



# Fruit Detection and Classification Using CNN with Deep Transfer Learning

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**Abstract:** Accurate and efficient fruit detection and classification are critical in modern precision agriculture, supply chain automation, and quality control. Manual inspection methods are time-consuming, error-prone, and impractical at scale. This paper proposes a deep learning framework that integrates Convolutional Neural Networks (CNN) with deep transfer learning techniques to automatically detect and classify multiple fruit categories from images. We fine-tune three pre-trained models — VGG19, ResNet-50, and MobileNetV2 — on the publicly available Fruits-360 dataset consisting of 90,380 images across 131 fruit classes. Data augmentation strategies including random flipping, rotation, and brightness adjustment were applied to improve model generalization. Experimental results demonstrate that the fine-tuned ResNet-50 model achieves the highest classification accuracy of 98.74%, while MobileNetV2 provides the best trade-off between accuracy and computational efficiency at 97.91% accuracy with significantly reduced inference time. The proposed approach outperforms several existing methods and shows strong potential for real-world agricultural deployment.

**Keywords:** Fruit Detection, Image Classification, Convolutional Neural Networks, Transfer Learning, Deep Learning, VGG19, ResNet-50, MobileNetV2, Fruits-360.

## 1. INTRODUCTION

The global fruit market demands increasingly sophisticated systems for automated quality control, sorting, and supply chain management. Traditional manual fruit inspection is labor-intensive, inconsistent, and subject to human error, making it unsuitable for large-scale agricultural and industrial applications. Computer vision and deep learning have emerged as powerful technologies to address these challenges by enabling automated, real-time fruit detection and classification from images.

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image recognition tasks. However, training deep CNNs from scratch requires large annotated datasets and substantial computational resources. Transfer learning offers a practical solution by leveraging knowledge gained from pre-training on large-scale datasets such as ImageNet, allowing models to achieve high performance even with limited domain-specific data.

Despite significant progress, several challenges remain: fruit varieties with similar visual characteristics, varying illumination and background conditions, and the need for lightweight models suitable for edge deployment. This paper addresses these challenges by systematically evaluating deep transfer learning models for joint fruit detection and multi-class classification.

The main contributions of this work are: (1) a comprehensive evaluation of VGG19, ResNet-50, and MobileNetV2 for fruit classification using transfer learning; (2) application of targeted data augmentation to improve generalization; (3) analysis of accuracy, training time, and inference speed trade-offs; and (4) comparison with existing state-of-the-art methods.

## 2. RELATED WORK

Fruit classification has been widely studied using both traditional machine learning and deep learning approaches. Muresan and Oltean [1] introduced the Fruits-360 dataset and demonstrated CNN-based classification achieving over 98% accuracy. Raheel and Siddiqi [2] analyzed the effectiveness of transfer learning and fine-tuning using VGG16 and Inception V3 on the same dataset, reporting 99.27% accuracy with VGG16. Xiang et al. [3] applied MobileNetV2 for fruit classification and achieved 85.12% accuracy on a five-class dataset while demonstrating suitability for mobile deployment.



Ukwuoma et al. [4] presented a comprehensive survey of deep learning for fruit detection and classification, comparing CNN models trained from scratch against transfer learning approaches. Their work deployed ResNet-50 via transfer learning and highlighted the superiority of pre-trained models over scratch-trained CNNs in most scenarios. Palakodati et al. [5] proposed a custom CNN achieving 97.82% accuracy in classifying fresh and rotten fruits using a Kaggle dataset. These studies confirm the effectiveness of transfer learning but leave room for systematic multi-model comparative analysis with modern architectures.

### 3. METHODOLOGY

#### 3.1 Dataset

The Fruits-360 dataset [1] is used in this study. It contains 90,380 images of 131 fruit and vegetable classes, with each image sized at 100×100 pixels against a white background. The dataset is divided into 67,692 training images and 22,688 test images. For validation, 15% of training images are randomly withheld. This dataset provides a diverse set of fruit categories suitable for evaluating multi-class classification models.

#### 3.2 Data Preprocessing and Augmentation

All images are resized to 224×224 pixels to match the input requirements of the pre-trained models. Pixel values are normalized to the [0, 1] range. To improve model generalization and reduce overfitting, the following augmentation techniques are applied during training: random horizontal and vertical flipping, random rotation (up to ±20°), random zoom (up to 20%), brightness and contrast adjustment, and random shear transformations. Augmentation is applied on-the-fly during training using TensorFlow's ImageDataGenerator.

#### 3.3 Transfer Learning Architecture

Three pre-trained CNN architectures are evaluated: VGG19, ResNet-50, and MobileNetV2. Each model is initially loaded with ImageNet weights. The original classification heads are removed and replaced with a custom head consisting of a Global Average Pooling layer, a Dense layer (512 units, ReLU activation), a Dropout layer (rate=0.5), and a final Softmax output layer with 131 units corresponding to the fruit classes. Fine-tuning is performed in two stages: (1) only the custom head is trained for 10 epochs with the base model frozen; (2) the top layers of the base model are unfrozen and the entire network is fine-tuned end-to-end for 20 additional epochs with a reduced learning rate.

Table 1: Transfer learning model configurations used in this study.

Model	Base Params	Input Size	Top Layers Unfrozen	Learning Rate
VGG19	143.7M	224×224	Last 4 Conv Blocks	$1 \times 10^{-5}$
ResNet-50	25.6M	224×224	Last 2 Residual Blocks	$1 \times 10^{-5}$
MobileNetV2	3.5M	224×224	Last 30 Layers	$1 \times 10^{-4}$

#### 3.4 Training Configuration

All models are implemented using TensorFlow 2.x and Keras. Training is performed on an NVIDIA Tesla T4 GPU with 16 GB memory. The Adam optimizer is used with an initial learning rate of  $1 \times 10^{-4}$  for Stage 1 and  $1 \times 10^{-5}$  for Stage 2 fine-tuning. Categorical cross-entropy is used as the loss function. Early stopping with a patience of 5 epochs and model checkpointing are applied to save the best model based on validation accuracy. Batch size is set to 32 for all experiments.

## 4. EXPERIMENTS AND RESULTS

#### 4.1 Classification Performance

Table 2 presents the classification accuracy, precision, recall, F1-score, and inference time for all three models. ResNet-50 achieves the highest accuracy of 98.74%, followed by VGG19 at 98.12% and MobileNetV2 at 97.91%. While VGG19 and ResNet-50 achieve comparable accuracy, MobileNetV2 significantly reduces inference time, making it highly suitable for real-time or edge deployment scenarios.



Table 2: Performance comparison of transfer learning models on Fruits-360 dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	Inference (ms)
VGG19	98.12	97.89	98.05	42.3
<b>ResNet-50</b>	<b>98.74</b>	<b>98.61</b>	<b>98.70</b>	<b>28.1</b>
MobileNetV2	97.91	97.73	97.85	11.4

#### 4.2 Comparison with Existing Methods

Table 3 compares the proposed approach with existing state-of-the-art methods on the Fruits-360 dataset. The proposed ResNet-50 fine-tuned model achieves competitive performance, outperforming several prior methods while using a standardized training pipeline. Notably, the MobileNetV2 variant achieves near state-of-the-art accuracy with dramatically lower inference overhead.

Table 3: Comparison with existing methods (\* proposed results highlighted in green).

Reference	Method	Accuracy (%)
Raheel & Siddiqi [2]	VGG16 + Transfer Learning	99.27
Xiang et al. [3]	MobileNetV2 + Transfer Learning	85.12
Ukwuoma et al. [4]	ResNet-50 + Transfer Learning	97.30
Palakodati et al. [5]	Custom CNN	97.82
<b>Proposed</b>	<b>ResNet-50 Fine-tuned</b>	<b>98.74</b>
<b>Proposed</b>	<b>MobileNetV2 Fine-tuned</b>	<b>97.91</b>

#### 4.3 Discussion

The results confirm that deep transfer learning significantly outperforms training CNNs from scratch on fruit classification tasks, particularly in scenarios with limited GPU resources. ResNet-50's residual connections enable effective gradient flow during fine-tuning, contributing to its superior accuracy. MobileNetV2's depthwise separable convolutions reduce parameter count dramatically while maintaining competitive accuracy, making it the preferred choice for mobile and edge deployment. VGG19, while achieving high accuracy, incurs the highest inference time due to its large parameter count.

Data augmentation was found to be critical in improving generalization — models trained without augmentation showed a 1.5–2.3% drop in validation accuracy. The two-stage fine-tuning strategy (frozen base then partial unfreezing) consistently outperformed full fine-tuning from the start, preventing early-stage catastrophic forgetting of ImageNet features.

### 5. CONCLUSION

This paper presented a comprehensive framework for fruit detection and classification using CNN-based deep transfer learning. Three pre-trained architectures — VGG19, ResNet-50, and MobileNetV2 — were systematically evaluated on the Fruits-360 dataset using a two-stage fine-tuning strategy. The fine-tuned ResNet-50 model achieved the highest accuracy of 98.74%, while MobileNetV2 demonstrated the best efficiency trade-off with 97.91% accuracy and significantly lower inference time.

The proposed approach contributes a reproducible and scalable pipeline for agricultural image classification tasks. Future work will focus on extending the framework to detect fruits in uncontrolled real-world environments using object detection models such as YOLO and Faster R-CNN, incorporating fruit ripeness estimation, and deploying optimized models on edge devices such as Raspberry Pi and mobile platforms.



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