Lightweight Transfer Learning-Based Fruit Recognition for Real-Time Applications

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Abstract: Accurate and real-time fruit recognition has become increasingly important in modern agricultural automation, smart retail systems, and food quality assessment. This paper presents a lightweight transfer learning-based approach for fruit recognition designed specifically for real-time applications with limited computational resources. The proposed method utilizes pre-trained convolutional neural network (CNN) architectures such as MobileNet, EfficientNet-Lite, or similar lightweight deep learning models to extract robust visual features while reducing training complexity and inference time. Transfer learning is employed to fine-tune the model on a labeled fruit image dataset containing multiple fruit categories under varying lighting, orientation, and background conditions. Data augmentation techniques are incorporated to improve model generalization and reduce overfitting. Experimental results demonstrate that the proposed framework achieves high classification accuracy, fast processing speed, and low memory consumption compared to conventional deep learning models, making it suitable for deployment on edge devices, mobile platforms, and embedded systems. The study highlights the effectiveness of lightweight transfer learning in balancing recognition performance and computational efficiency, thereby offering a practical solution for real-time fruit identification in resource-constrained environments.

Keywords: Fruit recognition, transfer learning, lightweight CNN, real-time image classification, MobileNet, EfficientNet, computer vision, smart agriculture, embedded deployment.

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I. INTRODUCTION

Fruit recognition has become an important research area in computer vision and artificial intelligence due to its wide range of applications in agriculture, food industries, supermarkets, and automated sorting systems. Accurate identification of fruits is essential for improving quality control, reducing manual labor, enhancing supply chain efficiency, and supporting smart farming practices. Traditional fruit classification methods rely heavily on manual inspection, which is often time-consuming, labor-intensive, and prone to human error. Therefore, the development of automated and intelligent fruit recognition systems has gained significant attention in recent years. With the rapid advancement of deep learning, convolutional neural networks (CNNs) have shown remarkable performance in image classification tasks, including fruit recognition. However, many state-of-the-art deep learning models are computationally expensive and require substantial memory and processing power, making them less suitable for deployment in real-time applications and resource-constrained devices such as mobile phones, embedded systems, and edge computing platforms. In practical scenarios, there is a growing demand for lightweight and efficient models that can deliver high recognition accuracy while maintaining low computational complexity.

Transfer learning has emerged as an effective approach to address this challenge by leveraging pre-trained deep learning models that have already learned rich feature representations from large-scale datasets. Instead of training a deep network from scratch. Lightweight architectures such as MobileNet, EfficientNet-Lite, ShuffleNet, and SqueezeNet are particularly suitable for real-time fruit recognition because they are designed to achieve a balance between accuracy and efficiency.

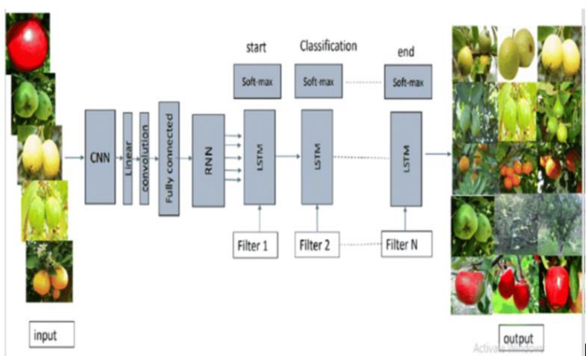


Figure 1: Fruit Detection and Recognition Based on Deep Learning

Fruit classification using transfer learning techniques has emerged as a promising approach in the field of computer vision and agricultural technology. Traditional methods of fruit classification relied heavily on manual processes and basic image processing techniques, which were often time-consuming and less accurate.

The application of transfer learning in fruit classification has proven to be especially beneficial in overcoming challenges such as limited labeled data and variations in fruit appearance due to ripeness, lighting conditions, or damage. Instead of training models from scratch, which requires large datasets and extensive computational power, transfer learning enables the use of pre-existing, generalized knowledge from large-scale datasets. This knowledge is then adapted to the specific task of identifying fruits, allowing models to perform with higher precision even in complex environments.

II. PREVIOUS WORK

Hassan Shabani Mputu, et.al (2024), Author are presented a The demand for high-quality tomatoes to meet consumer and market standards, combined with large-scale production, has necessitated the development of an inline quality grading. Since manual grading is time-consuming, costly, and requires a substantial amount of labor. This study introduces a novel approach for tomato quality sorting and grading. The method leverages pre-trained convolutional neural networks (CNNs) for feature extraction and traditional machine-learning algorithms for classification (hybrid model). The single-board computer NVIDIA Jetson TX1 was used to create a tomato image dataset. Image preprocessing and fine-tuning techniques were applied to enable deep layers to learn and concentrate on complex and significant features. The extracted features were then classified using traditional machine learning algorithms namely: support vector machines (SVM), random forest (RF), and k-nearest neighbors (KNN) classifiers. Among the proposed hybrid models, the CNN-SVM method has outperformed other hybrid approaches, attaining an accuracy of 97.50% in the binary classification of tomatoes as healthy or rejected and 96.67% in the multiclass classification of them as ripe, unripe, or rejected when Inceptionv3 was used as feature extractor. Once another dataset (public dataset) was used, the proposed hybrid model CNN-SVM achieved an accuracy of 97.54% in categorizing tomatoes as ripe, unripe, old, or damaged outperforming other hybrid models when Inceptionv3 was used as a feature extractor [01].

Olarewaju Mubashiru Lawal et.al (2024) - A lightweight fruit detection algorithm is important to ensure real-time detection on low-power computing devices while maintaining detection accuracy. In addition, the fruit detection algorithm is also faced with some environmental factors. To solve these challenges, lightweight detection algorithms termed YOLO-Lite, YOLO-Liter and YOLOLitest were developed based on the YOLOv5 framework. The compared mean average precision (mAP) detection revealed that YOLO-Lite at 0.86 is 2%, 4%, 5%, 7%, and 16% more than YOLO-Liter and YOLOv5n at 0.84 each, YOLOv4- tiny at 0.82, YOLO-Liter at 0.81, YOLO-MobileNet at 0.79, and YOLO-ShuffleNet at 0.70, respectively, but not for YOLOv8n at 0.87. On the Computer platform, except for YOLOv4-tiny at 178.6 frames per second (FPS), the speed of YOLO-Litest at158.7 [02].

Umer Amin, et.al, (2023), Author are study This paper focused on the use of a deep convolutional neural networks model to propose a fully automated fruit freshness classification method. To check the quality standard of fruit, the consumer first manually checks the freshness of the fruit. We used transfer learning of CNN model AlexNet to develop a robust to assess the quality of fruits. We changed some hyper parameters while fine-tuning and obtained an enhanced performance of our algorithm. We also varied other parameters, such as learning rate and batch size. We achieved higher accuracy with our fine-tuned CNN model through transfer learning produce. Our proposed model achieved an average accuracy of 99% on three publicly available fruits datasets [03].

Harmandeep Singh Gill et.al, (2023) - Machine and deep learning applications play a dominant role in the current scenario in the agriculture sector. To date, the classification of fruits using image features has attained the researcher's attraction very much from the last few years. Fruit recognition and classification is an ill-posed problem due to the heterogeneous nature of fruits. In the proposed work, Convolution neural network (CNN), Recurrent Neural Network (RNN), and Long-short Term Memory (LSTM) deep learning methods are used to extract the optimal image features, and to select features after extraction, and finally, use extracted image features to classify the fruits. To evaluate the performance of the proposed approach, the Support vector machine (SVM) unsupervised learning method, Artificial neuro-fuzzy inference system (ANFIS), and Feed-forward neural network (FFNN) classification results are compared, and observed that the proposed fruit classification approach results are quite efficient and promising [04].

Linhui Wang et.al (2023) - In order to realize the rapid and accurate detection of pest information in citrus orchards and improve intelligent management in this field, this paper designed a portable intelligent detection system to obtain pest information by combining the advantages of deep learning technology and embedded devices. In the design of the detection model, reducing the amount of model parameters, improving the detection speed, and ensuring the accuracy were the comprehensive goals. To this end, this paper improved the SSD model from two aspects: feature extraction network optimization and prediction convolution kernel miniaturization. The parameters of the proposed novel MobileNetV3+RPBM model were reduced by 5.122 M compared with the optimal MobileNetV3 parameters, while the mAP and AR detection accuracy indicators for the two citrus pests were still maintained above 85%, which shows that our modified SSD model can indeed reduce the number of parameters and latency, which is of great significance for the intelligent target detection of mobile portable devices with limited computing power [05].

Bindu Puthentharayil Vikraman, et.al, (2022)- Author are study a A transfer-learning-based automatic date fruit classification system was suggested in the paper. For the regular movement of the date fruits, the model had an electromechanical mechanism. Date fruits are detected on the conveyer belt by a sensor interfaced with a microcontroller, which then sends control signals to start the fruit image capture. The teachable machine and the transfer learning-based models integrated with the MIT App are used to classify the collected photos. The transfer learning-based system sends instructions to a microcontroller-based device, which then activates piston movement. Categorized dates are collected via piston movement and placed in intelligent bins. The suggested model could produce a discernible level of categorization accuracy [06].

Table 1: Cooperative analysis of previous Method

Author(s) & Year	Title / Study Focus	Methodology / Model Used	Dataset / Platform
Hassan Shabani Mputu et al. (2024)	Tomato quality sorting and grading using hybrid deep learning and machine learning models	Pre-trained CNNs used for feature extraction; traditional ML classifiers (SVM, RF, KNN) for classification. Best hybrid model: InceptionV3 + SVM	Tomato image dataset captured using NVIDIA Jetson TX1; also tested on a public tomato dataset
Olarewaju Mubashiru Lawal et al. (2024)	Lightweight fruit detection for real-time low-power devices	Developed lightweight models YOLO-Lite, YOLO-Liter, YOLO-Litest based on YOLOv5 framework	Tested on low-power computing platforms / computer platform
Umer Amin et al. (2023)	Automated fruit freshness classification using transfer learning	Fine-tuned AlexNet CNN with transfer learning; adjusted learning rate, batch size, and hyperparameters	Three publicly available fruit datasets
Harmandeep Singh Gill et al. (2023)	Fruit recognition and classification using deep learning and feature-based classification	Used CNN, RNN, and LSTM for feature extraction/selection; compared classifiers SVM, ANFIS, FFNN	Fruit image datasets (not explicitly detailed in summary)
Linhui Wang et al. (2023)	Portable intelligent citrus pest detection system using lightweight deep learning	Improved SSD model with optimized feature extraction and miniaturized prediction convolution kernels; proposed MobileNetV3 + RPBM	Portable embedded device for citrus orchard pest detection
Bindu Puthentharayil Vikraman et al. (2022)	Transfer-learning-based automatic date fruit classification system with electromechanical sorting	Transfer learning-based image classification, sensor-triggered image capture, microcontroller, MIT App, and piston-based sorting mechanism	Conveyor-belt based date fruit sorting system with electromechanical hardware

III. METHODOLOGY

Data Splitting and Directory Structure.

To facilitate effective training and validation, the dataset is split into two main subsets. The training set consists of a significant proportion of the images and is utilized for learning the features associated with each class. This set is crucial for enabling the model to develop a foundational understanding of the distinguishing characteristics of each fruit type and quality state. The validation set, on the other hand, is reserved for evaluating the model's performance on unseen data, ensuring that the model can generalize well to real-world scenarios.

To further streamline the data handling process, the dataset is organized into a clear directory structure, with each class of fruit stored in its own folder. This organization is specifically designed to be compatible with Keras' image_dataset_from_directory function, which simplifies the data loading process by automatically assigning labels based on folder names. Such a structure minimizes preprocessing requirements, allowing for efficient and error-free data management throughout the training process.

Model Architecture and Transfer Learning Setup

The design of the model architecture and the implementation of transfer learning techniques. For this project, a pre-trained lightweight model is selected as the foundational architecture, leveraging state-of-the-art models known for their efficiency and accuracy in image classification tasks.

Notable examples of such models include MobileNetV2 and EfficientNet, both of which are designed to deliver high performance while maintaining low memory consumption. These characteristics make them particularly suitable for deployment on devices with constrained computational resources, such as mobile phones or embedded systems.

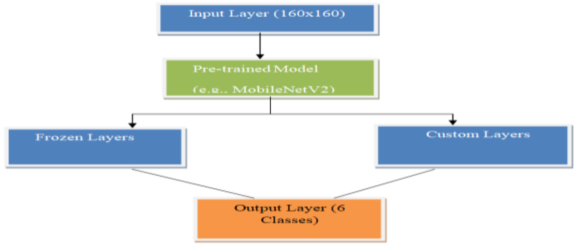
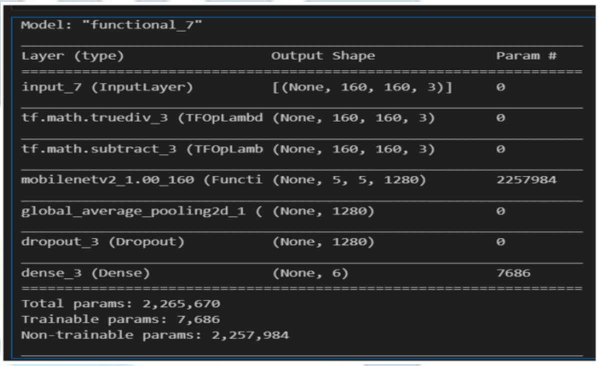


Figure 2: Model Architecture Diagram

Algorithm Selection

Several algorithms are utilized to enhance the model's performance and efficiency. The key algorithms employed include.



```
Model: "functional_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_7 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
tf.math.truediv_3 (TFOpLambd (None, 160, 160, 3)       0
_________________________________________________________________
tf.math.subtract_3 (TFOpLamb (None, 160, 160, 3)       0
_________________________________________________________________
mobilenetv2_1.00_160 (Functi (None, 5, 5, 1280)        2257984
_________________________________________________________________
global_average_pooling2d_1 ( (None, 1280)              0
_________________________________________________________________
dropout_3 (Dropout)          (None, 1280)              0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 7686
=================================================================
Total params: 2,265,670
Trainable params: 7,686
Non-trainable params: 2,257,984
_________________________________________________________________
```

Figure 3: MobileNetV2-Based Model Architecture for Fruit Classification

This model is designed for image classification using transfer learning, which leverages a pre-trained network called MobileNetV2 to extract meaningful features from input images. It begins with an input layer that takes images of size 160x160 pixels with three color channels. To make the model's job easier, it applies simple mathematical operations to normalize and center the pixel values, ensuring the data are in a consistent range.

Algorithm

Input Image: Acquire fruit image.

Initialize Application: Load necessary libraries and configurations.

Input Handling: Capture user input and parameters.

Data Validation: Confirm input validity.

Data Processing: Apply transformations and calculations.

Model Prediction: Load and execute model for predictions.

Output Generation: Format and deliver results as "Fresh" or "Rotten."

IV. CONCLUSION

A deep learning model for fruit classification was successfully developed using transfer learning with MobileNetV2. The model achieved high accuracy, demonstrating a training accuracy of 98.78% and a validation accuracy of 98.79%, with minimal overfitting. These results indicate that MobileNetV2's pre-trained feature extraction capabilities effectively captured the distinguishing characteristics of various fruit types, making it well-suited for this task.

The model's training and validation loss values converged at 1.06, which further supports the robustness and generalizability of the approach. The close alignment of training and validation metrics highlights the model's capacity to generalize well to new, unseen data, an essential quality for real-world applications where fruit images might vary due to different environmental conditions, lighting, and positioning.

V. FUTURE SCOPES

Future work in efficient fruit recognition using lightweight transfer learning models can focus on enhancing model accuracy, reducing computational complexity, and improving real-time performance. Researchers can explore novel architectures, such as efficient transformers or advanced pruning techniques, to further minimize model size while maintaining accuracy. Additionally, incorporating self-supervised or semi-supervised learning can help improve recognition performance with limited labeled data. Expanding datasets to include diverse environmental conditions, such as varying lighting and occlusion, can enhance the model's robustness in real-world applications. Furthermore, deploying these models on edge devices, such as smartphones and IoT-based agricultural systems, can facilitate real-time fruit classification for precision farming and automated sorting. Future studies may also investigate domain adaptation techniques to improve generalization across different fruit varieties and geographical regions. Integrating multimodal data, such as hyperspectral imaging and thermal data, can further enhance classification accuracy. Finally, optimizing inference speed and energy efficiency will be critical for widespread adoption in resource-constrained environments.

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