Flower Recognition Using Transfer Learning

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Abstract— **The objective of this article is to manifest the feasibility of a flower recognition system. This research is fully based on Transfer Learning & RESNET-50 Model. By using pre-trained weights of the RESNET-50 model on the flower recognition dataset & extended flower recognition dataset the system aims to classify species of flowers accordingly. During this execution, the system achieved a high accuracy rate, outperforming other state-of-the-art models. According to the results, transfer learning avoids the problem of local optimality and overfitting in deep convolutional networks. By comparing The accuracy of flower recognition on the floral dataset is clearly increased when using classical approaches,and the robustness and generalization ability is also improved. [1]**

Keywords: deep-learning; RESNET-50;Transfer Learning; flowers categorization;Convolution Neural Network;

I. Introduction

Throughout our daily lives, flowers are everywhere, and they contribute greatly to our culture, economy, and environment. Even though each flower differs greatly in shape, structure, and habit, understanding and classifying flowers can be challenging. Therefore, in order to identify flowers fast and accurately, a flower identification method is required. People are starting to utilize more and more vivid and understandable graphics instead of wordy sentences as a result of the rapid advancement of science and technology as well as the widespread use of smartphones. Although current flower recognition rates are quite low, better techniques are needed to ensure that flowers are correctly identified.

In the current process of classifying flower species, there are a number of shortcomings: In the first place, color, form, and texture are mainly taken into account when extracting classical features. These features' artificial selection is more challenging and challenging. Second, because the color and structure of different flower species are so similar, it can be quite challenging to identify them when they are present at different times and in different environments. The following significant academic advancements in flower identification have occurred recently: The approach used by Saitoh et al. [1] in 2000 to identify flowers requires the user to lay a black cloth behind the flower, which is impractical and inconvenient.

The recognition rate of flowers in the Oxford-102 dataset can reach 88.33% [4] whereas we compared two datasets name Flower Recognition and Extended flower recognition and we got an accuracy of about 89%. thanks to Maria(Elena et al.'s) (Elena et al.'s) proposed segmentation approach, as well as multi-core frame combination features, is followed by the extraction of Histogram of Oriented Gradient (HOG) features and uses Locality-constrained Linear Coding (LLC).[2][3].

Recent studies have demonstrated that ResNet-50 which is a convolution neural network can be used as a pre-trained model for flower detection because it has already been trained on massive datasets like ImageNet, which contains millions of tagged photos. This enables us to take advantage of the expertise the model has gained from the pre-training data to identify various flower varieties. To utilize ResNet50 for flower recognition a pre-trained needs to refine. Reeducating the final few layers of the model that had been trained upon the fresh dataset while maintaining the original layer weights is known as fine-tuning. This enables the model to maintain the knowledge it has learned from the pre-training data while adapting to the specific features of the new dataset.[2] In order to improve overall recognition performance, this work coupled the transfer learning strategy with the parameter initialization model and the transfer learning model, as well as other typical experimental techniques. The experimental results show that this strategy can not only improve resilience and generalization ability, but also significantly improve flower recognition accuracy.The experimental findings demonstrate that this method can, not only gain higher resilience and generalization ability but also clearly increase the accuracy of flower recognition.

II. Related Work

The convolutional neural network (CNN) is a widely used model in deep learning, particularly in the field of computer vision, such as image classification. CNNs are composed of convolutional layers and pooling layers that extract and process features from input images. The traditional structure of a CNN consists of an input layer, followed by multiple convolutional layers that extract low-level and progressively more abstract features. These characteristics are subsequently sent to pooling layers, which lower network parameters while retaining critical information. The CNN is frequently linked to one or more fully connected layers, which analyze and categorize the retrieved data. The output layer is connected to the final fully connected layer, and the neural network output is turned into a probability distribution using the Softmax layer,providing probability information for different target categories.

Transfer learning is a strategy for improving learning efficiency and performance in related activities by leveraging information from current models and data. Transfer learning allows the transfer of learnt characteristics from a pre-trained model to a new target task by leveraging the link between learning goals and existing information.. This approach is particularly useful when limited labeled data is available for

the target task. In transfer learning with CNNs, a pre-trained CNN model, trained on a large-scale dataset such as ImageNet, is used as a starting point. The pre-trained model's learned features are retained, and the final fully connected layers are replaced or fine-tuned to adapt to the new task. This allows the model to benefit from the general features learned by the pre-trained model while tailoring the network to the specific target task. Overall, transfer learning in CNNs offers a powerful and efficient way to apply existing knowledge and models to new tasks, leading to improved performance and reduced training time. It has been widely adopted in various machine learning applications, including computer vision tasks like
image classification.[3]

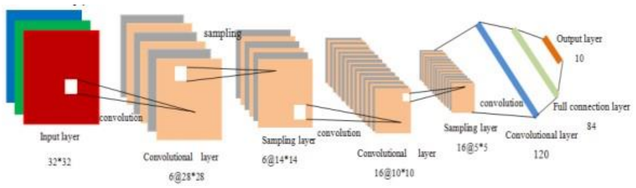


Figure 1. Traditional convolution neural network structure

III. METHOD

A) CNN Models

Resnet50 was the convolution neural network model employed in this investigation. The ResNet50 model would be designed to address the issue of vanishing gradients in very deep neural networks.The vanishing gradient problem arises when the gradients become very small as they propagate backward through the layers of the network during training, making it difficult to update the weights of the lower layers.[4]

ResNet50 is a particular variation of the ResNet architecture that has 50 layers. It combines a mix of fully connected layers, pooling, and residual blocks with varied numbers of convolutional layers to produce a cutting-edge performance on a variety of image classification tests. ResNet50 has a substantially greater depth than earlier neural network architectures, is more accurate, and requires less training time because of the inclusion of residual blocks.

The residual network joined the shortcut connection technology, which transfers the input flower species, with 600-900 flower photos for each species.[1]This data collection builds on the Extended Flowers Recognition data set. There are presently ten flower classes, each having approximately 600-900 images: aster, daffodil, dahlia, daisy, dandelion, iris, orchid, rose, sunflower, and tulip. The file sizes and resolutions of each image vary.

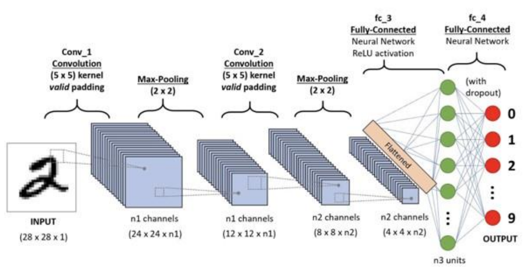


Figure 2. Convolution neural network structure

Currently, there are 8,100 photos of 10 different flower species that have labels. Since there are more flower species than in the Extended Flowers Recognition dataset and more similarities between the various types of flowers, the classification of flowers will be more difficult. The example of the Extended Flowers Recognition dataset is shown in Figure 3.

B) Experimental Strategy

This paper's dataset is separated into two sections. The training set is utilized for model training and validation, as well as parameter adjustment.

This dataset is an expansion of the Flowers Recognition data set. The original Flowers Recognition dataset inspired some machine learning (ML) floral categorization as well as online image scraping of new flower species. There are presently ten flower classes with 600-900 photos each: aster, daffodil, dahlia, daisy, dandelion, iris, orchid, rose, sunflower, and tulip. Each image has a distinct file size and resolution.

The Extended Flowers Recognition dataset discovered 8168 images in total, with 65535 images serving as a training set for 10 classes, 170 images serving as a validation set, and 170 images serving as a test set.[3] There must be no overlap across datasets to ensure that the trained model generalizes to unknown data. To test the effect of the transfer learning, This research employs two approaches of parameter initialization training and transfer fine-tuning training.

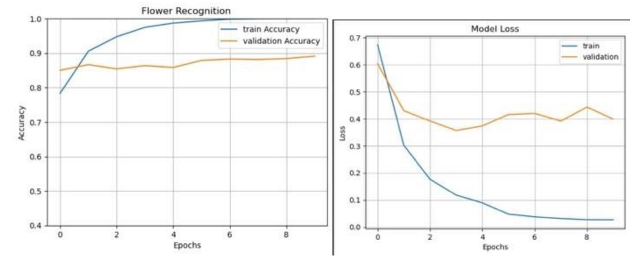
Control Experiment:To demonstrate the efficacy of our method experiments are carried out to compare the flower classification method based on the Extended Flowers Recognition dataset. Tables I present the findings. We can observe that ResNet50-transfer has a higher classification accuracy than other approaches.

IV. RESULTS

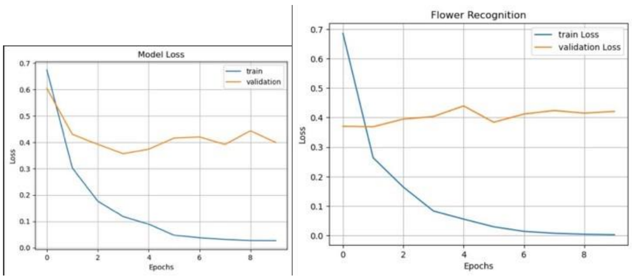
Table 1 compares the evaluation indices for two distinct datasets. Both the extended (10 class) and the basic (5 class) flower recognition datasets are purchased data sets taken from Kaggle. Figures a and c compare the ResNet50 transfer model's accuracy in the validation sets of the expanded and standard flower recognition datasets, respectively.

Dataset	Accuracy of the training set	Loss of training set	Loss of validation set	Accuracy of the validation set
Extended flower recognition	98% - 99%	0.0026	0.398	86% - 90%
Flower recognition	99% - 100%	0.0031	0.4070	86% - 89%

Table 1 Comparison Of Evaluation Index On Different Datasets



(a) (b)



(c) (d)

Figure. (a) (b) (c) (d) shows the comparison of the training and validation accuracy and loss for extended flower recognition and flower recognition datasets.

V. CONCLUSION

When compared to manual feature extraction methods, the deep convolutional neural network (CNN) model employed in this paper adopts a feature extraction strategy that is both convenient and practical.By using the deep CNN model, the process of feature extraction is automated, allowing the network to learn and extract relevant features directly from the input data. This eliminates the need for handcrafted feature engineering, making the approach more efficient and less dependent on domain expertise.

Furthermore, the integration of transfer learning into the neural network model enhances its performance. The addition of transfer learning enables the model to leverage pre-trained knowledge from a large-scale dataset, such as ImageNet. This pre-trained model provides a strong initial foundation, allowing the network to converge faster during training. Additionally, the model exhibits improved robustness and generalization abilities compared to randomly initialized models.

In comparison to traditional experimental methods, this approach demonstrates superior performance. Through experiments conducted in this study, it is evident that the proposed method significantly enhances the accuracy of flower recognition. The utilization of the deep CNN model combined with transfer learning has proven to be highly effective in improving recognition accuracy, surpassing the results achieved by traditional methods.[8]

In summary, the feature extraction method employed in this paper, based on deep CNN models, offers a convenient and practical alternative to manual feature extraction. By incorporating transfer learning, the model demonstrates faster convergence, improved robustness, and enhanced generalization abilities. Experimental results validate the effectiveness of this approach, showcasing a significant improvement in flower recognition accuracy.

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Source code : https://github.com/Juniadul/CVPR_20-41950-1/blob/main/Final/Transfer_Learning.ipynb

Dataset Link: https://drive.google.com/file/d/1DgGX4Ee-U0zqB9Q3rF3CQDOkCwRuY00n/view?usp=share_link