# Fruit Classification Using CNNs and Transfer Learning

**Project Aim**

The objective of this project is to classify different types of fruits using image data and deep learning models. This task involves recognizing subtle visual patterns such as shape, texture, and color across a wide range of fruit categories.

We approach this using two techniques:

* A custom-built Convolutional Neural Network (CNN)
* A transfer learning approach using pre-trained MobileNet for efficiency and better performance

Such models can be beneficial in real-time agricultural automation, smart grocery systems, or mobile food recognition apps.

**Dataset Overview**

The dataset consists of fruit images categorized into 33 classes, where each folder represents one fruit type. Each image is resized to **224x224 pixels** to ensure uniformity and compatibility with model input requirements.

To avoid overfitting and improve generalization, **image augmentation** techniques were applied during training:

* Rotation
* Zoom
* Width and height shift
* Shearing
* Horizontal flipping

This makes the model more robust to variations in image orientation, scale, and lighting.

**Model Architectures**

**1. Custom CNN**

A manually designed CNN was implemented with:

* Multiple convolutional + pooling layers
* Dropout layers for regularization
* Fully connected Dense layers for classification

This gave a decent performance and helped understand feature extraction and learning from scratch.

**2. Transfer Learning with MobileNet**

Due to the high training time with VGGNet and performance limitations, **MobileNet** was used:

* Lightweight and optimized for speed
* Pre-trained on ImageNet
* Only the classification head was retrained for our fruit dataset

MobileNet drastically reduced training time while achieving excellent accuracy, especially for large and diverse datasets.

**Training & Evaluation**

The final MobileNet-based model was trained over 10 epochs and achieved:

* **Training Accuracy**: ~98.6%
* **Validation Accuracy**: ~100%
* **Test Accuracy**: ~100%

Loss values steadily decreased while accuracy increased, indicating a well-trained model with no signs of overfitting thanks to dropout and augmentation.

**Accuracy and Loss Visualization**

Both training and validation accuracy/loss were plotted to observe learning dynamics. The graphs showed:

* Continuous rise in accuracy
* Rapid decline in loss
* Close overlap of training and validation lines, confirming excellent generalization

**Prediction**

A sample prediction was performed by uploading a new fruit image and passing it through the trained MobileNet model. The image was preprocessed using resizing and normalization.

Predicted class was printed using the model's output probability vector and class name mapping.

**Future Improvements**

1. **Add model explainability** using Grad-CAM to understand which image regions influence predictions.
2. **Deploy the model** using a simple web app (Flask/Streamlit) for interactive predictions.
3. **Handle image format issues** more robustly by preprocessing non-JPEG images (like .webp) properly before inference.

**Conclusion**

This project effectively applied deep learning techniques—using both a custom CNN and MobileNet—for classifying 33 types of fruits with high accuracy. Preprocessing, normalization, and transfer learning helped achieve strong performance with efficient training. The results highlight the model’s potential for real-world applications like automated sorting and food recognition. With minor enhancements, it can be deployed as a practical fruit classification solution.