# Research on Plant Image Identification Based on Deep Learning

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Xianfeng, Zeng*
*Institute of Intelligent Information Processing*
*South China Business College of Guangdong University of Foreign Studies*
Guangdong, China
jjtd@gwng.edu.cn

Jing Chang
*Institute of Intelligent Information Processing*
*South China Business College of Guangdong University of Foreign Studies*
Guangdong, China
201005@gwng.edu.cn

Changxiu, Dai
*Institute of Intelligent Information Processing*
*South China Business College of Guangdong University of Foreign Studies*
Guangdong, China
201006@gwng.edu.cn

***Abstract*—In recent years, increasing attention was paid to the methods from researchers that about the intelligent identification of plants and their diseases based on deep learning algorithms. In this paper, plant images were as the study object. Firstly we listed the Research results on traditional methods and deep learning methods of machine learning, and summarized the classification features of plant images and the general procedure of plant identification, Simultaneously we introduced the general algorithms for deep learning, and studied the structural features of convolutional neural networks, and described the classical model of convolutional neural networks, At the end, we compared experimentally the identification efficiency of VGG16+SVM classifier and VGG16+Softmax classifier on plant images. Experiments have shown that under the same conditions, the SVM classifier has a higher identification rate for plant images with single backgrounds, but the identification rate for plant images with complicate backgrounds is close to that of the softmax classifier, and the VGG16 algorithm needs improvement further in the identification rate on fine-grained plant images with too similar leaf shapes. This also proved that the identification and classification of plant images with complicated background and fine-grained is a major constraint in achieving intelligent identification on plant.**

***Keywords*—plant image, deep learning, Convolutional neural network, VGG16, SVM, fine-grained image**

## I. Introduction

There is a wide variety of plants, which are closely related to our lives, Human beings have never stopped studying and protecting plants. It's just a decade or so from reliance on botanists collected the plant information by manual to computed plant information intelligently by computer, it's depends on the rapid development of computer technology, especially machine learning technology. Machine learning techniques are the primary method for achieving artificial intelligence, which relies on "training" large amounts of data to obtain model algorithms to solve specific problems. In a sense, traditional machine learning methods are weak-minded in "intelligence", because it still needs the intervention by experts on feature selection and classification settings. With the rapid development of deep learning technology, machine's "intelligence" has been improved continuously, which can extract features automatically according to the image information entered. At present deep learning technology has become a major research direction in domain of artificial intelligence and it has shown powerful ability in areas such as image identification and speech identification. Nonetheless, the application of deep learning faces enormous challenges on the plants identification and their diseases. On the one hand, due to the wide variety of plant species, the large differences in characteristics between plant species and the small differences between plants of the same category, there is a feature extraction is not universal, data samples is difficult to be unified, it is difficult to find a universal identification model[1], on the other hand, because the large changes in the characteristics of the various growth stages of plants, and the influence of factors such as shooting light and vision, the accuracy of recognition results is difficult to guaranteed.

Image identification that based on plant flowers, leaves, stems and other organs is the major identification methods of plant; therefore the recognition of plant by machines is still essentially image recognition. Machine learning approaches to plant identification divided into two main categories: plant identification based on traditional feature engineering and plant identification based on deep learning models. Traditional machine learning algorithms are the primary methods in a long period because of their strong robustness and lower computing resources requirements. Abroad Ingrouille et al. acquired 27 leaf shape features and used principal component analysis method for classified of oak trees in 1986[3]. Guyer et al. extracted 17 kinds of leaf shape features to classify 40 types of plants in 1993[4]. Yonekawa et al. found that a simple leaf shape factor was effective for plant leaf identification in 1996[5]. Yang et al. proposed in 2009 to use sparse coding to characterize images and train support vector machine (SVM) with large volume of data to classify images[6], this method achieved the best results in the ImageNet image classification competition in 2010 and 2011, which activated a boom of machine learning research in image identification. In China, Qi Xiangnian et al. proposed to classify leaves by calculating the area and perimeter of the leaf to obtain the size and shape characteristics in 2003, which promoted the development of plant leaf identification[7]. Wang Lijun et al. extracted comprehensively features such as colour, shape and texture of 50 plant images and used a support vector machine classifier to achieve automatic leaf identification in 2015, that promoting the application of machine learning methods to plant identification and obtaining high achievement[8].Today, even deep learning is growing vigorously, traditional machine learning algorithms have a still widely used in plant identification, such as Li Y et al.

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mentioned Some classical DL models are still running importantly for plants and their disease identification[9].

Compared with the shortcomings of traditional machine learning algorithms, which cannot deal with massive data more efficiently and require manual intervention during feature extraction, deep learning algorithms, especially convolutional neural networks, have become current and frontier study hotspots because of their automatic and efficient feature extraction[10]. After 2010, with the popularity of ImageNet competition, there appeared successively classic network models such as Alex Net [11], Google Net [12], VGG[13], ResNet[14], Batch Normalization[15], etc. Which making deep learning is powerful model in image identification; it is also more applied in plant image identification. Osikar et al. [16] used BP feedforward neural network technology to classify 15 kinds of trees in Sweden in 2001, after referenced the geometric shape of some leaves. Ge ZY [17], Choi S [18], Lee SH [19] and so on trained GoogLeNet model and VGG model for plant identification, using a variety of different plant organs as training samples, and increasing the sample size and information to increase the empirical knowledge of the model. Sun Jun et al. normalized the input data of CNN to speed up the network convergence, and reduced greatly the number of features by global pooling[20]. In summary, the brilliance of deep learning, especially convolutional neural network, which in the fields of feature detection and pattern recognition has led to the rapid growth of plant and disease image identification research based on convolutional neural network algorithms.

In this study, we'll study the research situation of plant image identification by the literature and discover the classification features of plant images and find the processing of machine to plant image. Not only that, we'll go to summarize the general algorithms for deep learning, focusing on the structural features and primary models of convolutional neural networks, and to validate experimentally the efficiency of the VGG16+SVM classifier and the VGG16+Softmax classifier.

## II. Related with Plant Image

### A. *Taxonomic features of plant*

Plant species can be classified and identified according to their organ characteristics, Plant images such as flowers, stems, fruits, leaves, roots and seeds can be acquired as the information for plant image identification. Features commonly used in plant images include colour, shape and texture, etc. choosing and extracting characteristics of plant according by the characteristics of different images. Compared with the other organs of plant, the shape and structure of plant leaves are clear and stable, flat and nearly planar, and plant leaves have the outstanding features with long life cycle, easy acquisition and high feature identification, Hence scholars often choose the leaf images of plant for classification and disease identification studies [21].

In traditional machine learning methods, plant recognition algorithms are often designed based on features such as shape and texture, generally the pre-processing requirements are higher, and the algorithms are usually designed to work better for only one certain type data set. In the case of sufficient number of leaf image samples, deep learning can autonomously learn leaf features with high identification, and achieve the goal that the effective identification of plant leaf images, hence the plant image identification algorithms based Convolutional neural network are the current mainstream approach to plant identification.

### B. *Identification process in general of plant image*

Plant images can be pre-processed with operations such as colour space conversion, image segmentation and dataset augmentation after inputting. next feature extraction of plant images be used by traditional feature extraction methods or deep learning algorithms, in the end, the leaf feature vector is fed into the classifier to identify the plant species, so as to get the category information of the plant image. This is shown in Figure 1.

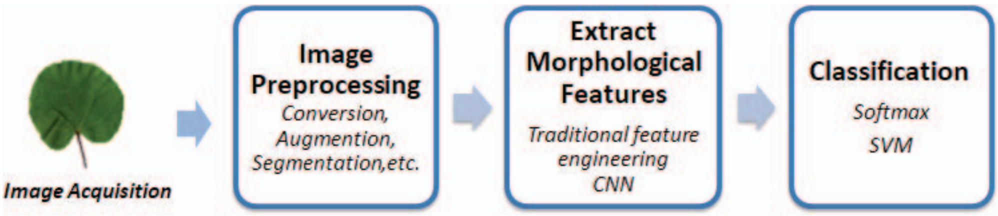


Fig. 1. Main steps of plant identification

### C. *Part of the dataset for plant images*

Datasets are the basis for building deep learning models, the quality and size of the dataset determines how effective of the deep learning model [22]. Some publicly available plant image datasets at home and abroad are shown in Table 1.

## III. Convolutional Neural Networks and Its Models

Introduced in 2006 by Geoffrey Hinton, the father of deep learning, the theory of deep learning has become a mainstreamed research and hotspots in Machine Learning (ML), and it into machine learning has brought its original goal - Artificial Intelligence (AI) [23]. Representative algorithms of deep learning include feed-forward Neural Network (FNN) [24], Recurrent Neural Network (RNN) [25], Convolutional Neural Network (CNN) [26-27], Deep Belief Network (DBN) [28], Generative Adversarial Network (GAN) [29] and Graph Neural Network (GNN) [30] etc. Different deep learning algorithms have their own advantages and characteristics, but those all have the problems that non-convex optimization, gradient disappearance and over-fitting with the network layers deepened. Therefore, we choose the learning algorithm should combine different business and amounts of data in work, and suitable deep learning technology can achieve the best goal, so we should choose suitable model rather than the most complicate model [30-31].

TABLE I. SOME PREVIOUSLY STUDIED PLANT IMAGE DATASETS

| Dataset | Authors | Species | Images | Acquisition | Background | Organs |
|---|---|---|---|---|---|---|
| Swedish leaf | [21] | 15 | 1,125 | scan | plain | leaves |
| Flavia | [60] | 32 | 1,907 | Scan +photo | plain | leaves |
| Leafsnap | [59] | 185 | 30,866 | scan+ photo | plain | leaves |
| ICL | [58] | 220 | 17,032 | scan+ photo | plain | leaves |
| Oxford Flower 17 | [57] | 17 | 1,360 | photo | natural | flower |
| Jena Flower 30 | [56] | 30 | 1,479 | photo | natural | flower |
| Oxford Flower 102 | [55] | 102 | 8,189 | photo | natural | flower |
| Plant Village | [54] | 14 | 54,036 | photo | Plain + natural | leaves |
| PlantCLEF16 | [53] | 1,000 | 113,205 | photo | natural | fruit, flower leaves, stem |
| PPBC | [52] | 17002 | 783,240 | photo | Plain + natural | fruit, flower leaves, stem |

### A. CNN

Yann Lecun proposed convolutional neural network (CNN) in 1998 [32], these characteristics of convolutional neural networks with local perception, weight sharing, pooling and multilayer structure, that not only reduce the feature parameters but also have spatial invariance for small changes such as translation, rotation and scaling of images, and making them more suitable for image classification and identification compared to other one[33]. The basic framework of convolutional neural network is shown in Figure 2. It consists of an input layer, multiple convolutional and pooling layers, one or more fully connected layers, and an output layer.

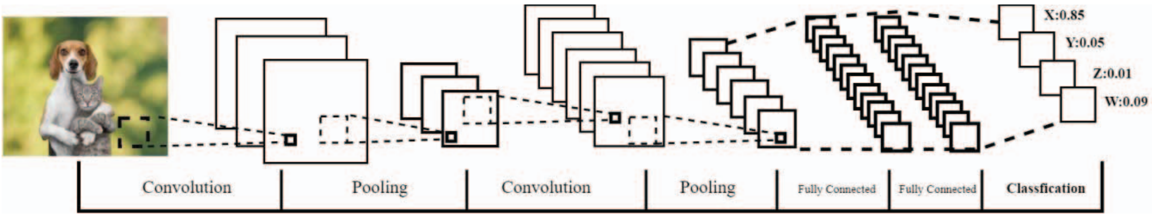


Fig. 2. Structure of CNN

### B. Convolution layer

There is a convolution kernel to extract features on the input image while convolution operation. A k×k convolution kernel is first determined to connect the input neurons with the convolution layer neurons, and then this convolution kernel is moved over the image in certain steps starting from the top left corner of the image, and it moves to a new position, the product sum is found for the the input neurons and the corresponding weight parameters, and an abstracted feature map be figure out when an image had been traversed. The two-dimensional convolution formula commonly used in convolutional neural networks is shown in Equation 1:

$$s(i,j) = (X * W)(i,j) + \mathrm{b} = \sum_m \sum_n x(i+m, j+n) w(m,n) + b \quad (1)$$

In the formula, *X* is the input signal of the convolutional network, *W* is the convolution kernel, *b* is the bias of the convolution kernel, and *(i, j)* is the position of the original image that to be computed feature

### C. Pooling layer

The output of the convolutional layer is the input of the pooling layer. The pooling layer is used to down-sample characteristic pattern that be computed from the convolution layer [33], and it keeps the number of characteristic pattern constant but reduces the dimensionality for better image classification. The two mainly pooling tools are Average pooling and Max pooling. Average pooling is to take the average value of the corresponding field as the pooled value, and Max pooling is to take the maximum value of the corresponding field as the pooled value. The pooling tools are shown in Figure 3.

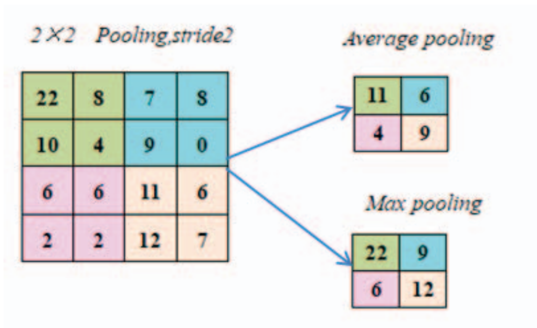


Fig. 3. Max pooling and Average pooling

### D. The connection layer

There are one or more fully connected layers be set up after the convolution and pooling layers, which to weight and sum the characteristic that computed earlier. If a fully connected layer is not the last fully connected layer, its output is also the characteristic pattern, and the last fully connected layer is output to the output layer. The output layer uses the logic function or the normalized exponential function, and to output the probability results of each category in each test image [34].

### *E. The classical model of CNN*

After continuous development and improvement, Convolutional Neural Network had some classical models. Table 2 lists the primary algorithm models of CNN. We should realize that sometimes there are limitations in the practical application of the basic convolutional neural network, and the network model cannot identify image characteristic quickly and accurately when facing overly complicated images, hence in practical application research, the above basic network structure maybe needs to be optimized accordingly according to the actual situation in order to improve the accuracy, practicality and economy of the network [35].

## IV. MULTI-CLASSIFIER IDENTIFICATION MODEL

### *A. VGG16*

VGG is an acronym for " Visual Geometry Group" of the University of Oxford, according to the size of convolution kernel and the number of convolution layers, VGG can be divided into six ConvNet configurations (A,A-LRN,B,C,D and E), among which D and E are more commonly used, called VGG16 and VGG19 respectively [24,36], as shown in Fig. 5.

| ConvNet Configuration | | | | | |
|---|---|---|---|---|---|
| A | A-LRN | B | C | D | E |
| 11weight Layers | 11weight Layers | 13weight Layers | 16weight Layers | 16weight Layers | 19weight Layers |
| Input(224×224 RGB image) | | | | | |
| Conv3-64 | Conv3-64<br>LRN | Conv3-64<br>Conv3-64 | Conv3-64<br>Conv3-64 | Conv3-64<br>Conv3-64 | Conv3-64<br>Conv3-64 |
| maxpool | | | | | |
| Conv3-128 | Conv3-128 | Conv3-128<br>Conv3-128 | Conv3-128<br>Conv3-128 | Conv3-128<br>Conv3-128 | Conv3-128<br>Conv3-128 |
| maxpool | | | | | |
| Conv3-256<br>Conv3-256 | Conv3-256<br>Conv3-256 | Conv3-256<br>Conv3-256 | Conv3-256<br>Conv3-256<br>Conv1-256 | Conv3-256<br>Conv3-256<br>Conv3-256 | Conv3-256<br>Conv3-256<br>Conv3-256<br>Conv3-256 |
| maxpool | | | | | |
| Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512<br>Conv1-512 | Conv3-512<br>Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512<br>Conv3-512<br>Conv3-512 |
| maxpool | | | | | |
| Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512<br>Conv1-512 | Conv3-512<br>Conv3-512<br>Conv3-512 | Conv3-512<br>Conv3-512<br>Conv3-512<br>Conv3-512 |
| maxpool | | | | | |
| FC-4096 | | | | | |
| FC-4096 | | | | | |
| FC-4096 | | | | | |
| Soft-max | | | | | |

Fig. 4. Six structural configurations of VGG

Analysis of Figure 6 shows that VGG16 contains 13 Convolutional layers, There are three Fully connected layers and five Pool layers, the Fully connected Layer structure is the same in all networks, and all hidden layers contain the correction (ReLU) nonlinear function [44]. The advantage of VGG16 is that the structure is simple and easy to understand, the convolutional layers all have the same convolutional kernel parameters, the pooling layers all have the same pooling kernel parameters, the model is made up of several convolutional and pooling layers stacked in a way, which makes it easier to form a deeper network. VGG16 model need large number of parameters, long training time, and large storage capacity, which is the disadvantage of VGG16. We selected the VGG16 model in our experiments.

### *B. Classifier*

To traditional convolutional neural networks, it usually adopted fully connected softmax regression model for classification after feature extraction. In this experiment, two classification methods, SVM and softmax, were designed to distinguish the efficiency of different models for the identification of plant images.

### *C. Softmax classifier*

Softmax Regression model is a generalization of Logistic Regression modeling (LR) for multi-classification problems. A logistic regression model is a generalized linear regression model, which is used in data mining, data prediction, classification and identification, etc. The essence of the classification operation of logistic regression model is that the probability of occurrence is divided by W and the logarithm of the probability of occurrence is taken to form a curve relationship, and the large probability area is determined through the distribution of sample points to complete clustering and discrimination [43], etc.

### *D. SVM classifier*

SVM is a classifier with sparsity and robustness. SVM can implicitly map the input to a high-dimensional feature space for nonlinear classification by kernel methods such as Gaussian kernel, polynomial kernel, sigmoid kernel, etc., and introduce a penalty variable C to solve the over-fitting problem[45]. The kernel function chosen for this experiment is the radial basis function kernel (RBF), as shown in Equation 2:

$$\mathrm{k}(\mathrm{X1}, \mathrm{X2}) = \exp\left(-\frac{\|X1-X2\|^2}{2\sigma^2}\right) \qquad (2)$$

TABLE III. CLASSIC MODELS OF CNN

| No | Model | Birth | Authors | Key Features and Pros/Cons | Parameters and structure | Ref |
|---|---|---|---|---|---|---|
| 1 | LeNet5 | 1998 | Yann Andre LeCun et.al, | First CNN model<br>Few parameters<br>Limited capability of computation | 60K，2 convolutional layers,<br>2 Pooling layers<br>2 Full-connected layers | [37] |
| 2 | AlexNet | 2010 | Hinton,<br>Alex Krizhevsky | Known as the first modern CNN.<br>Best image recognition performance in 2012<br>Used ReLU to achieve better performance.<br>Dropout technique was used to avoid overfitting | 60M，Hidden layer includes:<br>5 convolutional layers,<br>3 Pooling layers<br>3 Full-connected layers | [38] |
| 3 | VGGNet | 2014 | Visual Geometry Group | 3×3 convolution kernel<br>Computationally expensive model due to large number of parameters<br>Best image recognition performance of ILSVRC in 2014 | 133M–144M，It includes:<br>VGG-1, VGG-11-LRN<br>VGG-13,VGG-16, VGG-19 | [39] |
| 4 | GoogLeNet | 2014 | Christian Szegedy | Includes inception blocks<br>Fewer number of parameters as compared to AlexNet model. Better accuracy at its time<br>Best image recognition performance of ILSVRC in 2014 | 7M, Inception v1,<br>Inception v2<br>Inception v3, Inception v4 | [40] |
| 5 | ResNet | 2015 | Kaiming He<br>Xiangyu Zhang<br>Shaoqing Ren<br>Jiangxi Sun | Vanishing gradient problem was addressed<br>accuracy than VGG and GoogLeNet models<br>Best image recognition performance of ILSVRC in 2015 | 25.5M，Residual block includes:<br>2 convolutional layers,<br>1 Jump connection<br>BN and Activation Function, | [41] |

*we selected VGG16

In the formula, *x1* and *x2* are the high-dimensional features of the two sample mappings. In a way, the essence of the classification problem is to judge the similarity between samples. If the characteristics of the two mappings are very similar, the kernel value tends to 1. Otherwise, if they are very different, the kernel value tends to 0. This distribution satisfies a Gaussian distribution, with σ representing the standard deviation of the Gaussian distribution.

### E. *Plant image processing flow*

The plant image identification process based on convolutional neural network mainly includes the acquisition of plant images, preprocessing, dividing the data set, designing the model, and model training, as shown in Figure 5.

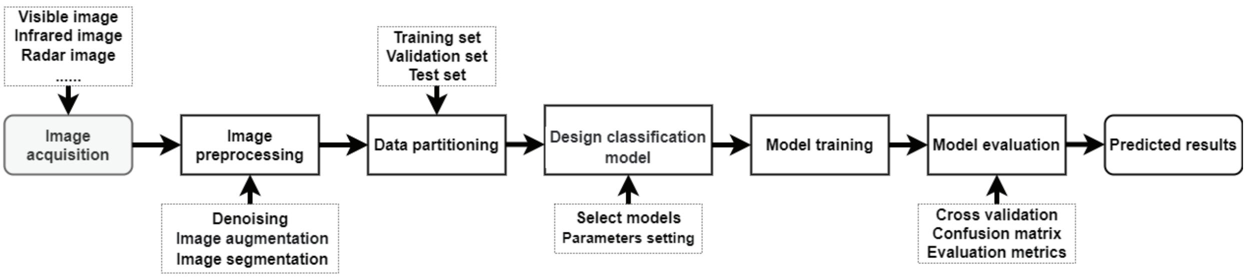


Fig. 5. Plant identification based DL

## V. EXPERIMENTS

### A. *The target*

In this study, we designed a plant leaf identification system based on VGG16+SVM/Softmax model. Using the HB74 leaf library[51] and some of the autonomous extended datasets as training sample datasets and test sample datasets, the identification rates of the VGG16+SVM classifier and the VGG16+Softmax classifier were compared under single background plant leaves and complicated background plant leaves, and the identification of similar plant leaves by VGG16[46-50]

### B. *Experiment condition*

The experimental software environment is windows10 (64 bits) operating system, python language and Pytorch framework. The experimental hardware environment is 16GB memory, Intel(R)Core (TM)i7-8700 CPU @3.20GHz processor. Nvidia RTX2070Ti graphics card with 8GB of video memory.

### C. *Dataset*

A total of 2,278 leaves of 12 plant species were selected from the HB72 dataset. In order to improve the quality of sample training and optimize the sample set, data augmentation is performed before leaf image training. The dataset is expanded by translation, rotation and scaling of leaf images and the total number of expanded datasets is 13582. In the first group of tests, 70% of simple background plant leaves were randomly selected to form the training set and 30% were used as the test set. In the second set of tests, 70% of plant leaves with complicated background were randomly selected to form the training set and 30% were used as the test set. In the third test group, 70% images of similar leaf groups were manually selected to form the training set, and the remaining 30% were used as the test set. An example dataset is shown in Figure 6.

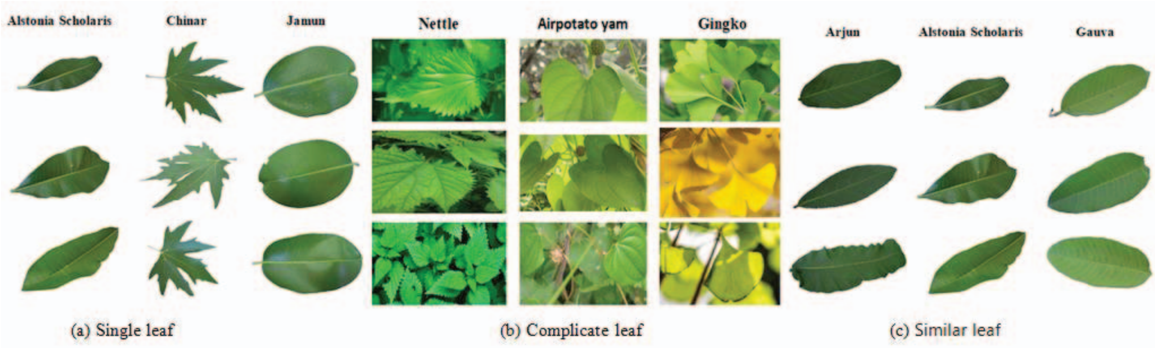


Fig. 6. Samples in the datasets.

### D. *Results*

Experiments were conducted to verify the identification rates of both VGG16+SVM classifier and VGG16+Softmax Classifier, with default parameters C=10 and σ=0.001. Through repeatedly iterations of training, observing the accuracy of the network, when the accuracy is no longer improved significantly, adjusting the value of the learning rate, and so on, until the overall system identification rate is no longer improved significantly, that is the system can be for testing experiments. Experimental comparison found that: (1) both classifiers had a higher recognition rate for the training set that has the simple background plant leaves in this paper, with an accuracy of over 94%, the SVM classifier is slightly higher than the Softmax classifier. (2) The training time of plant leaves with complicated background became significantly longer, and the recognition accuracy decreased more, and the training effect of the two classifiers did not differ significantly. (3) The training of similar leaf groups showed an overfitting state and insufficient generalization ability. The learning results are shown in Table 3.

### E. *Discussion*

The experimental comparison found that the SVM classifier is better than the Softmax classifier in the recognition of plant leaves with simple background. The recognition of plant leaves in complicated backgrounds was comparable with both are not very good, would the recognition rate be improved by adding image segmentation pre-processing or setting effective recognition regions? For the same kind of fine-grained images with similar leaf shape, the generalization ability is poor. Is it caused by the problem that the training data sample set is not large enough? Or because of the fine-grained features of similar plant leaves, that the size of the input image causes the loss of image details and reduces the classification accuracy of the model? At the same time, for fine-grained plant images, if using sequence-related and multi-organ images to training, would the learning efficiency be better in the same learning model? These are the new directions that will be experimented in next time.

TABLE IV. RECOGNITION RATE OF TWO CLASSIFIERS %

| Different classifiers | Single leaf | Complicate leaf |
|---|---|---|
| VGG16+SVM | 95.32% | 79.55% |
| VGG16+Softmax | 94.43% | 79.57% |

## VI. CONCLUSION

Plants, humans and the environment are most closely related. It is an important research work how to serve agriculture and improve the environment by identifying rapidly plants and their diseases with deep learning algorithms. As a representative of deep learning algorithm, convolutional neural network is one of the core algorithms in the field of image recognition, and it has stable performance when the training data is large and sufficient, specially, VGG16 is one of the classical models of convolutional neural network, which has a deeper network and a simple structure.

This paper studied the characteristics of traditional machine learning algorithms and deep learning algorithms, summarized and analyzed the research results of machine learning in the identification of plants and their diseases, and focused on the structure and characteristics of VGG16. According to the classification characteristics of plant images and the general procedure of plant recognition, we designed VGG16+SVM classifier learning model and compared to the efficiency of VGG16+Softmax classifier model. In the experiment, we selected 12 kinds of plant leaves in HB72 dataset, not only expanded to 13582 images for the training model, but also divided into three training sets with simple background images, complicated background images and similar leaves images for training. Experimental results show that under the same condition, the SVM classifier has a higher identification rate than the Softmax classifier for plant images identification with simple backgrounds, but close to or less Softmax classifier in complicated background, and the lower identification rate of fine-grained plant images with similar leaf shapes, it may be more related to the small number of data set or inadequate pre-processing. In summary, it shall be an important research trend and challenge that the identification and classification intelligently of fine-grained plant images and complicated backgrounds plant images.

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