ISSN 2616-5775 Vol. 4, Issue 3: 109-115, DOI: 10.25236/AJCIS.2021.040317

Leaf Image Classification Using Deep Learning Network

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Abstract: *This paper focuses on leaf cultivar classification, which is a long-established challenge in agricultural artificial intelligence. The difficulties in this task come from the fact that there is large amount of intra-class variability, arising from form changes during the growth of leaves and different physical development, and subtle inter-class differences, originating by belonging to the same species. To cope with this challenging task, we study the possibility of using deep learning techniques for distinguishing leaf cultivars. We employed a soybean leaf cultivar dataset and conducted extensive experiments on it for a comparison study of handcrafted methods and deep learning methods on leaves cultivar recognition tasks. The experimental results indicate the supervisor performance of the deep learning methods over the traditional methods.*

Keywords: *Deep Learning, Leaf Image Classification, Convolution Neural Network, Handcrafted Features*

1. Introduction

In recent years, artificial intelligence technology has continued to develop, involving various fields of agriculture. At the same time, with the rapid development of related research in agriculture, it has also greatly promoted the progress and development of smart agriculture. Therefore, the combination of artificial intelligence technology and smart agriculture can promote the Intelligent of the production field and the improvement of the service field. It is the future development direction of smart agriculture and promotes the modernization of agriculture [1,2].

As a species of legume herb with multiple uses, soybean is the main crop in many countries. It has become one of the most widely eaten food in the world because it is a food that is beneficial to human health and easy to cultivate [3]. Therefore, the research on soybean breeding, growth, development, and yield has always been a hot spot research in academia and agriculture. Among them, an important research direction in soybean research is the identification of soybean varieties, which plays a vital role in the evaluation, screening, and production of soybean varieties [4].

From the perspective of computer vision, a variety of characteristic information such as texture, shape, and color can be obtained through observation of plant leaves. They are widely used in plant species identification. In addition, researches by domestic and foreign experts and scholars have proved that leaf images contain valid information which can be used for variety identification. However, it is effective to extract the characteristic information even for human experts because of the extremely high inter-class similarity between the leaves of different varieties about the same species, besides, the different leaves of the same species also have large intra-class differences too. The valid breed information is also very difficult to be obtained from this characteristic information. Therefore, it is quite challenging to accurately and efficiently classify different leaf characteristics to different cultivar.

Deep Convolutional Neural Networks is a pattern recognition method that combines artificial neural networks and deep learning theory that has emerged in recent years. Deep learning algorithms based on convolutional neural networks can independently learn leaf characteristics and reduce manual intervention. For complex background leaf images, it can eliminate interference and improve image recognition efficiency. After the ALexNet method [21] achieved excellent results in the ImageNet Challenge, deep learning methods have been widely used in image classification tasks, such as VGG [24], ResNet [19] and MobileNet [25] have achieved considerable results. In addition, with the introduction of Recurrent Neural Networks [22,23], EfficientNet [27], SeNet [26], and other methods and the use of various improved methods based on GPU, deep learning methods have been widely used in the field of image recognition. Therefore, applying the related learning theory of deep neural network to the leaf cultivar recognition in this research has a higher recognition rate and wider practicality, and has the potential for further exploration.

It is worth pointing out that although the research work on general plant leaf image recognition and classification has been abundant so far, the research work focusing on leaf cultivar classification is still very small, and the use of computer vision technology with deep learning methods to achieve leaf cultivar recognize work is rarely. This paper applies deep learning methods to leaf cultivar classification and make it compared to traditional manual methods, the result proves that a good variety classification effect is achieved and the accuracy of deep learning method is better than handcrafted methods.

2. Related Work

Traditional leaf image classification methods include two stages, respectively are leaf image feature extraction stage and training classifier stage. The focus is on leaf image feature extraction, such as extracting leaf shape, texture, leaf veins, color, and other visual features as important clues for identifying plant species. In recent years, there is a wealth of literature [8-10] describing these leaf features for plant species identification. Lots of methods are put forward to rely on the contour-based descriptors which are related to the shape and boundary of the leaf. Hierarchical string cuts (HSC) [11] characterizes a contour segment using the spatial distribution information of the contour points relative to its string that cuts the segment off the whole contour. This method runs with low time complexity and it is suitable for large shape database retrieval with competitive accuracy. Also, a novel algorithm is developed to learn hierarchical sparse representation for species classification so that they can extract much deep feature, this approach can achieve better accuracy by combining the hierarchical sparse representation with the dictionary learning method. Besides, a program to automatically classify three-bean species: soybean, red bean, and white kidney bean had been designed [12] by analyzing the morphological characteristics of leaf veins. Another analysis related to it is an approach [13] that extracted the structural features of leaf veins to classify leaf images.

Leaf veins are a key feature for plant cultivar classification. By constructing the characteristic descriptors of leaf veins, it can greatly promote the analysis of plant varieties. At present, there are many pieces of research focusing on leaf veins and their extraction methods. Researchers have paid attention to the spatial structure relationship between leaf veins of different levels and inter-distances or density between leaf veins and density [14]. In addition, the contour information contained in the leaves is also an important research direction for cultivar classification. Analyzing the effectiveness of different characteristic information is an essential work for cultivar classification tasks. Multi-scale sliding string matching method [15] can verify the reliability of cultivar classification, which proved that there is enough information in the leaves that can be applied to the identification of plant cultivar, which greatly promotes the study of leaf identification from species to cultivar.

The motivation of deep learning methods is to build a model that simulates the human brain for analysis and learning, imitating the human brain's visual mechanism to interpret and learn the characteristic information of the data, such as images, sounds, and text. In recent years, with the development of computer vision technology, deep learning technology has been widely used in the field of image classification, and the combination with the agricultural field has also achieved great results. A new hybrid global-local feature extraction model for leaf data had been proposed [5] in which studied the way to use convolutional neural networks and deconvolutional networks to directly learn descriptions from leaf images when it integrating the learned feature information at the same time. Compared with the traditional feature extraction algorithm, it turns out that this information strengthens the discriminative ability of the neural network, and the descriptor based on deep learning has achieved better recognition accuracy.

From the perspective of learning methods, deep learning methods mainly include supervised learning, unsupervised learning, and reinforcement learning. From the perspective of research objects, the recognition of leaf cultivar based on deep learning is a fine-grained image classification task. Due to the data set has the characteristics of subtle differences between sub-categories and huge differences within sub-categories, current fine-grained image classification tasks still have great Expansion capacity. For example, some experts created a New weak supervision framework successfully [6] which pays attention to classification tasks completely and avoids the trade-off between recognition and localization. As an end-to-end fashion, this framework makes the mid-level patches could be studied and distinguished easier away from the similar characteristics. Also, another method NTS-Net [7] which is based on the

ISSN 2616-5775 Vol. 4, Issue 3: 109-115, DOI: 10.25236/AJCIS.2021.040317

self-supervised learning method has also obtained good results in fine-grained image classification tasks. A new loss function was proposed in the study that is named sort loss function, and the method of multi-agent collaborative learning is adopted. Multiple scales and scales may be used to evaluate and weigh the features of the region with a large amount of image information, and then connect these vectors for classification, the results show that this method has better performance for image feature acquisition and fine-grained classification or prediction tasks.

3. Deep Convolution Neural Network

In our analysis, as one of the most popular Deep Convolution Neural Network, ResNet [19] is proposed to be used as a frame network and is improved and optimized to improve the ability of effective feature extraction according to fine-tuning operation so that we can achieve effective leaf image features.

With the introduction of the ResNet, which was used to solve the problem of over fitting between network and data a few years ago, the deep learning method applied to image processing has been greatly improved. In this study, we propose to use ResNet34 [19] as the frame for its state-of-the-art performance in many cultivar classification tasks and try to improve its feature extraction capabilities. Besides, though many deep networks run with high computational complexity and high time cost such as ResNet-101, VGG, etc., yet ResNet34 [19] has an acceptable level of performance and reasonable resources requirements.

The ResNet [19] won the first place in the classification task of the ImageNet competition in 2015, and the ResNet34 used in our paper is also one of the residual networks. This network framework contains 34 layers, the input feature map first passes through a 7*7 convolutional layer, then passes through a 3*3 maximum pooling down-sampling operation, and 3+4+6+3=16 residual structures which contains 32 layers of convolution is introduced in Figure. 1, finally the feature through the average pooling down-sampling operation and a fully connected layer to obtain the final output which may be changed into the probability distribution though the softmax.

As the main highlight of the residual network, the residual module is used with Batch Normalization instead of dropout to accelerate the training process of the network so that the network can runs without the problem of gradient disappearance.

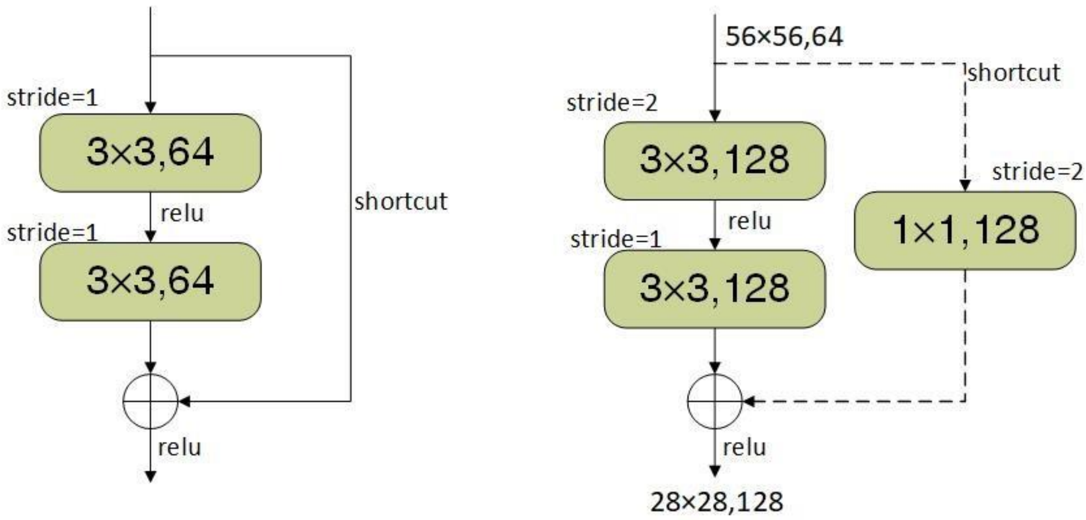

Figure 1: Example graphs of two Residual Modules [19].

As is shown in Figure. 1, here are two different modules which constitute the main part of the above 32-layer convolutional layer. In the residual structure of the left half of the figure, the result of the input feature matrix on the main branch through two 3*3 convolutional layers is added to the input feature matrix from shortcut, and then output through a relu function. Differences between the two residual structures in figure. 1 lies in two parts. One is that stride has changed, because on the main branch we have to change the W*H of the feature vector from 56*56 into 28*28 by stride=2, and the depth of our feature matrix is changed from 64 to 128 by 128 convolution kernels. On the other hand, we added a 1*1 convolution kernel on the shortcut, which makes the W*H of the input matrix on this channel is also reduced to half of the original map. Similarly, the depth of the feature matrix is doubled due to 128

ISSN 2616-5775 Vol. 4, Issue 3: 109-115, DOI: 10.25236/AJCIS.2021.040317

convolution kernels, so that we can guarantee that the output characteristics of the main branch and shortcut branch can be added with the same shape of the matrix.

As we know, with the number of network layers increases, we can extract more abstract features. Due to the innovative structure of residual networks in the residual network, it is necessary for us to select the appropriate number of residual networks to participate in the classification work. In this study, we propose to use ResNet34 [19] introduced in the previous paragraph as the network framework to analyse the image recognition of soybean leaves.

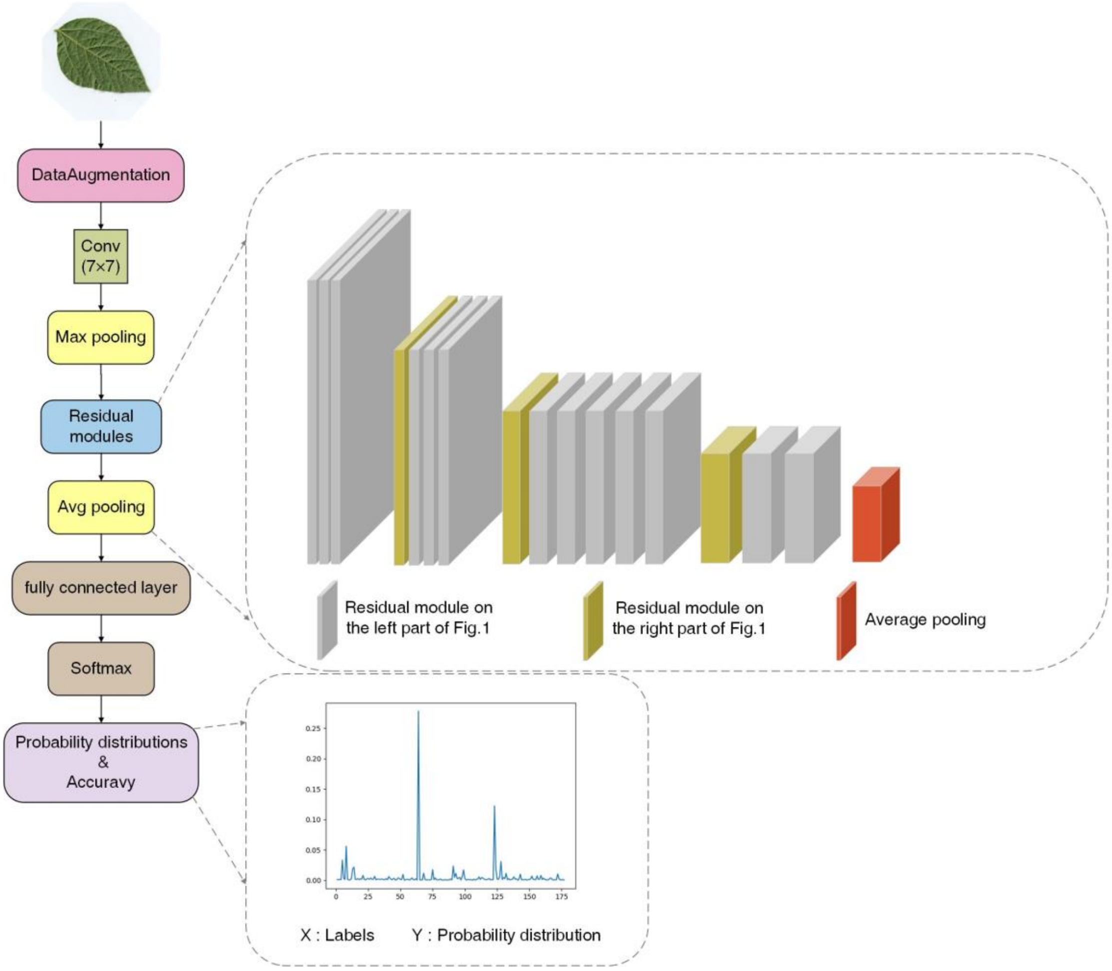

Figure 2: Structure diagram of ResNet34 [19].

4. Experimental Results and Discussions

To examine the effectiveness of deep learning method for leaf cultivar classification tasks, five groups of experiments are conducted on the Soybean-Cultivar leaf dataset. In all the experiments, for the proposed method, various parameters used in image training and testing are listed in Table. 1.

4.1. Dataset

In this research, we built a leaf database by collecting the leaf images from soybean plants of different cultivars. The database contains 1770 leaves collected from plants of 177 soybean cultivars. For each cultivar, there are 10 samples. Figure. 3 shows samples of soybean cultivars leaves taken from the plants of each cultivar.

ISSN 2616-5775 Vol. 4, Issue 3: 109-115, DOI: 10.25236/AJCIS.2021.040317

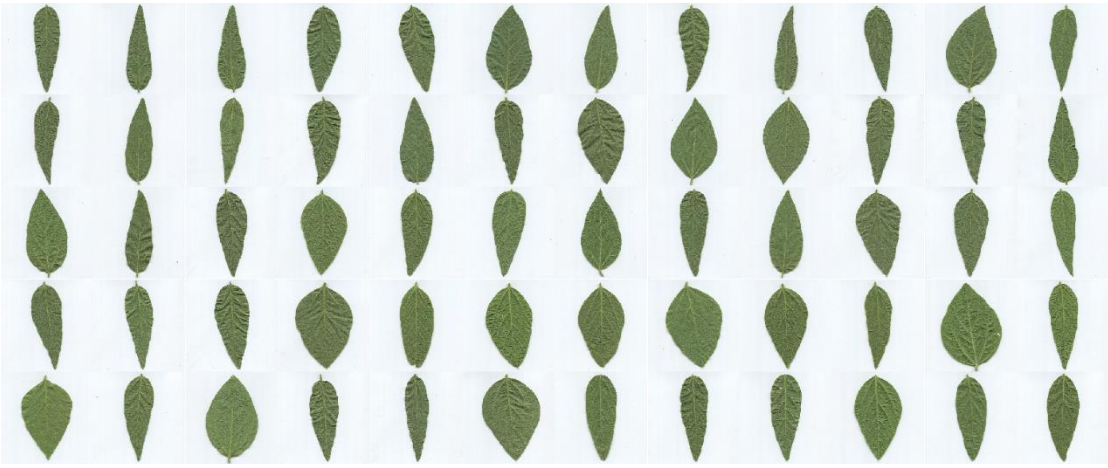

Figure 3: Part of soybean leaves taken from the leaf dataset.

The leaves taken from the soybean plants of 2 cultivars are shown in Figure. 4 as examples. It reveals 20 leaf images of 2 cultivars randomly, which are listed as 2 rows with each row displaying all the ten leaves taken from the same cultivar.

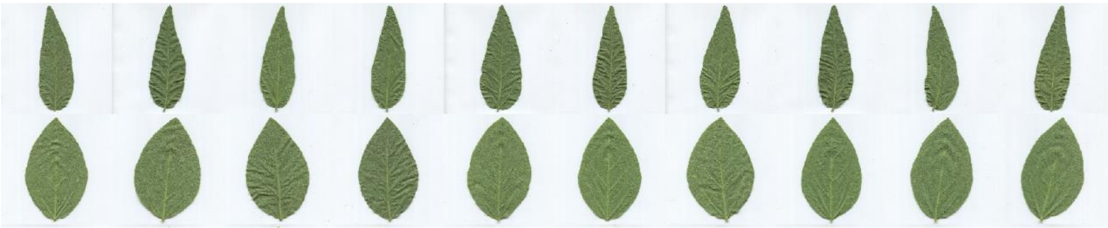

Figure 4: Example leaves of 2 cultivars from the Soybean dataset. The number of the samples of each species is ten which are listed as 2 rows with each row displaying all the ten leaves taken from the same cultivar.

After global analysis of the dataset, we find that for some soybean cultivars, the leaves from the same period are completely different in shape, outline, and other characteristics, while the leaves of some soybean cultivars have extremely high similarities, which are difficult to distinguish easily. However, compared to the species leaf image databases Leaf100 [11], MEW2012 [28], ICL, the leaves in the Soybean-Cultivar database are highly similar while the fact that they all belong to the same species, making a challenging dataset.

4.2. Implementation Details

Considering the fact that there is a large amount of intra-class variability, arising from form changes during the growth of leaves and different subtle inter-class differences, originating by belonging to the same species in Figure. 3. In this study, we only choose the leaf image that is scanned by a reflective image of the back side, also we randomly choose one stage from five periods in a soybean growth cycle. Therefore, there are 177 soybean cultivars and a total of 1770 leaf images used in our experiments.

Then, five groups of experiments are conducted which should be acknowledged as three traditional methods and a deep learning method. Among them, the HSC method has been verified to be able to extract the contour feature of the leaf successfully. Also, the LBP operator is suitable for calculating the local texture information in the leaf. Finally, an SVM classifier is learned for feature information based on three traditional methods.

Different from the traditional methods, deep learning has a great dependence on the number of data samples, which causes great difficulties in preparing datasets and training network models. For this reason, this research uses some approaches for data augmentation and pre-processing. Also, the learning method trains the parameters and optimizes them with the help of transfer learning. The basic parameter information of the proposed method together with the choice of Optimizer and function are listed in Table 1.

Table 1: The basic parameter information of the used Resnet34 model [19] in our experiments.

Parameters	Messages
Model	Resnet34
Training images	1062
Test images	708
Crop size	224*224
Learning rate	0.0001
Optimizer	Adam
Batch size	64
loss	CrossEntropyLoss

4.3. Results and Comparison

We compared the above-mentioned methods on the soybean leaf dataset. The experimental results are shown in Table 2. It can be seen that the deep learning method ResNet34 achieves the best classification accuracy of 69.20%. Compared with the handcrafted methods, the classification accuracy of deep learning method is 50.40%, 46%, 44.50% and 38.27% higher than the stat-of-the-art handcrafted methods HOG [17], HSC [11], LBP [16], and MSCM [15], respectively. These results demonstrate that when we use ResNet34 as deep learning method framework, it works better on characterizing leaf image patterns which holds good generalization ability and flexibility and presents a powerful characterization for leaf cultivar recognition.

Table 2: The classification performance comparisons of the deep learning methods ResNet34 [19] with the four state-of-the-art handcrafted methods on soybean leaf dataset.

Algorithm	Accuracy (%)
HOG [17]	18.80
HSC+SVM [11]	23.20
LBP+SVM [16]	24.70
MSCM [15]	30.93
ResNet34 [19]	69.2

5. Conclusions

This paper studied the leaf cultivar recognition problem and made a comparative study of deep learning methods with handcrafted methods on this challenging problem. The popular deep learning models ResNet34 network [19] are applied to leaf cultivar classification and compared with the four state-of-the-art traditional manual feature classification methods. The experimental results demonstrate that the deep learning methods outperform the traditional methods in a large margin. In our future work, new deep learning models will be developed for further improving the classification performance of leaf cultivars.

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