Advancing Plant Leaf Disease Identification Using Improved Residual Networks

Xiong Bi, Hongchun Wang*
School of Mathematical Sciences, Chongqing Normal University, Chongqing 401331, China.

Abstract: In agriculture, crop yield and quality are critical for global food supply and human survival. Challenges such as plant leaf diseases necessitate a fast, automatic, economical, and accurate method. This paper utilizes deep learning, transfer learning, and specific feature learning modules (CBAM, Inception-ResNet) for their outstanding performance in image processing and classification. The ResNet model, pretrained on ImageNet, serves as the cornerstone, with introduced feature learning modules in our IRCResNet model. Experimental results show our model achieves an average prediction accuracy of 96.8574% on public datasets, thoroughly validating our approach and significantly enhancing plant leaf disease identification.
Keywords: Image Recognition; Transfer Learning; Deep Convolutional Neural Network; Deep Learning

1. Introduction

Under climate influence, numerous microorganisms like bacteria and fungi inhabit the air. Prolonged exposure renders plant leaves vulnerable to diseases, significantly impacting crop yield and quality, thereby limiting agricultural productivity. Precise identification of plant leaf diseases is vital for implementing effective preventive measures to enhance yield and quality while minimizing economic losses.

However, in remote areas, reliance on manual observation persists, necessitating observers with specialized knowledge and experience. Yet, this method is time-consuming, expensive, subjective, inefficient, and prone to misdiagnosis. Moreover, it is only applicable to small-scale cultivation. Therefore, traditional manual methods are impractical, replaced by automatic disease identification systems, which not only demonstrate high efficiency but also offer satisfactory accuracy.

With the rapid development of computer vision and deep learning technologies, especially the widespread application of Convolutional Neural Networks (CNNs), automatic extraction of image features has become the mainstream approach. Compared to traditional machine learning algorithms, CNNs can automatically learn and extract multi-level features. Additionally, their recognition capabilities and stability are stronger, effectively handling various types of plant leaf disease images, even maintaining high recognition accuracy in the presence of factors such as lighting and obstruction. In recent years, researchers have conducted in-depth studies on plant leaf and other parts (such as roots, flowers, and stems) disease recognition using deep neural networks and their corresponding improved algorithms. For instance, Jiang *et al.* [1] fused Support Vector Machine (SVM) with Convolutional Neural Network (CNN) to build a disease recognition model. They utilized CNN to extract features from rice leaf disease images and applied SVM for disease classification and prediction. Results showed the model achieved an average accuracy of 96.8%, demonstrating satisfactory performance. Deb *et al.* [2] initially discussed the impact of rice diseases on agricultural production and traditional detection method limitations. They suggested the potential use of artificial intelligence for early diagnosis. Additionally, they outlined the performance of five CNN models (Inception-V3, VGG-16, AlexNet, MobileNet V2, and ResNet-18) on a rice leaf disease image dataset. The study revealed Inception-V3 with the highest accuracy of 96.23%. Deb *et al.* [3] introduced LS-Net, a novel CNN model for rose plant leaf segmentation and recognition, outperforming existing models. Pandian *et al.* [4] presented a 5-layer CNN model using data augmentation and hyperparameter optimization for plant leaf disease identification. With outstanding average accuracy of

98.41% on the test set, their model surpassed other methods. Kaur *et al.* [5] proposed a CNN model for tomato leaf disease identification, achieving an impressive 98.92% accuracy based on InceptionNet, ResNet V2, and transfer learning. Omer *et al.* [6] introduced a tuned CNN model for healthy and diseased cucumber leaf identification, outperforming Inception-V3, ResNet-50, and AlexNet.

In this paper, using the innovative IRCResNet network, we aim to offer a more reliable and efficient solution for plant leaf disease recognition. We believe this research will advance methods for monitoring and controlling plant diseases, enhancing agricultural production efficiency and quality for sustainable development.

2. Methods and Principles

2.1 ResNet

ResNet, introduced by He *et al.*[7] in 2015, is a type of deep convolutional neural network. In order to address the issues of vanishing and exploding gradients in deep networks, they introduced residual connections, allowing input feature maps to be directly passed to subsequent layers. The constructed ResNet includes residual connections and multiple residual blocks, each composed of two or more convolutional layers. Equation (1) illustrates the working principle of residual blocks and residual connections.

$$X_L = H_L(X_{L-1}) + X_{L-1} \qquad (1)$$

where X_L and X_{L-1} represent the output of layer L and $L-1$ separately. H_L represents the transformation function of layer L, which may include operations such as convolution, batch normalization, and activation function.

2.2 CBAM module

The CBAM [8][9] module enhances CNN performance through an attention mechanism. It incorporates Channel Attention Module (CAM) and Spatial Attention Module (SAM) to concentrate on channel and spatial information in feature maps, adaptively adjusting weights. Embedding CBAM in different CNN architectures improves feature capture across scales and complexities. This attention mechanism has shown performance improvements in diverse computer vision tasks, such as image classification and object detection.

2.3 Inception-ResNet module

To boost deep neural network performance, one approach is increasing network depth. However, this can result in excessive parameters and higher computational resource consumption. To tackle this issue, the Inception-ResNet-A module [10] combines Inception module's multi-scale feature extraction with ResNet's residual connections, aiming to decrease computational complexity and parameter count.

2.4 Transfer learning

Transfer learning is a deep learning approach utilizing a CNN trained on one task as the starting point for another. Due to the computational resources required to build deep networks and the expense of training large datasets, transfer learning is widely used in practical applications. Instead of initializing weights from scratch during training, we use a pre-trained ResNet model on ImageNet[11]. The core process of transfer learning is as follows:

(1) Determine the base network:

Select the ResNet-50 model, load its pre-trained weight parameters.

(2) Build a new network structure:

Adjust the network structure for other layers, retaining some lower-level structures, to meet specific task requirements.

(3) Train the new model:

After constructing the new network, train the entire model to update weight parameters.

3. Model construction

ResNet, with its residual connections, excels in feature extraction, addressing gradient vanishing and exploding issues, enabling support for deeper network structures. The introduction of CBAM, incorporating CAM and SAM modules, enhances the model's focus on crucial image regions. In transfer learning, we integrate Inception-ResNet-A and CBAM modules into the base network, creating IRCResNet for plant leaf disease identification. Adjustments to the pretrained model's structure include:

(1) Remove the last 3 bottleneck structures of the third layer and the entire fourth layer.

(2) Retain the final fully connected layer.

(3) Introduce a dual-branch structure after the removed layers, housing the CBAM and Inception-ResNet-A modules.

The IRCResNet model, illustrated in Figure 1, comprises the base network (ResNet-50) for feature extraction and the head network with dual branches. One branch features the Inception-ResNet-A module for multiscale feature extraction, while the other uses the CBAM module to extract features in affected areas, specifically local features.

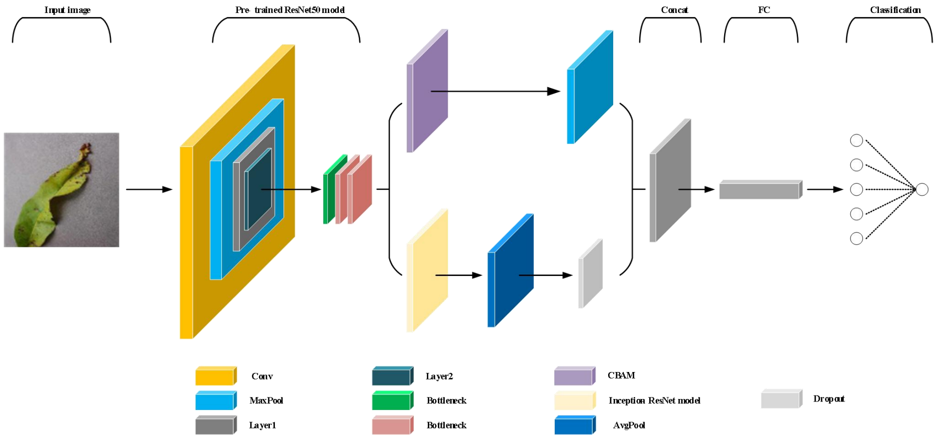

Figure 1. Schematic diagram of the network structure of the IRCResNet model.

4. Numerical experiments

4.1 Image data acquisition

First, we chose apple, corn, and potato leaf images from the Plantvillage public dataset[12]. Following several preprocessing steps, such as resizing, deduplication, and excluding unidentifiable images, we acquired a smaller public dataset with eight types of diseased leaves and three types of healthy leaves, totaling 9174 images. Afterward, we partitioned this dataset into training, validation, and test sets in a 6:2:2 ratio. Figure 2 illustrates the symptoms of plant leaf diseases in this dataset.

4.2 Experimental platform and evaluation indicators

The experiments in this article utilize the PyTorch framework, and training is expedited on experimental devices with GPUs. The hardware configuration is: Intel(R) Xeon(R) Platinum 8157 CPU @ 2.30GHz; two NVIDIA GeForce RTX 3090 GPUs, each with 24GB of memory; PyTorch 1.7.1; Python 3.8; CUDA 11.0; CUDNN 8.0. To assess various model performances, we choose four image classification metrics: $Accuracy$, $Precision$, $Recall$, and $F1-Score$. Formulas (2-5) [13] illustrate the calculation methods for these metrics.

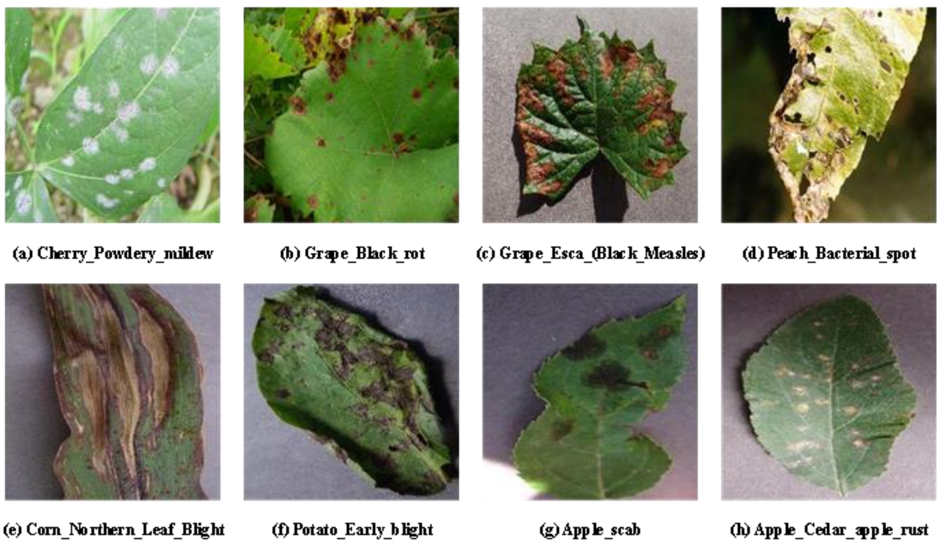

Figure 2. Schematic diagram of plant leaf disease symptoms.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{5}$$

4.4 Experimental results and analysis

We tested the proposed IRCResNet model on the public dataset and documented its performance, comparing it with other benchmark models on the same dataset, as detailed in Table 1. By analyzing the data in this table, it is evident that the proposed model demonstrates promising results, surpassing current popular methods in image recognition. Specifically, our model exhibits the highest average prediction accuracy, reaching 96.8574%. Furthermore, our model outperforms benchmark models in other evaluation metrics. To further explore the classification effectiveness and validate the improved accuracy, we also present the predictive capabilities of the model through a confusion matrix, as illustrated in Figure 3.

Table 1 Performance comparison of different models on the public dataset (%).

Model	Accuracy	Precision	Recall	F1-Score
VGG-19	82.4656	80.1854	80.4862	80.7562
ResNet-50	91.4263	91.7521	91.2285	91.8624
EfficientNet-B0	86.1982	84.2542	86.1923	85.7214
IRCResNet	**96.8574**	**96.8043**	**95.8953**	**95.5231**

Among them, 0-10 represent the labels of various plant leaf images in the dataset (corresponding to the disease types from a to h in Figure 3). It can be observed that the model in this article accurately identifies most disease types, with only a few being either unidentified or incorrectly identified. Thus, it can be demonstrated that the model proposed in this paper is effective and addresses the issue of low accuracy in identifying plant leaf diseases.

5. Conclusion

The rapid and precise identification of plant leaf diseases is vital for crop yield and quality. Thus, finding a rapid, automated, cost-effective, and accurate method is crucial. Deep learning, particularly Convolutional

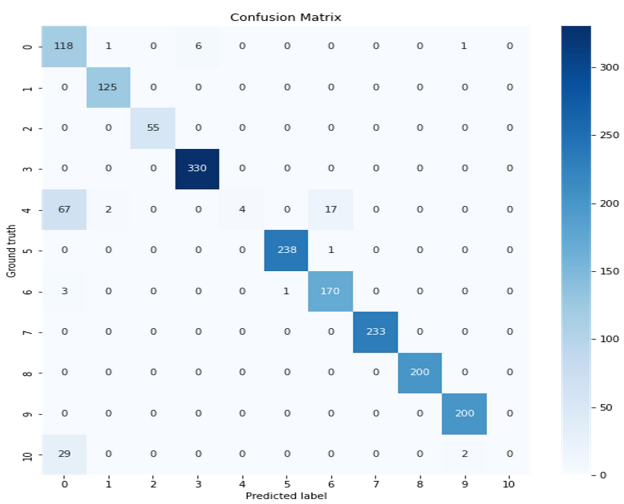

Figure 3. Confusion matrix generated when using the IRCResNet model to identify plant leaf diseases.

Neural Networks (CNNs), has excelled in classifying plant leaf diseases. In this paper, we introduce IRCResNet, a novel deep learning architecture. It employs the pre-trained ResNet-50 model on ImageNet and other feature learning modules for transfer learning. This enhances feature extraction and reduces computational complexity by introducing a new fully connected Softmax layer to truncate the network's top. IRCResNet not only improves feature extraction but also reduces computational complexity without compromising accuracy. Experimental results showcase the model's exceptional performance on a plant leaf disease image dataset. In the future, we aim to deploy this model on mobile devices for automated monitoring and identification of plant leaf diseases. Furthermore, we intend to apply it to a wider range of practical scenarios.

References

[1] Jiang F., Lu Y., Chen Y., Cai D., Li G.F. 2020. Image recognition of four rice leaf diseases based on deep learning and support vector machine. COMPUT ELECTRON AGR. 179:105824.

[2] Deb M., Dhal K.G., Mondal R., Gálvez J. 2021. Paddy Disease Classification Study: A Deep Convolutional Neural Network Approach. OPT MEMORY NEURAL. 30:338-357.

[3] Deb M., Garai A., Das A., Dhal K.G. 2022. LS-Net: a convolutional neural network for leaf segmentation of rosette plants. NEURAL COMPUT APPL. 34:18511-18524.

[4] Pandian A.J., Kanchanadevi K., Kumar D.V., Jasinska E., Gono R., Leonowicz Z., Jasinski M. 2022. A Five Convolutional Layer Deep Convolutional Neural Network for Plant Leaf Disease Detection. ELECTRONICS-SWITZ. 11.

[5] Kaur P., Harnal S., Gautam V., Singh M.P., Singh S.P. 2022. A novel transfer deep learning method for detection and classification of plant leaf disease. J AMB INTEL HUM COMP.

[6] Omer S.M., Ghafoor K.Z., Askar S.K. 2022. An Intelligent System for Cucumber Leaf Disease Diagnosis Based on the Tuned Convolutional Neural Network Algorithm. MOB INF SYST. 2022:1-16.

[7] He K.M., Zhang X.Y., Ren S.Q., Sun J. 2016. Deep residual learning for image recognition. Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. 2016-Decem:770-778.

[8] Chen L., Zhang H.W., Xiao J., Nie L.Q., Shao J., Liu W., Chua T.S. 2017. SCA-CNN: Spatial and channel-wise attention in convolutional networks for image captioning. Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017. 2017-Janua:6298-6306.

[9] Woo S., Park J., Lee J.Y., Kweon I.S. 2018. CBAM: Convolutional block attention module. ECCV. pp. 3-19.

[10] Szegedy C., Ioffe S., Vanhoucke V., and Alemi A. 2016. Inception-v4, Inception-ResNet and the impact of residual connections on learning. Comput Sci.

[11] Russakovsky O., Deng J., Su H., Krause J., Satheesh S., Ma S., Huang Z., Karpathy A., Khosla A., Bernstein M., and Berg AC. 2015. ImageNet Large Scale Visual Recognition Challenge. Int J Comput Vis Springer US.

[12] Plantvillage dataset. Available from: https://www.kaggle.com/search?q= plantvillage+dataset

[13] Zeng W.H., Li H.D., Hu G.S., Liang D. 2022. Lightweight dense-scale network (LDSNet) for corn leaf disease identification. COMPUT ELECTRON AGR. 197:106943.

About the author: Xiong Bi, master student, research direction: computer vision, deep learning, image recognition

*Corresponding author: Hongchun Wang, professor, research interests include uncertainty reasoning, data mining, machine learning and probability and statistics limit theory.