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Research Article

Automated Flower Species Recognition Using Deep Learning

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ABSTRACT

This research examines the capability of Convolutional Neural Networks (CNNs) to automatically detect plant species from images of flowers. Flowers are well-suited for species identification because they have a unique shape, color, and structural pattern that tends to be constant even when exposed to different environmental conditions like changes in weather or aging of plants.Traditional recognition approaches usually depend on manually designed features, which may miss important natural cues and tend to need expert domain knowledge. By contrast, CNNs learn and extract deep feature representations automatically from image data, detecting subtle visual details that are crucial for correct classification.In this paper, a model based on CNN is trained and fine-tuned for flower species classification. The model was tested over a benchmark dataset of 967 flower species, and the classification accuracy at rank-1 and rank-10 was 67.45% and 90.82%, respectively. These performances dramatically surpass conventional methods such as Kernel Descriptor (KDES), with as much as six times higher accuracy.The report presents CNNs as a robust and effective tool for designing next-generation image-based plant identification systems with potential applications in botanical research, tracking biodiversity, and digital information retrieval.

Keywords: DeepLearning, Convolutional Neural Networks (CNN), Flower Species Classification, Image Recognition, Computer Vision, Automated Plant Identification, Feature Extraction, Image Classification, Artificial Intelligence, Pattern Recognition.

INTRODUCTION

Plant recognition is an important job for scientists, students, and experts in disciplines like agriculture, forestry, and conservation of biodiversity. With the progress in computer vision, there has been increasing emphasis on automating plant recognition using images of different parts of plants like leaves, fruits, stems, and flowers. Among them, flower images are found to be especially significant because of their very distinctive characters like color, shape, and texture.Unlike other organs of plants, flower forms generally persist with comparative uniformity throughout various weather patterns and plant life stages, allowing them to serve as a steady source for differentiation. Botanically, flowers present some of the most diagnostic visual signals used in the discrimination of species. While having their benefits, creating an automatic plant identification system based on flower images is challenged by several problems. They consist of high visual similarity across species (inter-class similarity), low-level differences among the same species (intra-class variation), as well as problems introduced by varying lighting conditions, camera viewpoint, partial occlusion, background clutter, and natural flower deformations. The above challenges are demonstrated in Figure 1, which indicates some examples of the above difficulties for different flower species.

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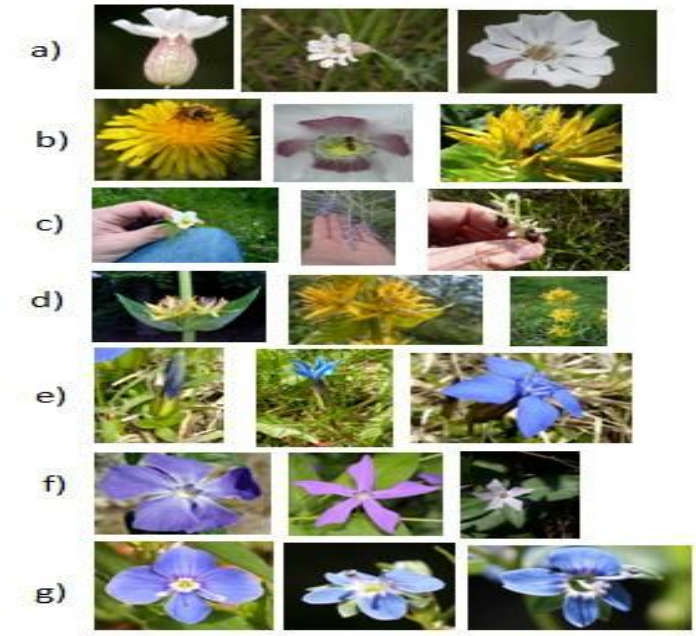

Fig.1. Challenges in Flower Species Identification. (a)Viewpoint changes; (b) Occlusion; (c) Cluttered background; (d) Illumination changes; (e) Deformation of petals; (f) Small intra-class similarity; (g) Large inter-class similarity.

In the literature, various techniques for flower species identification have been put forward [1], [2], [5]. These techniques usually follow four main steps: image pre-processing, segmentation, feature extraction, and classification. Because of the difficulties presented by complex backgrounds and variations in the appearances of flowers, these methods are usually time-consuming and tend to produce low accuracy, particularly when there are many species. In recent times, the application of Convolutional Neural Networks (CNNs) for feature representation learning has proven to be very successful in numerous computer vision tasks like image classification, object detection, and segmentation [9]. Feature learning techniques, including deep neural networks, provide a natural means of capturing discriminative information from raw image data without manual feature extraction. These approaches are useful since they can learn the inherent nature of flowers directly from the images. Thus, this paper discusses and proves the efficacy of deep CNNs in enhancing flower species recognition, displaying their capability in addressing issues such as occlusion, lighting differences, and intra-class or inter-class large similarity.

RELATED WORK

There are two basic methods for automated flower species identification from images of flower organs: hand-designed features and deep learning. A few hand-crafted (or hand-designed) features have been utilized for flower species identification, e.g., Kernel Descriptors (KDES) [1], color, shape, and texture [2]. In [2], the authors derived different kinds of features, such as HSV values, MR8 filter, SIFT, and Histogram of Oriented Gradients (HOG) on a 17-flower class dataset. They then used a Support Vector Machine (SVM) classifier, with multiple linearly weighted kernels combined. After testing and choosing the best features, they used them on a 102 flower species dataset and obtained a good recognition rate. In [3], the authors emphasized extracting shape and color features from flower images and applied Principal Component Analysis (PCA) to identify various flower species. In [4], the authors extracted HOG features and utilized an SVM classifier for classification. In [5], the authors introduced a flower image retrieval system based on region-of-Interest (ROI). They made use of the color histogram of a region corresponding to a flower and two features based on shape—Centroid-Contour Distance and Angle Code Histogram—to represent the shape of the flower. The performance was tested on a database with 14 plant species. Le et al. [1, 2] employed KDES, which was initially proposed by Leefung Bo et al. [10] for plant classification. KDES is a strong feature extraction method that facilitates constructing hierarchical models from low-level (pixel) to high-level (patch and/or complete flower image) features. Following the calculation of KDES, an SVM classifier was employed for classification. KDES performed well for leaf-based plant classification, but the recognition rate was still below its

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optimum when utilized for classification of flower species.Compared with that, feature learning methods have been gaining a lot of momentum in recent years. In the Plant CLEF 2015 competition [7], a few research groups utilized Convolutional Neural Networks (CNNs) for multi-image plant observation query-based plant identification tasks. Each query observation image belonged to one of seven view types: entire plant, branch, fruit, leaf, flower, stem, or leaf scan. Nonetheless, only few studies have targeted flower image recognition using CNNs. Herein, we target the application of CNNs in the automated flower species classification. We contrast the performance of CNNs with manually designed feature methods, proving the strength and competence of CNNs in dealing with the intricacies of flower classification.

OBJECTIVES

The purpose of this work is to experiment and show how Convolutional Neural Networks (CNNs) can be effectively used in automated recognition and identification of flower types from photographic images. The work intends to deal with difficulties such as intra-class variability, inter-class similarity, and intricate backgrounds through the utilization of deep models that are able to automatically extract rich, discriminative features from unprocessed image data. In particular, the paper compares the performance of different CNN models—AlexNet, CaffeNet, and GoogLeNet—on a large flower image dataset (PlantCLEF 2015), both with and without preprocessing methods. Through comparisons with conventional hand-engineered features such as Kernel Descriptors (KDES), the research aims to prove that deep learning, specifically GoogLeNet, is an excellent high-accuracy substitute for identifying flower species. Finally, this research helps to build intelligent, scalable, and effective plant recognition systems beneficial in biodiversity research, ecological monitoring, and educational resources.

METHODS

Flower photographs are generally taken against cluttered backgrounds with several objects. Even though Convolutional Neural Networks (CNNs) can directly be used to these images, in this work, we plan to analyze how background affects the identification of flowers. For that purpose, we apply a variety of preprocessing techniques to the flower photographs. Those techniques are so chosen that the flower areas get isolated and the rest of the natural image excluding the flower parts gets eliminated, which is redundant background noise. By looking at the flower itself, we can more effectively evaluate how background clutter influences the performance of CNN-based flower species classification and enhance the accuracy of the classification.

Preprocessing

Flower areas tend to be embedded in complex and crowded backgrounds, which makes it difficult to separate them from the background accurately. To overcome this, we use saliency-segmentation-based methods to detect and extract the Region of Interest (ROI) in flower images. The entire process of our preprocessing pipeline is shown in Fig. 2. We first apply a saliency extraction process as reported in [13], followed by a normal segmentation method, like the mean-shift algorithm. The segmented object is then chosen based on a certain condition: its corresponding saliency value should be above a predetermined threshold, implying that it is probably within the salient flower region.After segmentation, region-connected methods are used to combine meaningful segments into coherent regions of interest. As indicated in Fig. 3, the detected ROIs (left panel) are superimposed as bounding rectangles, whose top-left and bottom-right coordinates define them, on the original images (right panel). This process serves to concentrate the classification model on significant flower regions and reduce background noise, thereby improving the accuracy and reliability of flower species recognition.

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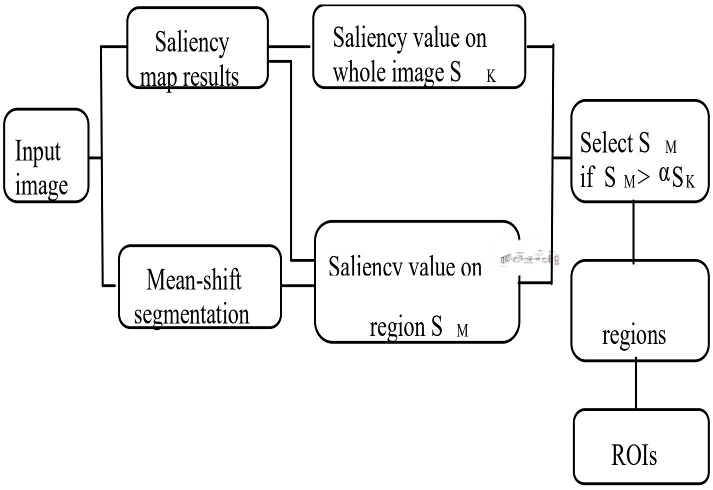
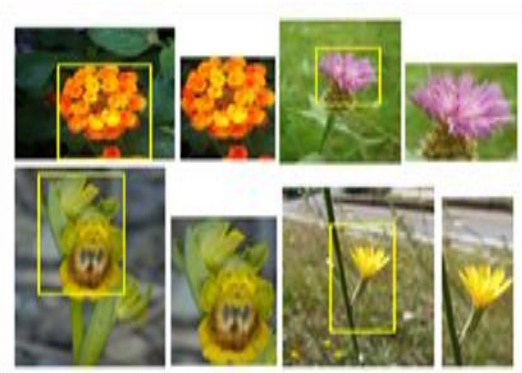


Fig.2. The proposed pre-processing to select the regions of interest (ROI) of flower.



layers (independent building blocks) used for the construction of the network is about 100. Googlenet incorporates *Inception* module with the intention of increasing network depth with computational efficiency. Googlenet with 5 million parameters gets 6.7% at top 5 error.

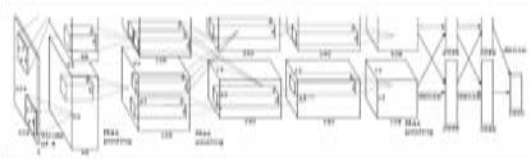


Fig.4. An illustration of Alexnet's architecture (adapted from [11])

Fig.3. Flower images and detected ROIs.

Convolutional neural network

Convolutional Neural Networks (CNNs) are among the most effective and popular deep learning models, particularly in image processing and visual recognition applications. They have excelled with tremendous performance in grand-scale competitions like the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), which is a competition of more than 1.2 million images of 1000 categories. Some of the popular CNN architectures are LeNet, Alex Net, Clarifai, SPPNet, VGG, Google Net, and ResNet.A CNN also consists of more than one convolutional layer, and then pooling (sub-sampling) layers, and then fully connected layers, like the conventional neural networks. The major advantage of CNNs is that they reduce the number of parameters heavily relative to fully connected networks, hence they are simpler to train but with high accuracy, especially for tasks like flower species classification.In this work, we investigate the performance of deep CNNs for classifying a large variety of flower species with a dataset having images from 1000 classes. To identify the most appropriate model, we compare some popular CNN architectures such as AlexNet, CaffeNet, and GoogLeNet.AlexNet, proposed by Krizhevsky et al. [11], won ILSVRC 2012 with a top 5 error rate of 15.3%. It has 8 layers, approximately 60 million parameters, and approximately 650,000 neurons. Its structure is shown in Fig. 4.CaffeNet, introduced in [12], is a variation of AlexNet with similar structure—5 convolutional and 3 fully connected layers—but with modifications such as reordered layers and modified filter biases to enhance efficiency and minimize memory use.GoogLeNet, by Szegedy et al., was the winner of ILSVRC 2014. It brought a new design approach using Inception modules, which help capture features at different scales. This

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architecture is much deeper than earlier models, with 22 trainable layers (or 27 when including pooling layers), as visualized in Fig. 5.With this comparative analysis, we will be able to determine the CNN architecture that produces the most accurate results for automated classification of flower species and demonstrate how deep learning can solve issues in fine-grained image recognition.

RESULTS

We performed three experiments in our research. In the first experiment, we performed a comparative analysis of different Convolutional Neural Networks (CNNs) on a pre-processed flower image dataset. In the second experiment, we compared CNN performance with a strong handcrafted descriptor, namely Kernel Descriptors (KDES) [1].

Finally, we evaluate the effect of preprocessing techniques on the flower identification.

Fig.4. Examples of flower with complicated background images on PlantCLEF 2015 .

Table 1 shows the performance results of three CNN models on the pre-processed flower image dataset. It can be seen that GoogLeNet has the best performance among the tested models. This result is in agreement with the results of the annual ILSVRC competition. GoogLeNet performs better than AlexNet and CaffeNet because it has a deeper architecture and the incorporation of the Inception modules, which improve feature extraction abilities.

Table 1. Accuracy at Rank-1 of various CNN models on the pre-processed flower image dataset.

CNN Model Accuracy (%)

	Alexnet	Caffenet	Googlenet
Accuracy	50.60	54.84	**66.60**

As shown in Table 1, GoogLeNet achieves the highest accuracy at Rank-1 with 66.60%, outperforming both AlexNet (50.60%) and CaffeNet (54.84%). This superior performance is attributed to GoogLeNet's deeper architecture and the use of Inception modules, which allow for more effective multi-scale feature extraction.

Table 2 shows the outcome of the second experiment, where we compare the performance of the handcrafted descriptor KDES and the deep learning-based model GoogLeNet on the pre-processed flower image dataset. The accuracy obtained by GoogLeNet is around six times greater than that of KDES.

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Note that KDES is a strong descriptor, commonly known to perform well in general object recognition tasks. It has shown excellent performance in leaf-based plant recognition because it can extract rich and diverse features [2]. Nonetheless, when dealing with other organs of plants, e.g., flowers, KDES is not flexible enough to well describe the complex and varied structures that occur in various species. In such instances, Convolutional Neural Networks (CNNs), such as GoogLeNet, provide a more flexible and powerful solution for feature extraction and classification.

Tab. 2. The obtained results for KDES and Googlenet on pre-processed flower images.

	Rank 1	Rank 10
KDES	10.95	24.62
Googlenet	**66.60**	**90.23**

Table 3 presents the comparison of GoogLeNet results on raw and pre-processed images. The results obtained on raw images are a bit higher than pre-processed images. The reason is that using pre-processing techniques, in certain situations, we may lose flower and natural context information. The result verifies that for flower identification using CNN, we do not have to use pre-processing techniques. correct matching even flowers in the photographs are shot in extremely different point-of-view.

Tab. 3. The result of Googlenet on raw and preprocessed images.

	Rank 1	Rank 10
Raw images	67.45	90.82
Processed images	66.60	90.23

A few sample results of the identification procedure are shown in Figure . The queried flower images appear in the first column, with the top 5 retrieved plant species in order of similarity score appearing in subsequent columns. A green bounding box indicates the correct identification among the retrieved results. As seen, the CNN model is found to possess high capability in retrieving visually similar and related images, showing that it performs well in extracting discriminative features required for precise flower species identification.

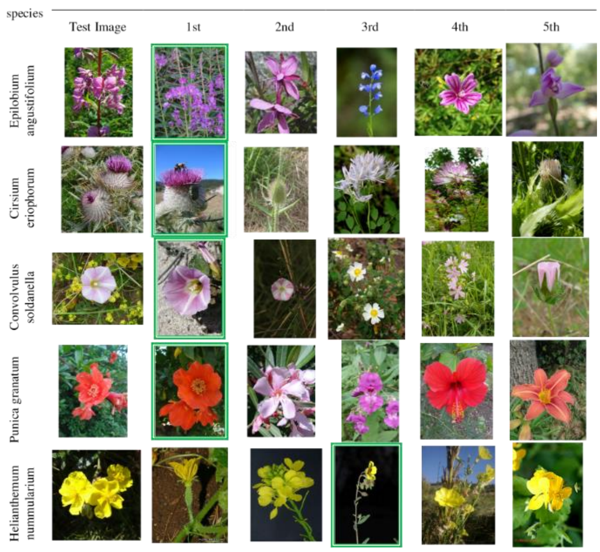

Fig.5. Some example of identification results. The first column shows query images and the remaining columns show the top 5 retrieved plants. The correct identification is marked by a green frame.

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DISCUSSION

In the current work, we suggested the application of Convolutional Neural Networks (CNNs) towards the task of identifying flower species. We performed a series of experiments to compare the performance of different CNN architectures over a pre-processed flower image dataset. The results obtained show the efficiency of the CNNs in the task, as the Rank-10 accuracy was over 90% over a set with a high number of classes. The Rank-1 accuracy is still quite constrained, though, pointing towards potential avenues for further advancement.

For future research, we intend to modify the CNN architecture to enhance accuracy at the higher retrieval ranks. We also intend to investigate multi-organ image fusion methods, fusing information from various plant organs (e.g., leaves and stems) to further enhance overall recognition performance.

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