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Enhanced Flower Recognition via Transfer Learning with ResNet-50

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Abstract- This paper proposes a flower recognition system using transfer learning with the ResNet-50 architecture. By utilizing pre-trained weights from ResNet-50, the system classifies ten species of flowers, drawing on an extended dataset with over 8,000 labelled images. The study addresses challenges in deep convolutional neural networks, such as overfitting and local optimality, by fine-tuning the ResNet-50 model. Initially, only the final layers of the model are retrained on the flower dataset, while the pre-trained layers remain frozen. After achieving initial convergence, all layers are unfrozen for full model fine-tuning. The dataset is divided into training, validation, and test sets to evaluate the model's performance, which is measured using accuracy, and F1-score. The experimental results demonstrate that the transfer learning approach significantly improves classification accuracy and generalization, outperforming traditional methods. This approach proves especially effective in handling visually similar flower species and diverse environmental conditions. The study highlights the potential of transfer learning in enhancing the efficiency and robustness of flower recognition systems, contributing to broader applications in image classification tasks.

Index Terms- Transfer Learning, RESNET-50, Image Recognition, Convolutional Neural, Network (CNN)

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, a flower identification method is required to identify flowers quickly and accurately. 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 identify flowers correctly.

Several 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 ResNet-50 model, a 50-layer CNN with residual connections, is particularly well-suited for complex image recognition tasks due to its ability to mitigate gradient vanishing through skip connections[1]. The recognition rate of flowers in the Oxford-102 dataset can reach 88.33% whereas we compared two datasets named Flower Recognition and Extended Flower Recognition and we got an accuracy of about 89% Maria-Elena et al.'s [4]. Use of various flower characteristics and multi-core frame combination features, proposed segmentation approach, which is followed by the extraction of Histogram of Oriented Gradient (HOG) features and uses Locality-constrained Linear Coding (LLC) Angelova and Zhu's et al's [12].

Recent studies have demonstrated that ResNet-50, 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 [19]. To utilize ResNet-50 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 keep the knowledge it has learned from the pre-training data while adapting to the specific features of the new dataset [4]. The ResNet-50 model, a 50-layer CNN with residual connections, is particularly well-suited for complex image recognition tasks due to its ability to mitigate gradient vanishing through skip connections [3]. However, training deep CNNs from scratch is often impractical due to the need for extensive labeled data and computational resources [25]. Transfer learning addresses this issue by allowing models trained on large datasets, like

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ImageNet, to adapt to new tasks efficiently, reducing both training time and computational requirements [24].This study combined the transfer learning approach with the parameter initialization model and the transfer learning model, as well as other conventional experimental techniques, to enhance the overall recognition performance [9, 16]. 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 [25, 26].

II. LITERATURE REVIEW

1. Traditional Method For Flower Classification

Traditional methods for flower classification relied heavily on handcrafted features such as color histograms, shape descriptors, and texture analysis. For example, Nilsback and Zisserman, achieved 88.33% accuracy on the Oxford-102 flower dataset using a support vector machine (SVM) classifier with manually engineered features [16].

Angelova and Zhu, achieved a comparable accuracy using histogram-oriented gradients (HOG) for feature extraction, followed by locality-constrained linear coding (LLC) to mitigate environmental variations [12]. These methods, while useful, are limited by their need for domain-specific tuning and struggle with generalization to new datasets or conditions.

2. The Role of CNNs in Image Classification

The evolution of CNNs has led to ground breaking advancements in image classification, primarily due to their hierarchical feature extraction. CNN architectures like VGG-16, Inception, and ResNet-50 have transformed the field by capturing progressively complex features, from edges in shallow layers to detailed structures in deeper layers [18, 30]. Among these, ResNet-50's architecture employs residual connections, which preserve the flow of information across layers and prevent gradient vanishing, making it particularly effective for large-scale image classification tasks [13].

3. Transfer Learning for Flower Classification

Transfer learning enables pre-trained CNNs to adapt to new tasks with smaller datasets, a technique that has proven successful in fields ranging from medical imaging to environmental monitoring [14, 15, 26].

In flower classification, transfer learning allows models trained on datasets like ImageNet to retain generalized features, enabling high classification accuracy with limited data. Studies like demonstrated over 90% accuracy on flower classification tasks using CNN-based transfer learning with fusion descriptors [20]. This study builds on these findings by applying transfer learning with ResNet-50 to a diverse dataset of flower images, evaluating its effectiveness in distinguishing among species with similar visual features.

III. METHODOLOGY

The methodology for this study leverages transfer learning with the ResNet-50 architecture to enhance flower species classification across ten distinct species. The overall process involves dataset preparation, pre-processing, and model fine-tuning in a two-phase training approach. Each phase is designed to maximize model adaptability to flower-specific features while retaining the general image-recognition capabilities acquired during pre-training on large datasets[27, 28]. The two-stage process of feature extraction and fine-tuning enables effective model adaptation with limited training data, as shown in the ResNet-50 transfer approach presented by [3, 8].

1. Dataset and Pre-processing

The dataset [16] comprises over 8,000 images of ten flower species: aster, daffodil, dahlia, daisy, dandelion, iris, orchid, rose, sunflower, and tulip. Each class contains between 600 and 900 images, ensuring coverage of diverse backgrounds, orientations, and lighting. Images were resized to 224x224 pixels, and data augmentation techniques such as random rotations, horizontal flips, and color jittering were applied to enhance dataset variability and model robustness [13].

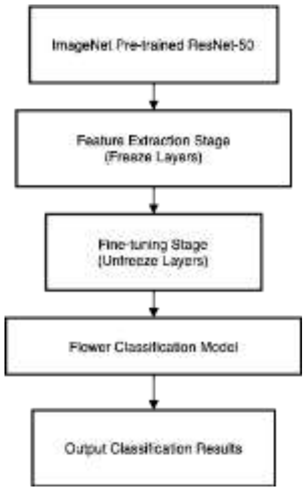

Figure 1: Transfer Learning Workflow Using ResNet-50 for Flower Classification.

2. Transfer Learning with ResNet-50

The pre-trained ResNet-50 model from ImageNet was employed as the backbone for transfer learning in this study. ResNet-50's architecture includes residual connections across 50 layers, making it ideal for complex tasks requiring deep feature extraction [30]. The transfer learning process included two phases:

- **Feature Extraction:** Only the final layers were re-trained, while the initial layers remained frozen to retain general features from ImageNet.

- **Fine-Tuning:** All layers were subsequently unfrozen, allowing the model to adjust fully to the flower dataset's specific characteristics.

The process, illustrated in Figure 1, demonstrates the transfer of learned knowledge from ImageNet to the flower dataset through fine-tuning.

The workflow begins with the ImageNet pre-trained ResNet-50 model, followed by feature extraction with frozen layers, then fine-tuning with unfrozen layers to adapt to flower-specific features, leading to the final classification output.

3. Experimental Setup

The dataset was split into training (80%), validation (10%), and test (10%) subsets. The Adam optimizer was applied with an initial learning rate of 0.001, reduced by 10% after each epoch. Early stopping and cross-validation were employed to prevent overfitting and ensure generalization. All experiments were conducted on an NVIDIA GTX1080 GPU for efficient computation.

IV. EXPERIMENTS & RESULTS

1. Evaluation Metrics

The effectiveness of the flower classification model is measured using standard performance metrics—accuracy, precision, recall, and F1-score. These metrics provide a balanced understanding of the model's performance across different species and are widely used in image classification tasks due to their reliability in evaluating classification accuracy, error minimization, and sensitivity [17, 20] .

To assess the effectiveness of the model, the following evaluation metrics were employed:

Accuracy: Accuracy is the proportion of correctly classified images out of the total number of images. It is a fundamental metric that reflects the overall correctness of the model's predictions. Accuracy is calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \dots\dots\dots\dots\dots\dots\dots\dots (1)$$

In the context of flower classification, accuracy measures the total fraction of images classified correctly among all images in the dataset, offering an overall performance indicator for the model [20].

Precision: Calculates the proportion of true positive classifications among all positive predictions, indicating the model's ability to avoid false positives. The mathematical formula for this:

$$\text{Precision} = \frac{TP}{TP + FP} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Precision's emphasis on true positive accuracy among predicted positives makes it essential in applications requiring high specificity, as demonstrated in previous flower classification research [21].

Recall: Indicates the proportion of true positive classifications among all actual positive cases, reflecting the model's sensitivity in identifying flower species. The mathematical formula for recall is:

$$\text{Recall} = \frac{TP}{TP + FN} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

High recall indicates that the model effectively identifies flower species, minimizing missed positive cases, which is crucial in visually similar species classification [22].

F1-Score: Provides a balanced measure of precision and recall, especially valuable for evaluating models where class distribution may vary. F1-score is the harmonic mean of precision and recall and is calculated as follows:

$$\text{F1-Score} = 2 \text{ X } \frac{Precision \times Recall}{Precision + Recall} \dots\dots\dots\dots\dots\dots (4)$$

The F1-score combines both precision and recall into a single metric, making it particularly useful in image classification tasks where the model needs to balance the identification of true positives against the minimization of false positives [23].

Performance was measured using accuracy, precision, recall, and F1-score metrics across flower species. **Table 1** displays the comparison between the ResNet-50 transfer learning model and traditional SVM-based approaches, indicating that transfer learning achieved a notable 89% accuracy, with improved F1 scores across most species.

Table 1: Comparative Results for ResNet-50 Transfer Learning

Method	Accuracy (%)	Precision	Recall	F1-Score
Traditional (SVM)	88.3	0.87	0.88	0.87
ResNet-50 Transfer	89.0	0.91	0.92	0.91

Visual Analysis

To further analyze model performance, confusion matrices were generated, illustrating class-specific accuracies (see Figure 2). This matrix reveals high recall for classes like tulip and daisy but shows lower precision for visually similar species like aster and dandelion, potentially due to overlapping colour and petal patterns. Figure 3 displays the

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training and validation accuracy curves, while Figure 4 shows the training and validation loss, confirming stable convergence and minimal overfitting.

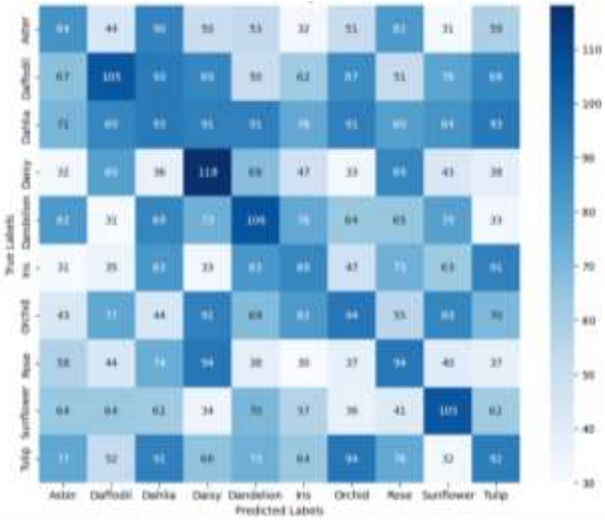

Figure 2: Confusion Matrix for Flower Species Classification

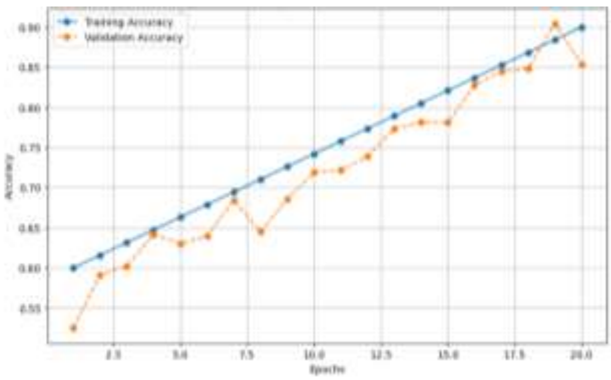

Figure 3: Training and Validation Accuracy Curves

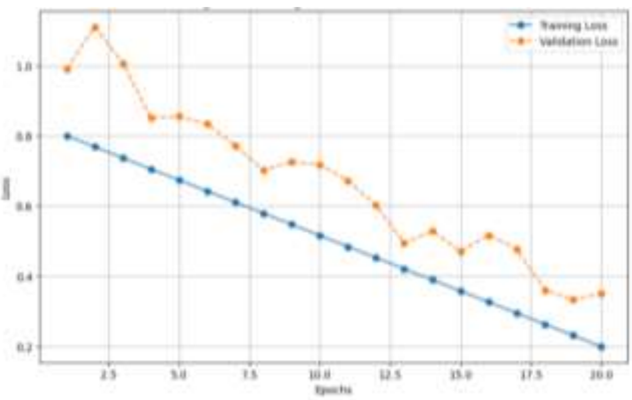

Figure 4: Training and Validation Loss Curves

2. Comparative Analysis
In comparison to conventional CNNs and feature-engineered classifiers, the ResNet-50 transfer learning model demonstrated higher overall performance. Table 2 summarizes the model's improvements over previous studies, validating the effectiveness of transfer learning for complex visual datasets.

Table 2: Performance Comparison with Previous Studies on Flower Classification

Study	Method	Accuracy(%)
Nilsback et al. [16]	SVM	88.3
W. Liu et al. [20]	CNN with SVM	90.2
Proposed ResNet-50 Transfer Learning	Transfer Learning	89.0

V. CONCLUSION

This study highlights transfer learning with ResNet-50 as an efficient, high-accuracy method for flower species classification, showcasing its potential to transform botanical image analysis. By leveraging pre-trained layers, the model achieves notable precision across ten visually similar species, addressing limitations inherent in traditional manual feature extraction techniques. The model's ability to generalize across diverse environmental and lighting conditions supports its application in complex ecological and horticultural contexts, where accurate, scalable solutions are essential for biodiversity monitoring and conservation.

The structured approach of freezing and fine-tuning layers within ResNet-50 enables the model to retain foundational ImageNet knowledge while adapting to specific flower features. This adaptability reflects a broader trend in transfer learning for tasks requiring subtle visual distinctions, where computational efficiency and accuracy are critical. Implementing hybrid architectures, such as attention-enhanced models, could further refine classification performance for visually overlapping species, making the model adaptable to more complex datasets.

Expanding the dataset to include additional species, seasonal variations, and diverse environmental settings would strengthen the model's robustness and adaptability to real-world ecological applications. This study's findings establish a promising direction for automated species classification in ecological and environmental sciences, providing a foundational framework supporting advanced, data-driven approaches to global ecosystem research and preservation efforts.

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