

The Design and Implementation of Flower Image Classification based on Deep Convolutional Neural Networks

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Abstract: In recent years, the recognition and classification of flower species have become increasingly important in fields such as botany, agriculture, and ecological conservation. This paper improves a flower image classification model utilizing deep convolutional neural networks (ResNet) by incorporating deeper residual structures, hence enhancing the model's capacity to capture intricate feature correlations effectively. Additionally, novel data augmentation techniques, including random cropping, rotation, and color alteration, are employed to enhance the model's resilience to diverse input data. During the experiment, a public dataset containing five flower categories (approximately 3,660 images) was used, and the dataset was split into training and testing sets. The ResNet model was pre-trained, and the network architecture was fine-tuned. During training, the author recorded the loss and accuracy for each epoch to track the model's progress. The experimental results demonstrate that the proposed model can efficiently and accurately recognize flower species in the dataset. Traditional image classification methods typically achieve an accuracy of around 80%, while the optimized ResNet model achieves an accuracy of 90%.

Keywords: Computer vision, Image recognition, Deep learning, Image classification, ResNet

1. Introduction

With the rapid development of computer technology, especially the gradual maturation of machine learning techniques, significant progress has been made in the field of image recognition [1,2]. Image detection and recognition have emerged as complex subjects in contemporary academic research, characterized by extensive applications and ongoing innovation. Medical image analysis use image recognition technology to aid physicians in disease diagnosis; autonomous vehicles depend on real-time image recognition to detect road signs and barriers; intelligent surveillance systems improve security using facial recognition technology. The development of image recognition methods reflects the technological evolution in the fields of computer vision and machine learning. From traditional image processing methods to deep learning approaches, the research in image recognition has made remarkable advancements. This paper aims to study the flower image recognition problem based on deep convolutional neural networks, specifically using the ResNet model for classification [3]. This research investigates the use of deep learning for flower recognition by training and testing on a flower image dataset. The goal is to contribute to the development of smart agriculture by accurately recognizing flowers, thereby improving agricultural productivity; it

also has a positive impact on ecological conservation and biodiversity monitoring. Finally, the research findings could provide scientific support for landscape planning, thus promoting sustainable development.

2. Literature Review

Conventional image processing algorithms have restricted feature extraction abilities in intricate contexts, whilst machine learning-based image identification systems, despite notable advancements, continue to encounter difficulties in managing fine-grained features. In 2012, AlexNet, the inaugural deep convolutional neural network (CNN) developed by Alex Krizhevsky for image classification, attained remarkable results in the ILSVRC (ImageNet Large Scale Visual Recognition Competition), generating significant interest in CNNs for image classification and recognition applications [4]. Since that time, CNNs have been extensively utilized in image recognition applications, resulting in considerable performance enhancements [5]. Many researchers have attempted to use different CNN structures, such as VGG (VGGNet, a classic convolutional neural network architecture), to improve image recognition accuracy [6]. Specifically, CNN-based image classification accuracy has seen significant improvement over the past decade. Taking the ImageNet dataset as an example, in 2012, the error rate of AlexNet was 16.4%, while in 2015, ResNet reduced the error rate on the same dataset to 3.0%, approaching human-level performance. This discovery represented a significant advancement in the utilization of CNNs for picture recognition, substantially bolstering the accuracy of diverse image categorization jobs. This paper investigates the issue of visual flower recognition, informed by prior studies.

3. Methodology

3.1. Data Source and Preprocessing

This study utilizes a flower classification dataset obtained from TensorFlow's public resources, comprising about 3,660 photos representing five flower varieties: roses, sunflowers, chrysanthemums, tulips, and daffodils [7]. The author initially preprocessed the dataset to enable model training and evaluation.

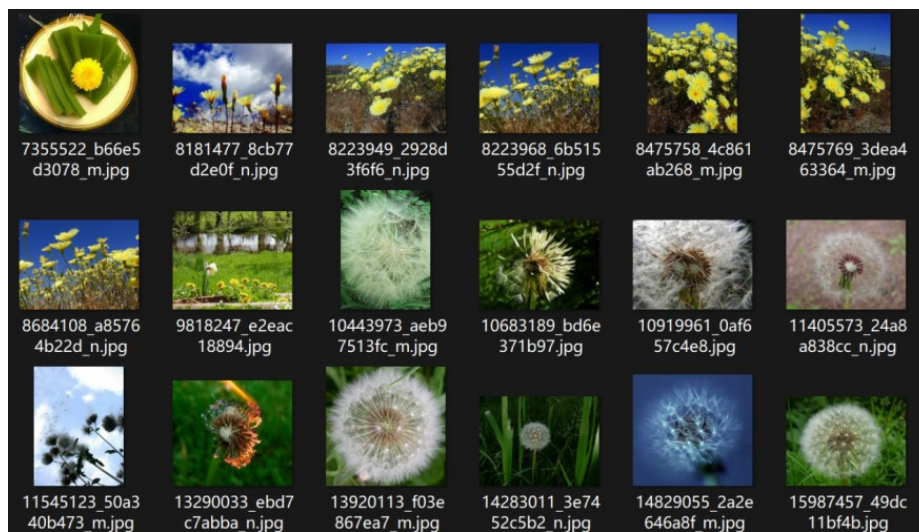


Figure 1: Sample Images from the Dataset[7]

During the preprocessing, the author first created a folder named *flower_data* and extracted the downloaded flower classification dataset into this folder. Then, by executing the *split_data.py* script,

the author automatically divided the dataset into training and testing sets. Specifically, the training set contains 3,306 samples, while the testing set contains 364 samples. This division ensures that the model can effectively learn the data features during the training process and be evaluated on the testing set, thereby reducing the risk of overfitting [8].

3.2. Model Construction

ResNet (Residual Network) is a convolutional neural network architecture for deep learning introduced by Kaiming He and colleagues in 2015. The fundamental novelty resides in the implementation of residual learning. Traditional deep neural networks often face issues like vanishing gradients and performance degradation as the number of layers increases. However, ResNet mitigates this problem by designing residual blocks, allowing the network to learn the residual function between the input and output, effectively addressing these issues [9].

The main structure of ResNet18 includes:

Residual Blocks: Each residual block comprises two convolutional layers, with the input directly appended to the output via a shortcut connection. This framework guarantees the seamless transmission of information, even inside profoundly deep networks.

Convolutional Layers: Employing 3x3 convolutional kernels, numerous convolutional layers extract features and augment the model's expressive capacity.

Batch normalizing: Batch normalizing is implemented subsequent to each convolutional layer, facilitating accelerated training and enhancing the model's stability.

Global Average Pooling: At the end of the network, a global average pooling layer replaces the fully connected layer, reducing the model's parameter count and effectively reducing the risk of overfitting.

Utilizing a pre-trained ResNet18 model enables the exploitation of features acquired from extensive datasets (e.g., ImageNet) for transfer learning [10]. This means that when performing flower image classification, the model already possesses strong feature extraction capabilities, enabling it to adapt quickly to the new task. The pre-trained ResNet18 excels in feature extraction, significantly improving the accuracy of flower image recognition.

4. Results

After completing data preprocessing and model construction, the model training was conducted in this study. During the training process, the training set was used to optimize the model parameters, and the testing set was used to evaluate the model's performance. The batch size for each training iteration was set to 64, with a learning rate of 0.001. To reduce the risks of underfitting and overfitting, the training was set for 20 epochs. The author also recorded the loss and accuracy for each epoch to monitor the training progress of the model.(Figure 2).

```
258.015252 s
train loss: 79 % [*****->.....] 0.242
263.586712 s
train loss: 81 % [*****->.....] 0.239
269.318110 s
train loss: 83 % [*****->.....] 0.247
274.738668 s
train loss: 84 % [*****->.....] 0.226
280.228907 s
train loss: 86 % [*****->.....] 0.439
285.673419 s
```

Figure 2: The training status at a specific moment in the design

Subsequent to many training iterations, the final model had a recognition accuracy of 90%, exemplifying the robust potential of deep learning techniques in floral image categorization (Figure 3).

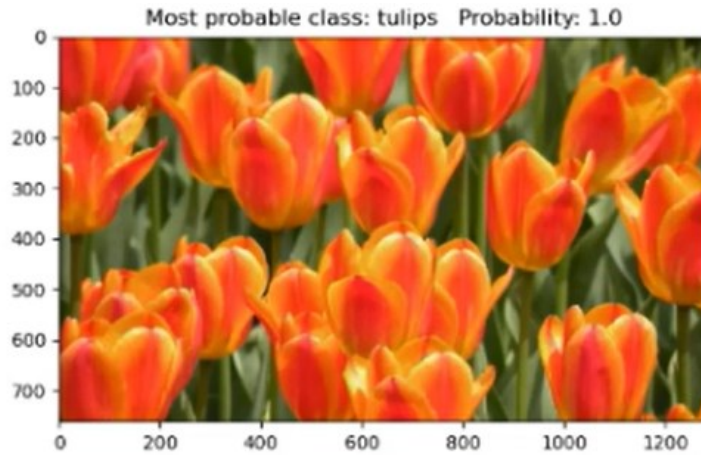


Figure 3: Randomly test and recognize an image

This work demonstrates the efficacy of the pre-trained ResNet18 in flower recognition and offers useful insights and methodologies for further research. These findings provide theoretical validation and practical guidance for applications in domains such as intelligent agriculture and ecological preservation.

5. Conclusion

This research employs deep convolutional neural networks, utilizing the pre-trained ResNet18 model to categorize floral photos, attaining a recognition accuracy of 90%. This outcome confirms the efficacy of deep learning methods in plant identification, especially in the context of intricate characteristics. The efficient partitioning of the flower dataset and the examination of ResNet18's architecture illustrate the capabilities of deep learning in fields like ecological conservation and precision agriculture.

Despite the positive outcomes, there are still some limitations. First, the dataset is relatively small, which may restrict the model's generalization ability. In real-world applications, flower species are diverse and complex, and increasing the diversity and number of samples in the dataset will help further improve the model's performance. Additionally, insufficient data augmentation during training may have led to suboptimal performance when the model encounters unseen samples.

To mitigate these restrictions, subsequent research may explore the following avenues: On one hand, augmenting the dataset by include floral photos from diverse environments and lighting situations; on the other hand, employing sophisticated data augmentation techniques, including rotation, scaling, and cropping, to improve the model's resilience. Furthermore, investigating additional sophisticated deep learning architectures, such as YOLO or Transformer, may enhance recognition accuracy.

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