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Flower Image Classification Using Deep Learning and Transfer Learning

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Introduction

Image classification is a fundamental problem in computer vision that aims to automatically assign a semantic label to an image. With the rapid growth of digital images and visual data, traditional image processing techniques have become insufficient to handle complex visual patterns. Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized image classification by enabling models to automatically learn hierarchical visual features directly from data.

However, training deep neural networks from scratch requires large labeled datasets and significant computational resources. To address this limitation, *transfer learning* has emerged as an effective approach. This project focuses on applying transfer learning using a pre-trained ResNet50V2 model to classify flower images from a relatively small dataset. The objective is to demonstrate that leveraging knowledge learned from large-scale datasets such as ImageNet can significantly improve performance on specialized tasks like flower classification.

Chapter 1

Key Concepts and Definitions

1.1 TensorFlow

TensorFlow is an open-source machine learning framework developed by Google. It provides a comprehensive ecosystem for building, training, and deploying machine learning and deep learning models. TensorFlow supports both low-level operations and high-level APIs, making it suitable for research and production environments.

1.2 Keras

Keras is a high-level neural network API that runs on top of TensorFlow. It is designed to enable fast experimentation with deep learning models through a simple and user-friendly interface. Keras abstracts many complex operations while remaining flexible enough for advanced model customization.

1.3 Convolutional Neural Networks (CNNs)

A Convolutional Neural Network is a class of deep neural networks specifically designed for processing grid-like data such as images. CNNs use convolutional layers to automatically extract spatial features such as edges, textures, and shapes. These features are learned hierarchically, allowing the network to recognize complex objects.

1.4 Transfer Learning

Transfer learning is a machine learning technique where a model trained on a large and general dataset is reused for a different but related task. Instead of training a model from scratch, previously learned features are transferred and adapted to the new task. This approach reduces training time, lowers data requirements, and often improves model performance.

1.5 ResNet50V2

ResNet50V2 is a deep convolutional neural network consisting of 50 layers and based on residual learning. Residual connections help mitigate the vanishing gradient problem by allowing gradients to flow directly through skip connections. The V2 version introduces improvements in normalization and activation ordering, leading to better optimization and performance.

Chapter 2

Dataset Description

The dataset used in this project is the **Oxford Flowers 102** dataset. It contai-ns 8,189 images of flowers categorized into 102 distinct classes. Each class represents a specific flower species, and labels are encoded as integers.

The dataset is divided as follows:

- 80% for training
- 10% for validation
- 10% for testing

This split ensures that the model is trained on the majority of the data while preserving separate subsets for hyperparameter tuning and final evaluation.

Chapter 3

Data Preprocessing and Augmentation

Before feeding images into the neural network, several preprocessing steps are applied. All images are resized to 224×224 pixels to match the input requirements of the ResNet50V2 architecture. Images are then converted to floating-point values and normalized using the ResNet-specific preprocessing function, which scales pixel values to the range $[-1, 1]$.

To improve generalization and reduce overfitting, data augmentation techniques are applied to the training dataset. These include random horizontal flipping, random rotation, and random zooming. Data augmentation artificially increases dataset diversity and helps the model become more robust to variations in input images.

Chapter 4

Model Architecture

The proposed model is based on transfer learning using ResNet50V2 pre-trained on the ImageNet dataset. The original classification head of the network is removed, allowing the model to act as a feature extractor.

On top of the pre-trained base model, custom layers are added:

- A Global Average Pooling layer to reduce spatial dimensions
- A Dropout layer with a rate of 0.3 to reduce overfitting
- A Dense layer with 102 neurons and softmax activation for multi-class classification

The softmax activation function converts raw outputs into a probability distribution over the 102 flower classes.

Chapter 5

Training Strategy and Hyperparameters

The training process is conducted in two main phases.

In the first phase, the base ResNet50V2 model is frozen, and only the newly added top layers are trained. This allows the classifier to adapt to the flower dataset while preserving the generic visual features learned from ImageNet.

In the second phase, fine-tuning is performed by unfreezing the last 30 layers of the base model. A very small learning rate is used to carefully adjust high-level features without destroying previously learned representations.

The main hyperparameters used are:

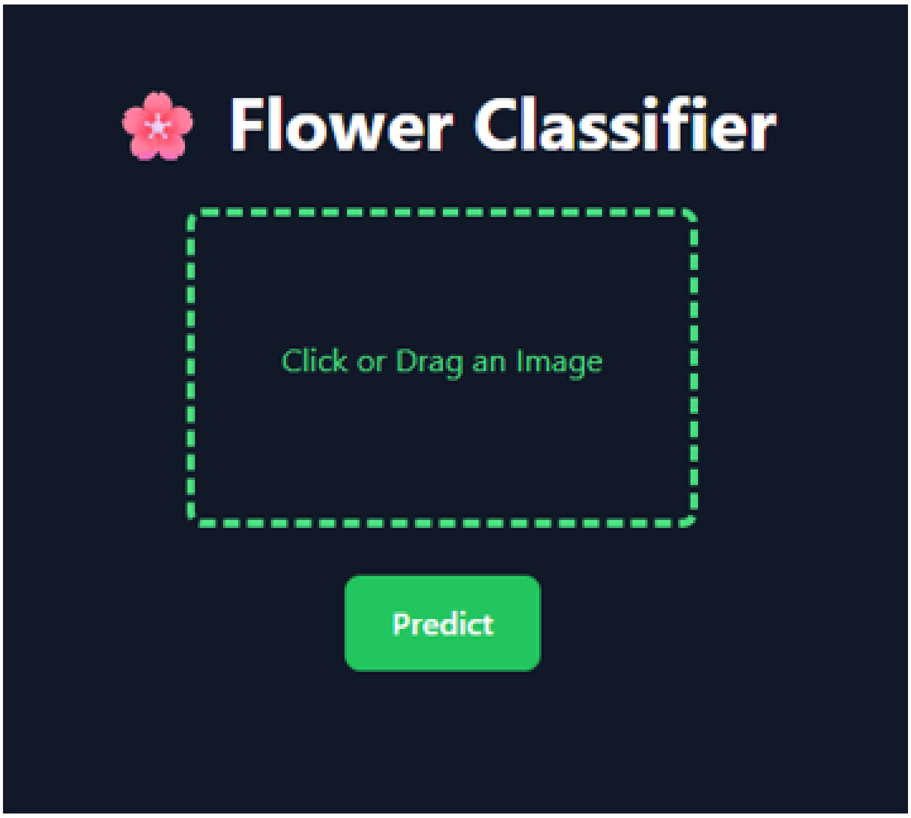
- Optimizer: Adam
- Initial learning rate: 0.001
- Fine-tuning learning rate: 1×10^{-5}
- Batch size: 32
- Loss function: Sparse Categorical Crossentropy
- Metric: Accuracy
- Early stopping patience: 3 epochs

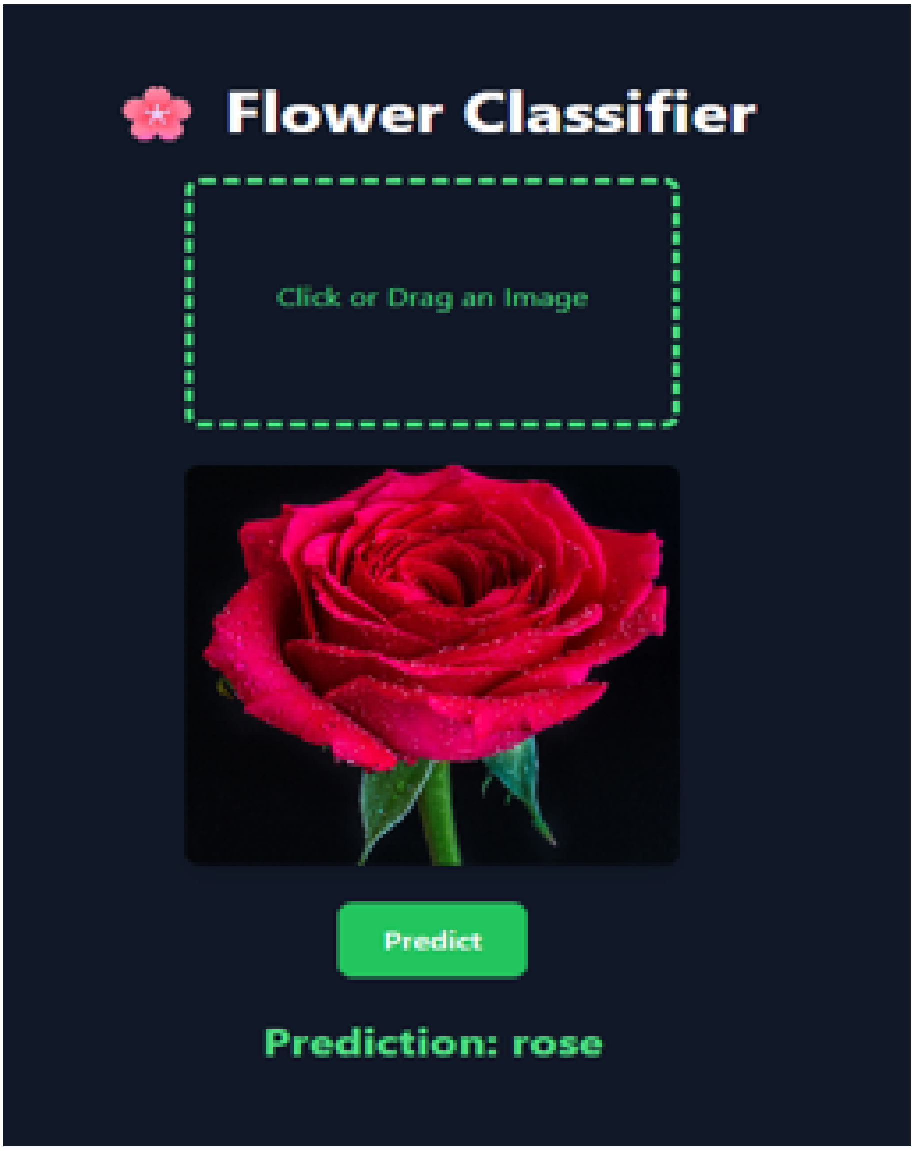
Chapter 6

Results

The trained model achieved strong performance on the validation dataset. The validation accuracy reached approximately 92%, while the validation loss converged to around 0.21. These results indicate that the model successfully learned discriminative features for flower classification.

The use of transfer learning significantly accelerated convergence and improved performance compared to training from scratch.




Flower Classifier
Click or Drag an Image
Predict
Prediction: rose

Chapter 7

Critical Analysis

The results demonstrate the effectiveness of transfer learning for image classification tasks with limited data. Freezing the base model during initial training helped prevent overfitting, while fine-tuning further improved accuracy.

However, the model remains computationally expensive due to the depth of ResNet50V2. This may limit deployment on resource-constrained devices. Additionally, although performance is strong, misclassifications may still occur between visually similar flower species.

Chapter 8

Conclusion

This project successfully applied transfer learning using a pre-trained ResNet50V2 model to classify flower images from the Oxford Flowers 102 dataset. The approach achieved high accuracy while reducing training time and data requirements.