303
GoogLeNet	5.6	0.92003
ResNet	11.2	0.92141
DenseNet	7.0	0.94432
MobileNetV2	2.3	0.92555
SqueezeNet	0.743	0.84935
ShuffleNetV2	1.3	0.88966
EfficientNet	20.2	0.95711

Table 2 presents transfer learning results using a single pre-trained CNN model for foreign weed classification. It is observed that the EfficientNet and DenseNet models, which were pre-trained with the ImageNet dataset, demonstrated superior classification performance with an accuracy of 95.71% and 94.43%, respectively. The hyperparameters utilized for transfer learning in these two CNN models include a batch size of 64, an Adam optimizer, a learning rate of 0.0001, and 20 training epochs.

4.2 Pre-trained CNN cascaded structure for exotic weed classification

In light of the superior performance of EfficientNet and DenseNet models in foreign weed classification, as determined through transfer learning in a single CNN model, an experiment was conducted to evaluate the effectiveness of a cascaded pre-trained CNN structure for foreign weed classification. The proposed architecture is designed to prioritize ease of model design by utilizing the largest and smallest pre-trained CNN models instead of custom-designing CNN model structures for each family and species.

Table 3. Performance of DenseNet cascaded structure.

	large model	small model	classification	Asteraceae	bindweed	Pigweed	Amaranthaceae	Ginsengaceae
Model Size	18.2	7	7	7	7	7	7	7
			42.0					
accuracy	0.9538	0.9443	0.9795	0.9631	0.9349	0.9691	0.9097	0.98
			0.9605					
batch size	32	64	64	64	64	64	64	64
learning time (s)	12	06:04						

As shown in Table 3, a comparison experiment was conducted between DenseNet201, with a model size of 18.2MB, and DenseNet121, with a model size of 7MB, and it can be observed that the size difference between the single largest transfer-learned CNN model and the single smallest transfer-learned CNN model is approximately threefold or more. The results demonstrate that the foreign weed classification accuracy is 95.386% for the single largest transfer-learned model and 96.057% for the CNN cascaded structure model. Furthermore, the CNN cascaded structure, which learns by dividing several small models into family and species models, is more suitable for a parallel server architecture. Additionally, it can be noted that the learning time is reduced by about two times, even when learning sequentially on a single server, at 6 minutes and 4 seconds.

Table 4 illustrates the results of a comparative experiment conducted using EfficientNet_b5, with a model size of 28.4MB, and EfficientNet_b0, with a model size of 4MB, for the classification of foreign weeds. The classification accuracy for the single giant transfer learning CNN model was 94.617%, and for the CNN model was 94.617% while reducing the model size by 18.3%. The results confirm that the cascaded structure model demonstrated superior performance, with an accuracy of 96.24%. Furthermore, due to the ability of the CNN cascaded structure to learn by dividing several small models into family and species models, it is well-suited for parallel server architecture. Even when learned sequentially on a single server, it resulted in a reduction of learning time by a factor of approximately 3, and on a parallel server architecture, it is possible to train six small models simultaneously, resulting in a reduction of learning time by a factor of approximately 20.

Table 4. Performance of EfficientNet cascaded structure.

<table>
<tr><th></th><th>large model</th><th>small model</th><th>classifi-cation</th><th>Aster-aceae</th><th>bind-weed</th><th>Pig-weed</th><th>Amaran-thaceae</th><th>Ginsengaceae</th></tr>
<tr><td rowspan="2">Model Size</td><td rowspan="2">28.4</td><td rowspan="2">4</td><td>4</td><td>4</td><td>4</td><td>4</td><td>4</td><td>4</td></tr>
<tr><td colspan="6">24</td></tr>
<tr><td rowspan="2">accuracy</td><td rowspan="2">0.9461</td><td rowspan="2">0.9523</td><td>0.9936</td><td>0.9859</td><td>0.9791</td><td>0.9943</td><td>0.9710</td><td>0.9961</td></tr>
<tr><td colspan="6">0.9624</td></tr>
<tr><td>batch size</td><td>4</td><td>64</td><td>64</td><td>64</td><td>64</td><td>64</td><td>64</td><td>64</td></tr>
<tr><td>learning time (s)</td><td>59</td><td colspan="7">03:34</td></tr>
</table>

Table 5. Comparison with the previous study

	Model Size (MB)	Accuracy (ACC)
ResNet-based CNN cascaded structure [8]	10.4	0.9561
Single DenseNet	18.2	0.9443
Single EfficientNet	28.4	0.9461
DenseNet-based CNN cascaded structure	42(7)	0.9538
EfficientNet-based CNN cascaded structure	24(4)	0.9624

The results of this study have confirmed that the proposed pre-trained CNN cascaded structure for foreign weed classification can achieve higher classification accuracy with fewer parameters than a single large transfer-learned CNN model. Additionally, as demonstrated in the ResNet-based CNN cascaded structure study presented in Table 5, when the CNN cascaded structure is tailored to the foreign weed dataset and based on the researcher's experience and knowledge, it is possible to achieve a reduction in overall CNN cascaded structure model size while simultaneously improving classification accuracy when compared to a single large CNN model. Furthermore, it was found that not only is it possible to achieve a reduction in model size but also high accuracy can be obtained if the researcher constructs the CNN cascaded structure in the order of the transfer learning results of the pre-trained CNN model.

5 Conclusions

In this study, we investigate using a pre-trained convolutional neural network (CNN) cascaded structure for classifying foreign weeds. To this end, a dataset was constructed for 40 species of foreign weeds identified as ecosystem disruptors and selected in consultation with domestic plant and weed experts. A comparative experiment was conducted with EfficientNet_b5, a model size of 28.4MB, and EfficientNet_b0, a model size of 4MB. The results showed that the accuracy of the classification of foreign weeds was reduced by 18.3% for the single giant transfer learning CNN model, with an accuracy of 94.617%. However, the CNN cascaded structure model demonstrated superior performance, with an accuracy of 96.24%. Additionally, the deep learning CNN cascaded structure is well-suited for parallel server architecture, as it learns by dividing several small models into family and species models. This not only results in a reduction of learning time by approximately 3 when learned sequentially on a single server but also by approximately 20 when trained on a parallel server architecture.

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This paper is an extended version of the paper “Exotic Weeds Classification: Hierarchical Approach with Convolutional Neural Network” which has been published in " The Journal of Korean Institute of Information Technology."