Fruit and Vegetable Detection Project

Introduction

This project aims to classify fruits and vegetables from images using machine learning techniques. With practical applications in agriculture and food sorting, automating this task can improve efficiency and accuracy. In addition to a custom CNN model, transfer learning was explored to enhance performance.

Analysis

The dataset consists of labeled fruit and vegetable images. After resizing and normalizing, data augmentation was applied to increase variability and avoid overfitting. The dataset provided enough samples for a balanced training process.

Methods

Two approaches were used for this project: a custom Convolutional Neural Network (CNN) and transfer learning with a pretrained model.

1. Custom CNN

Input: Images resized to 128x128 pixels.

Layers: Several Conv2D layers with ReLU activation and MaxPooling2D.

Output: Dense layers followed by a softmax output layer.

Loss Function: Categorical Crossentropy.

Optimizer: Adam.

2. Transfer Learning:

A pretrained model (VGG16) was finetuned on the dataset.

The final fully connected layers were replaced to match the number of classes in the fruit and vegetable dataset.

Transfer learning provided the benefit of using pre-learned feature extraction from large image datasets, requiring fewer training epochs.

Results

Custom CNN: The accuracy value went over 90%, but the val_accuracy value stayed around 50 %. This means that our model is overfitting. It has difficulty recognizing new images.

Transfer Learning: The pretrained model improved performance, achieving approximately 90% validation accuracy. Transfer learning helped the model capture more complex visual patterns, improving classification accuracy, especially in previously challenging categories.

Comparison of Models:

Accuracy: The transfer learning model outperformed the custom CNN, with a 40% increase in validation accuracy.

Training Time: Transfer learning required fewer epochs to converge due to its prelearned features, while the custom CNN needed more training to extract features from scratch.

Generalization: Transfer learning generalized better to unseen data, particularly for more visually similar categories, thanks to the robustness of the pretrained model.

Reflection

Using transfer learning significantly improved performance and efficiency compared to building a custom model from scratch. Future iterations could explore finetuning more layers of the pretrained model for further improvements or adding more data augmentation to enhance model robustness.