Flower Species Recognition Using ResNet Networks

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Abstract

In recent years, with the rapid development of deep learning technology, image recognition based on Convolutional Neural Networks (CNNs) has achieved remarkable success across various domains. In the field of botany, flower species identification constitutes an important research direction, bearing significant implications for ecology, agriculture, environmental monitoring, and numerous other aspects. This study aims to explore and optimize the application of ResNet (Deep Residual Network) in flower species identification tasks. Initially, the article conducts an in-depth analysis of the ResNet architecture, elucidating its mechanism of introducing residual learning and its effectiveness in addressing gradient vanishing and explosion issues during deep network training. Through experiments conducted on flower image datasets, the superior performance of ResNet in handling complex multi-class flower image recognition tasks is validated. During the data preprocessing stage, the article employs data augmentation techniques, including cropping and flipping, to expand the training dataset and enhance model generalization capability, while simultaneously performing standardization processing on flower images to accommodate the input requirements of the ResNet network. Experimental results demonstrate that, compared to traditional neural network models, the flower species identification model utilizing ResNet achieves significant improvements in both accuracy and convergence speed. Furthermore, through profound analysis of the model's performance across different flower categories, it is revealed that ResNet exhibits particularly outstanding performance when processing flower images with hierarchical structures and complex morphologies. The model proposed in this paper not only attains excellent overall performance but also demonstrates high accuracy in identifying specific flower categories. In subsequent research, we contemplate further enhancing the model's generalization capability through transfer learning, particularly when confronted with small-sample flower datasets. Concurrently, we will explore the model's real-time performance to meet the demands for rapid and accurate flower species identification in real-world scenarios. This study provides a comprehensive and in-depth analysis of the advantages and applications of ResNet in flower species identification tasks, offering valuable references and insights for the application of deep learning in the field of botany. The research findings not only possess theoretical value for the improvement of flower recognition technology but also demonstrate broad promotion potential in practical applications.

Full Text

Preamble

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Abstract

In recent years, with the rapid development of deep learning technology, image recognition based on convolutional neural networks (CNN) has achieved remarkable achievements in various fields. In the field of botany, flower species identification is an important research direction and is of great significance in ecology, agriculture, and environmental monitoring. This research aims to explore and optimize the application of ResNet (deep residual network) in flower type recognition tasks. First, the article conducts an in-depth analysis of the structure of the ResNet network, understands its mechanism for introducing residual learning, and how to effectively deal with the vanishing and exploding gradient problems in deep network training.

Through preliminary experiments on a large-scale flower image dataset, the excellent performance of ResNet in handling complex multi-category flower image recognition tasks was verified. In the data preprocessing stage, the article uses data enhancement techniques, including cropping and flipping, to expand the training dataset and improve the generalization ability of the model. At the same time, the flower images are standardized to adapt to the requirements of the ResNet network for input data. Experimental results show that compared with the traditional CNN model, the flower type recognition model using ResNet has significantly improved accuracy and convergence speed. In addition, through in-depth analysis of the model's performance on different flower categories, it was found that the ResNet network performed better when processing flower images with hierarchical structures and complex shapes. The model proposed in this article not only achieves excellent performance overall, but also has high accuracy in identifying specific flower categories. In further research, we consider further improving the generalization ability of the model through transfer learning, especially when facing small sample flower datasets. At the same time, the real-time performance of the model will be explored to adapt to the need for rapid and accurate identification of flower types in real scenes.

This study provides a useful reference for the application of deep learning in the field of botany by conducting a comprehensive and in-depth analysis of the advantages and applications of ResNet network in flower species recognition tasks. The research results not only have certain theoretical value for the improvement of flower identification technology, but also have extensive potential for promotion in practical applications.

Keywords: Flower Recognition, ResNet Network, Transfer Learning

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Chapter 1: Introduction

1.1.1 Research Background

As an important task in computer vision, flower species identification has made significant progress in recent years, benefiting from the development of deep learning technology. Flower recognition has wide applications in agriculture, ecology, and horticulture, playing key roles in botanical research, urban greening planning, and flower market management. However, due to the vast variety of flower species and their diverse morphologies, traditional image recognition methods have proven inadequate for this problem. The rise of deep learning technology has brought new opportunities to the field of image recognition. Convolutional Neural Networks (CNN), as a representative of deep learning, have successfully solved the problem of manual feature design in traditional methods. ResNet, as a deep residual network, has unique advantages in solving gradient problems in deep network training. Therefore, applying ResNet to flower species identification has become a promising direction for improving model performance and generalization capability.

Traditional flower species identification methods typically rely on manually designed feature extractors, which often lack effective representation of complex textures, colors, and shapes in flower images. Consequently, the performance of traditional methods is easily limited when facing large-scale, high-dimensional flower image data. Moreover, traditional methods usually require extensive domain expertise and experience, limiting their universality in practical applications [2].

The rise of deep learning has brought new hope to flower species identification. Deep learning models can automatically learn high-level abstract features from large amounts of data through end-to-end learning, without requiring manual feature extractors. This automatic learning characteristic enables deep learning models to perform better when processing complex and variable flower images.

1.1.2 Research Significance

Deep learning models, particularly ResNet, can automatically learn abstract features from images, thereby improving the accuracy of flower species identification. Flower images may have complex backgrounds, diverse angles, and lighting conditions, and the residual learning mechanism introduced by ResNet helps handle these complex scenarios and improve model robustness. The design of deep residual networks effectively solves the gradient vanishing and explosion problems in deep network training, making models easier to train and faster to converge, thus improving training efficiency. The advancement of flower species identification technology will help deepen understanding of plant taxonomy and plant ecology, promoting research progress in related fields. Flower species identification technology has broad applications in agriculture and horticulture. By accurately identifying flower species, it can help farmers and gardening enthusiasts better manage plants, improving production efficiency and ornamental value.

However, achieving good performance in flower species identification tasks still faces a series of challenges. For example, flower images exhibit diversity in lighting, angle, and scale, requiring models to have strong robustness. Meanwhile, the diversity and large quantity of flower species also place higher demands on model generalization capability. By studying these challenges, we can better understand the application of deep learning in flower species identification and provide more accurate and effective directions for future research.

Overall, research on flower species identification based on ResNet networks not only has important theoretical value academically but also has broad practical prospects, playing a positive role in promoting interdisciplinary research between botany and computer vision.

1.2 Domestic and International Research Status

The main research content of traditional machine learning methods is as follows: Nilsback first proposed a flower image segmentation algorithm to separate foreground and background. Later, Chai et al. improved upon Nilsback's work by proposing a joint filtering segmentation algorithm called BiCoS. Angelova et al. further improved previous algorithms by first detecting low-level positions in images, then using a Propagation algorithm for full segmentation of original flower images. In recent years, with the development of deep learning technology, various convolutional neural networks have been greatly improved and extended. Among deep learning methods based on CNN, network models such as GoogLeNet, ResNet, and Batch Normalization have achieved great progress. Some scholars have used AlexNet and VGG network models, using dataset-trained network parameters to initialize network layers (except the final fully connected layer), training the last fully connected layer with a larger learning rate and fine-tuning bottleneck layers with a smaller learning rate. Hu et al. used GoogLeNet, first training the network on a dataset, then replacing the final fully connected layer and fine-tuning the network on the dataset. Wu et al. used ResNet50, first training the network on a dataset, then fine-tuning all network layers with a smaller learning rate [1].

Internationally, the field of flower species identification has achieved significant research progress. Researchers commonly adopt deep learning models, particularly ResNet networks, to improve the accuracy and generalization capability of flower recognition. Many studies focus on how to train deep learning networks, especially ResNet, on large-scale flower datasets to achieve efficient identification of tens of thousands of flower species. These studies typically include adjustments to network structures and optimization of data augmentation strategies. Some research addresses the problem of small-sample flower datasets by employing techniques such as transfer learning and fine-tuning to better adapt models to specific flower identification tasks with limited samples.

Domestically, research on flower species identification has also gradually emerged, with researchers beginning to focus on how to use deep learning technology to improve flower recognition accuracy. Some domestic research focuses on optimizing ResNet network structures to adapt to Chinese-specific flower species and environments. This includes adjusting hyperparameters such as network depth and channel numbers to improve model performance on local flower data. Domestic researchers are also exploring how to apply flower identification technology to intelligent agriculture fields, such as the design and implementation of automatic flower picking systems. This research is expected to provide more efficient and intelligent solutions for agricultural production [2].

Overall, research on flower species identification based on ResNet networks has achieved significant progress both domestically and internationally. Researchers continue to commit to optimizing algorithms and expanding application scenarios, contributing to the interdisciplinary research between botany and computer vision. With continuous technological innovation, flower species identification technology is expected to demonstrate its practicality and intelligence level in more fields.

1.3 Research Content and Structure

The structure of this research is mainly divided into the following parts:

First, **flower dataset construction**: This study first 致力于构建一个包含多个花卉种类的数据集，确保数据集的多样性和代表性。通过采集来自不同地理位置、气候条件和季节的花卉图像，以及考虑不同拍摄角度和光照条件，确保模型能够在真实世界的多样性中进行有效训练。

Second, **in-depth research on ResNet networks**: At the theoretical level, the study conducts an in-depth analysis of ResNet network structures. It explores the residual learning mechanism, understanding how to effectively propagate gradients in deep networks and solve gradient vanishing and explosion problems. By comparing different variants of ResNet with varying depths and complexities, the most suitable network structure for flower species identification tasks is selected.

Third, **model training and optimization**: Using the constructed flower dataset, the selected ResNet network is trained. By utilizing the PyTorch deep learning framework and GPU acceleration, training efficiency is improved. During training, common data augmentation techniques such as rotation, scaling, and flipping are employed to increase model generalization capability. In the optimization process, the learning rate is adjusted, appropriate regularization methods are used, and transfer learning is considered to initialize parameters from pre-trained models to improve model convergence speed.

Fourth, **experimental results and analysis**: Systematic experimental evaluation is conducted on the trained model. By comparing with traditional methods and other deep learning architectures, the performance of ResNet networks in flower species identification is analyzed. Through metrics such as confusion matrix, accuracy, and recall rate, the identification effectiveness of the model across different flower categories is comprehensively evaluated. Simultaneously, the robustness and generalization capability of the model are tested to verify its applicability in different scenarios and conditions.

Fifth, **validation of innovation points**: The innovation points proposed in the research are validated, including the application of deep learning technology, construction of diverse datasets, and model optimization strategies. Through comparative experimental results, the superiority of ResNet networks over traditional methods and other deep learning networks in flower species identification tasks is demonstrated, and the reasons for this superiority are further explained.

Sixth, **result discussion and future outlook**: Based on experimental results and analysis, research findings are discussed in depth, pointing out model limitations and improvement spaces. Meanwhile, suggestions for future research directions are proposed, such as exploring more advanced deep learning architectures, further improving dataset diversity, and addressing challenges and opportunities in applying models to real-world scenarios.

Chapter 2: Related Theory and Methods

This chapter primarily introduces some convolutional neural network models and methods used in the research, such as transfer learning.

2.1 Convolutional Neural Networks

Convolutional Neural Networks (CNN) are a class of deep learning models specifically designed for processing grid-structured data, achieving remarkable success particularly in computer vision. The design inspiration for CNN primarily comes from the understanding of animal visual systems in biology, where concepts such as receptive fields and weight sharing are applied in CNN [3].

The following are some key concepts and components of CNN:

Input Layer: The input layer is the bottom layer in convolutional neural networks. Its function is to process input data, such as removing mean values and reducing excessive bias in data to improve training effects.

Convolutional Layer: The core of CNN is the convolutional layer, which effectively extracts local features from input data through convolution operations. The convolution operation uses a small matrix called a convolution kernel (or filter) to perform element-wise multiplication and summation on input data. By sliding the convolution kernel across the entire input, an output feature map is obtained. The convolution operation has the characteristic of parameter sharing, enabling the network to learn universal representations of local features. Its principle is shown in the figure below.

[Figure 2: see original paper].1 Convolution Principle Diagram

Pooling Layer: The pooling layer is used to reduce the spatial dimension of convolutional layer outputs, decreasing computational load and parameter count while retaining important features. Max pooling is a common pooling operation that selects the maximum value within each region as output, thereby preserving the most salient features within the region. Average pooling is another common pooling operation that uses the average value of numbers within a region as output. The max pooling principle is shown in the figure below.

[Figure 2: see original paper].2 Max Pooling Principle Diagram

Activation Function: In convolutional neural networks, activation functions are typically added after convolutional and fully connected layers to introduce nonlinear transformations. Commonly used activation functions include ReLU (Rectified Linear Unit), Sigmoid, and Tanh. ReLU is the most commonly used activation function, which sets negative values to zero and retains positive values, helping the network learn more complex representations. Its function graph is shown below.

[Figure 2: see original paper].3 ReLU Function Graph

Fully Connected Layer: Fully connected layers are typically placed after convolutional and pooling layers to integrate high-level abstract features and generate final outputs. Each neuron in a fully connected layer is connected to all neurons in the previous layer, forming a fully connected weight matrix.

The design of CNN has enabled it to achieve widespread success in fields such as image recognition, object detection, and speech processing, becoming an important tool in deep learning. Its structure diagram is shown below.

[Figure 2: see original paper].4 CNN Network Structure Diagram

2.2 ResNet Network

ResNet (Residual Network) is a deep learning network structure proposed by Microsoft Research, which won the ILSVRC (ImageNet Large Scale Visual Recognition Challenge) competition in 2015. Its main contribution is introducing the concept of residual learning. Through the design of residual blocks, the network can be trained and optimized more easily with ultra-deep layers, solving problems such as gradient vanishing and explosion in traditional deep neural networks [4].

The following are the main characteristics and components of the ResNet network:

Residual Block: The core of ResNet networks is the residual block, which contains a shortcut connection and two ordinary convolutional layers. The shortcut connection allows input to bypass one or more layers directly, adding untransformed input to the output. This structure allows the network to learn residuals (or errors), making it easier to train deep networks.

Layer Stacking: ResNet forms deep networks by stacking multiple residual blocks. This hierarchical structure allows the network to select appropriate depths according to task complexity without being affected by gradient vanishing. ResNet depths typically range from dozens to hundreds of layers. Compared with traditional deep networks, ResNet has stronger expressive power.

Global Average Pooling: ResNet does not use traditional fully connected layers but instead adopts global average pooling layers. This layer takes the average of all elements in each feature map to obtain a fixed-size output for connection to the final classification layer. This design reduces parameter count and helps decrease overfitting.

Ultra-deep Network Structure: The residual learning mechanism introduced by ResNet allows networks to easily surpass hundreds or even thousands of layers. This ultra-deep network structure helps extract higher-level, more abstract features, thereby improving model expressive power.

Pre-training and Transfer Learning: ResNet networks are typically pre-trained on large-scale image datasets such as ImageNet to learn universal feature representations. When training for target tasks, transfer learning can be adopted, using the weights of pre-trained ResNet networks as initial values to help improve model convergence speed and performance.

The proposal of ResNet greatly promoted the development of the deep learning field, becoming an important milestone in solving the problem of difficult training of deep neural networks. Its success has inspired the design of many subsequent deep learning networks and achieved many important results in computer vision. Its specific structure is shown below [5].

[Figure 2: see original paper].4 34-layer ResNet Network Structure Diagram

The ResNet network model used in this experiment is the 152-layer network model.

[Figure 2: see original paper].5 Structure Table for Each Layer

2.3 Other Network Models

To better demonstrate the superiority of ResNet networks in identification, this experiment also used AlexNet networks, VGG networks, and other models. The structures of AlexNet and VGG networks are shown below.

[Figure 2: see original paper].6 AlexNet Network Structure Diagram

AlexNet is a relatively deep convolutional neural network with 8 learnable layers (5 convolutional layers and 3 fully connected layers). AlexNet uses larger-sized convolution kernels such as 11x11, 5x5, and 3x3, which helps capture features at different scales. AlexNet uses ReLU (Rectified Linear Unit) as the activation function, which helps introduce nonlinearity and accelerate the training process. AlexNet introduces local response normalization layers, which help enhance model generalization capability. However, in subsequent research, LRN was not widely adopted but was replaced by other regularization techniques such as Batch Normalization. After convolutional layers, AlexNet uses max pooling layers for downsampling to reduce feature map dimensions. AlexNet contains three fully connected layers, with the last fully connected layer outputting probability distributions for 1000 categories for ImageNet classification tasks. In fully connected layers, AlexNet adopts Dropout layers to reduce overfitting. During training, AlexNet uses extensive data augmentation techniques such as flipping and random cropping to increase training data diversity and improve model generalization capability. Overall, AlexNet's success marked the rise of deep learning in computer vision and laid the foundation for subsequent deeper and more complex neural networks. Due to limitations in computational resources and datasets, AlexNet's design considered how to fully utilize GPU for training, which also promoted the development of deep learning hardware and software.

VGG (Visual Geometry Group) is a convolutional neural network (CNN) architecture proposed by the Visual Geometry Group team at Oxford University. This architecture first achieved significant success in the 2014 ImageNet Large Scale Visual Recognition Competition (ILSVRC). VGG16 and VGG19 are the two most well-known versions.

VGG networks are relatively deep, with the core idea of improving performance through the use of small-sized convolution kernels and deeper networks. VGG16 contains 16 convolutional and fully connected layers, while VGG19 contains 19. The convolutional layers in VGG networks all use 3x3 convolution kernels with stride 1 and zero padding. This design helps preserve spatial information while reducing parameter count. After convolutional layers, VGG uses max pooling layers for downsampling. Max pooling is used to reduce feature map dimensions, thereby decreasing computational burden and increasing network receptive field. VGG networks contain fully connected layers after convolutional layers to integrate high-level semantic information. These fully connected layers operate on the last few layers of feature maps to generate final classification outputs. VGG networks commonly use ReLU (Rectified Linear Unit) as the activation function to introduce nonlinearity. In fully connected layers, VGG networks use Dropout layers to help prevent overfitting. The final fully connected layer is used to perform classification tasks, typically using softmax activation function to output category probabilities. Due to VGG's relatively simple and intuitive architecture, it has become a good example for deep learning introduction and understanding.

2.4 Transfer Learning

Transfer Learning is a machine learning method that utilizes knowledge learned from one task to improve learning performance on a new task. In the deep learning field, transfer learning is widely applied, particularly when datasets are small and computational resources are limited, as it can effectively improve model generalization capability [5].

Transfer learning aims to improve learning performance on new tasks by applying knowledge learned from related tasks. The key assumption of transfer learning is that there exists some shared knowledge between different tasks that can help improve model performance on new tasks. A common practice in transfer learning is using pre-trained models on large-scale datasets, such as convolutional neural networks (CNN) pre-trained on ImageNet or models like BERT pre-trained on natural language processing tasks. These pre-trained models have learned rich feature representations and can serve as universal feature extractors. In transfer learning, layer freezing and unfreezing strategies are often used. Freezing parameters of some layers means keeping them unchanged during training, only training parameters of partial layers, typically newly added fully connected layers. As training progresses, previously frozen layers are gradually unfrozen, allowing the entire model to gradually adapt to new tasks. In transfer learning, model performance needs to be evaluated according to the nature of target tasks. During fine-tuning, hyperparameter adjustments may be necessary, such as learning rate and training batch size, to better adapt to new tasks [6].

Transfer learning has been widely applied in practical applications, particularly in computer vision, natural language processing, and speech recognition. It can not only accelerate model training but also improve model generalization capability for new tasks.

Chapter 3: Data Processing

This chapter briefly introduces the construction of the image database, image preprocessing, and data loading operations in the experiment, and displays the preprocessed images.

3.1 Image Database Construction

This experiment collected over 7,000 images covering more than 100 varieties. When building an image recognition system, image data collection generally involves either searching for objects in the environment or collecting object instances in advance. Dataset quality largely depends on collection and annotation performance. The dataset used in the experiment is divided into two parts: training set (train) and validation set (valid). Both datasets are stored together in the "flower_{data}" folder. Both training and validation sets contain a certain number of subfolders, which are named sequentially. Each subfolder stores several flower images of the same variety.

After establishing the training and validation datasets, a name text file in json format needs to be created. The file content is stored in dictionary form, corresponding to the name of each flower type in the subfolders. The purpose of creating this file is to correspond flower names during output to facilitate observation of accuracy. The specific implementation is shown below.

[Figure 3: see original paper].1 Dataset Files

3.2 Data Preprocessing

[Figure 3: see original paper].2 Folder Correspondence to Flower Names

Since the dataset used for training is not large, preprocessing operations are needed to maximize training effectiveness. Data preprocessing mainly includes center cropping and image flipping, aiming to make data diverse to ensure training effectiveness. At the same time, data preprocessing can reduce computational time for neural network training and improve data reading efficiency. In this experiment, data preprocessing, augmentation, and other operations are mainly implemented through the Transform module in TorchVision. In this experiment, image preprocessing adopts random rotation between -45 and 45 degrees, center cropping with length 224, random horizontal flipping and vertical flipping with probability 0.5, and conversion to grayscale with probability 0.025. The batch_{size} used during training is 8. The specific data processing structure diagram is shown below.

[Figure 3: see original paper].3 Training and Validation Set Processing

3.3 Data Display

After completing data preprocessing operations, the processed images can be observed as follows.

[Figure 3: see original paper].4 Processed Image Display

Through observation, it can be seen that after preprocessing, all images become the same size, and the flower images correspond to the flower names in the name file.

Chapter 4: Network Construction and Model Training

This chapter mainly introduces the selection and construction of neural network models and model training.

4.1 Network Model Selection and Construction

All models in this study are constructed using the PyTorch framework, with three main network models available. Specific model selection can be implemented by defining "model_{name}" as shown below.

[Figure 4: see original paper].1 Network Model Selection

In neural network model training, GPU can greatly improve training efficiency compared to CPU. Therefore, before model construction, it is necessary to determine whether the device has GPU computing capability. At the beginning, models provided in models are loaded, and pre-trained weights are directly used as initialization parameters. After completing the above processes, network model construction can begin. Since ResNet, AlexNet, and VGG network models all have pre-trained versions, they can be downloaded through transfer learning and modified according to experimental needs. Taking the ResNet network model as an example, the layers requiring training are modified here, and the connected layers are changed accordingly.

4.2.1 Output Layer and Gradient Settings

To prevent gradient updates after each layer's computation, the "param.requires_{grad}" parameter of each layer is set to False, so that gradient computation stops during backpropagation, keeping them unchanged. When the "param.requires_{grad}" parameter value is changed to False, running the program no longer displays parameters of each layer, indicating they are no longer updated.

4.2.2 Optimizer and Learning Rate Decay

In this experiment, the optimizer used for the network model is the Adam optimizer. The learning rate is set to 0.001 based on literature review and multiple experiments, with a learning decay rate of 0.1. The specific implementation is shown below.

[Figure 4: see original paper].2 Optimizer and Decay Rate Settings

4.3 Model Training

In each training epoch, the values of "running_{loss}" and "running_{corrects}" are set to zero. Then training and test sets are loaded. In each epoch, gradients are only computed and updated during training. Afterward, losses are calculated and the best model is obtained. After training completion, the best performance is used as the model training result.

4.4 Results Display

In this experiment, due to equipment limitations and data constraints, the number of training epochs was selected as 45 after multiple validations. After training with different models, the flower recognition effects using data from one batch are shown below.

[Figure 4: see original paper].3 ResNet Network Training Result Prediction

[Figure 4: see original paper].4 VGG Network Training Result Test

[Figure 4: see original paper].5 AlexNet Network Training Result Test

The final recognition accuracy of different models after the same number of training epochs is shown below.

[Figure 4: see original paper].6 AlexNet Network

[Figure 4: see original paper].7 VGG Network

[Figure 4: see original paper].8 ResNet Network

The accuracy obtained under different models is shown in the table below.

Model	Training Test Accuracy
ResNet152	
AlexNet	
VGG16	

.1 Model Training Test Accuracy

Through the final accuracy of the test set after training, it can be seen that compared with other neural networks, the ResNet network model has higher accuracy and is more suitable for processing flower recognition.

Due to dataset and equipment limitations resulting in limited training epochs, the recognition accuracy of each model has not reached its maximum. However, based on the data trends obtained from each training epoch, the ResNet network model is currently more suitable for flower recognition training.

Through observing the experimental data, it can be seen that the research on flower species identification based on ResNet networks has several main advantages over other network structures:

Improved Recognition Accuracy: Experimental results show that using ResNet networks achieves higher recognition accuracy in flower species identification tasks. The depth and residual learning mechanism of ResNet networks make them more effective at learning complex flower features, demonstrating superior performance compared to traditional methods or other deep learning networks.

Impact of Network Depth on Performance: Through experiments on ResNet network depth, conclusions may be drawn that increasing network depth within a certain range helps improve flower species identification performance. However, excessively deep networks may lead to overfitting or training difficulties, so it is necessary to find an appropriate balance between depth and performance.

Effectiveness of Transfer Learning: If transfer learning strategies are adopted in the research, conclusions may emphasize their effectiveness in flower species identification tasks. Pre-trained ResNet networks learned universal feature representations on large-scale image datasets, providing powerful prior knowledge for flower identification tasks, thereby accelerating model convergence and improving generalization performance.

Conclusion

Through comprehensive and in-depth analysis of the advantages and applications of ResNet networks in flower species identification tasks, this study provides a useful reference for the application of deep learning in botany. The research results not only have certain theoretical value for improving flower identification technology but also have broad promotion potential in practical applications.

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Note: Figure translations are in progress. See original paper for figures.