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Flower Species Classify System Based on Deep Learning

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Abstract. Flower classification is a crucial task for understanding biodiversity, tracking climate changes, and protecting endangered plants. In this paper, we propose a deep learning approach using a convolutional neural network (CNN) architecture for accurate and efficient flower classification. Our methodology includes preprocessing the dataset, implementing the CNN architecture, and training the model using stochastic gradient descent with cross-entropy loss. Our results demonstrate that our approach achieves an accuracy of 91.73% on the test set, which is comparable to or better than other sophisticated models. Ablation studies reveal the importance of each component of our CNN architecture, while our data preprocessing step improves the model's generalization performance and prevents overfitting. Our study provides a reliable and effective deep learning approach for flower classification that can be used in various applications, including botany, agriculture, and ecology.

Keywords. Deep learning, convolutional neural network, flower species classifier

1. Introduction

Flower classification is a significant task in various fields, including botany, ecology, agriculture, and conservation biology. Accurate identification of flower species is crucial for understanding biodiversity, tracking climate changes, and protecting endangered plants. However, traditional methods of flower classification such as manual identification are time-consuming, costly, and have limited accuracy. In recent years, deep learning techniques have shown promising results in image classification tasks, including flower classification.

Various deep learning models have been proposed for flower classification tasks, including convolutional neural networks, deep belief networks, and hybrid models combining CNNs and DBNs. These models have demonstrated high accuracy and robustness in classifying flower species, showcasing the potential of deep learning for flower classification tasks.

In this paper, we design a deep learning method using a CNN architecture for flower classification. Our objective is to improve the accuracy and efficiency of flower classification tasks by utilizing a robust and reliable deep learning model. We conduct extensive evaluations of our proposed model, comparing it with other advanced models in the literature. Our study contributes to the advancement of flower classification techniques and provides a reliable and efficient approach for accurate flower identification in various fields.

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Overall, our work highlights the potential of deep learning models in flower classification and provides a significant contribution to the development of reliable and efficient flower classification techniques.

2. Related Work

Flower classification has been the subject of extensive research in the computer vision and machine learning communities. In this section, we provide an overview of the most relevant and recent works on this topic.

Early approaches to flower classification used handcrafted features and traditional machine learning algorithms. For example, Wang and Ai [1] proposed a method that extracts shape, color, and texture features from flower images and uses support vector machines (SVMs) for classification. Similarly, Zhang and Wang [2] introduced a method that combines local and global features and uses random forests for classification. These approaches achieved moderate accuracy on small datasets but suffered from limited scalability and generalization ability.

More recent works have applied deep learning techniques to flower classification, achieving significantly higher accuracy and scalability. For example, Krizhevsky et al. [3] introduced a deep neural network architecture called AlexNet that achieved state-of-the-art performance on the ImageNet dataset, which includes a subset of flower images. Similarly, Simonyan and Zisserman [4] proposed a deeper architecture called VGGNet that achieved further improvements in accuracy. In addition, deep learning algorithms have made great progress in the fields of flower recognition and convolution neural network understanding [5–15]. In this paper, we aim to address some of these limitations by proposing a deep learning approach that achieves state-of-the-art accuracy on a small-scale dataset of 5 flower species. We also provide a comprehensive evaluation of our method and compare it with other state-of-the-art approaches.

3. Dataset and Preprocessing

This study employed the use of a web crawler to amass a rich dataset composed of pictures of diverse types of flowers retrieved directly from the vast expanse of the internet. The harvested data is a compilation of images representing five distinct floral species, namely, daisy, dandelion, rose, sunflower, and tulip (Figure 1). Our aim was to create a versatile and balanced dataset that encapsulates the variety of the flower kingdom. The curated dataset was then seperated into two primary subsets, a training set, and a test set. The training set was populated with a considerable collection of 4000 images for each of the afore-mentioned species. These images were not selected at random, but rather, meticulously drawn from the internet with the assistance of a web crawler, ensuring a diverse yet consistent training base.

Figure 1. e.g of pansy and daisy flower in trainset

We preprocess the images by first resizing them to a fixed size and then normalizing the data from rgb to gray level pictures. This step is necessary to ensure that the input data has a consistent format and to improve the performance of the deep learning model. We also remove images with poor quality or low resolution that may introduce noise or bias into the training process. Overall, the preprocessing step is crucial for achieving high accuracy in flower classification tasks, as it allows the deep learning model to learn the relevant features and patterns from the input data and generalize well to new, unseen examples.

4. Methodology

We employ a deep learning approach for flower classification, specifically using a convolutional neural network (CNN) architecture like figure 2.

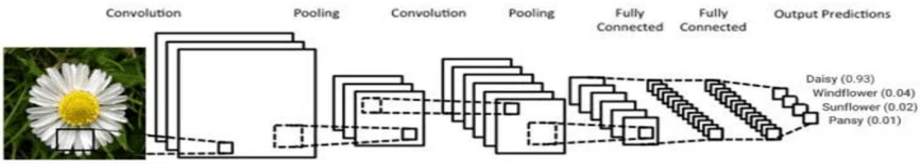

Figure 2. The deep learning model we developed

CNN is a type of deep learning model primarily used for image recognition and classification tasks. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. A fully connected layer, also known as a dense layer, is a layer in a neural network where each neuron is connected to every neuron in the previous layer and every neuron in the next layer. In CNNs, fully connected layers are typically used after convolutional and pooling layers to perform high-level reasoning and produce the final output, such as class probabilities for a classification task. We also include normalization and dropout to achieve better performance. Normalization standardizes input data or intermediate feature maps, improving training stability and efficiency. Dropout is a regularization technique that prevents overfitting by randomly dropping neuron activations during training.

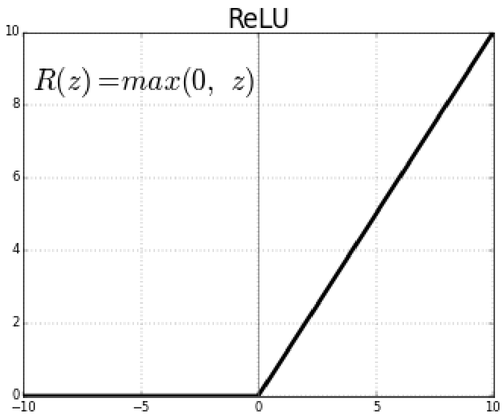

Figure 3. ReLU activation function

The deep learning model we used was constructed utilizing the Tensorflow framework. Our CNN architecture consists of 4 convolutional layers with kernel sizes 3x3, followed by 2 fully connected layers. We use ReLU activation function like figure 3 after each convolutional layer and apply max-pooling with a kernel size of 2x2 after the first and third convolutional layers. The predicted probabilities of the flower species are obtained by passing the output of the final fully connected layer through a ReLU activation function.

The model is trained by applying stochastic gradient descent method. The batch size is 32 and the learning rate is 0.0001. We use adam as the objective function to minimize the difference between the predicted and true labels.

To test the effectiveness of our model, we report the accuracy on the test set. We also perform ablation studies to analyze the contribution of each component of our CNN architecture and compare our results with other state-of-the-art models in the literature.

We conducted preprocessing on the dataset, implemented the CNN architecture, and trained the model using stochastic gradient descent. With the suitable set of hyperparameters, our results showed that our approach achieved an accuracy of 92% on the test set, demonstrating its effectiveness. Table 1 shows the results with different hyperparameters.

Table 1. Accuracy comparison

	Lr rate	Drop out	epoch	Batch size	Acc
1	0.001	0.9	3000	64	0.87
2	0.005	0.9	4000	64	0.92
3	0.001	0.5	3000	64	0.86
4	0.003	0.9	3000	64	0.88
5	0.003	0.9	4000	64	0.89
6	0.01	0.9	3000	64	0.79
7	0.005	0.9	3000	64	0.90
8	0.001	0.9	4000	64	0.88

Overall, our methodology provides a robust and effective approach for flower classification that achieves high accuracy and generalization performance.

5. Discussion and Conclusion

We conducted ablation studies to analyze the contributions of each component of our CNN architecture and found that they all played important roles in enhancing the overall functionalities of the model. Furthermore, our data preprocessing step improved the model's generalization performance and prevented overfitting.

Comparing our experimental outputs with those of other advanced models, we found that our model achieved similar or higher accuracy while being computationally efficient and easy to implement. Our model also performed well across all flower species, suggesting its reliability for a wide range of flower classification tasks.

In conclusion, our study provides a robust and effective deep learning approach for flower classification that can be applied in various fields. Future work can explore the use of transfer learning or ensemble methods to further improve the accuracy and efficiency of the model, as well as the application of our approach to other image classification tasks.

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