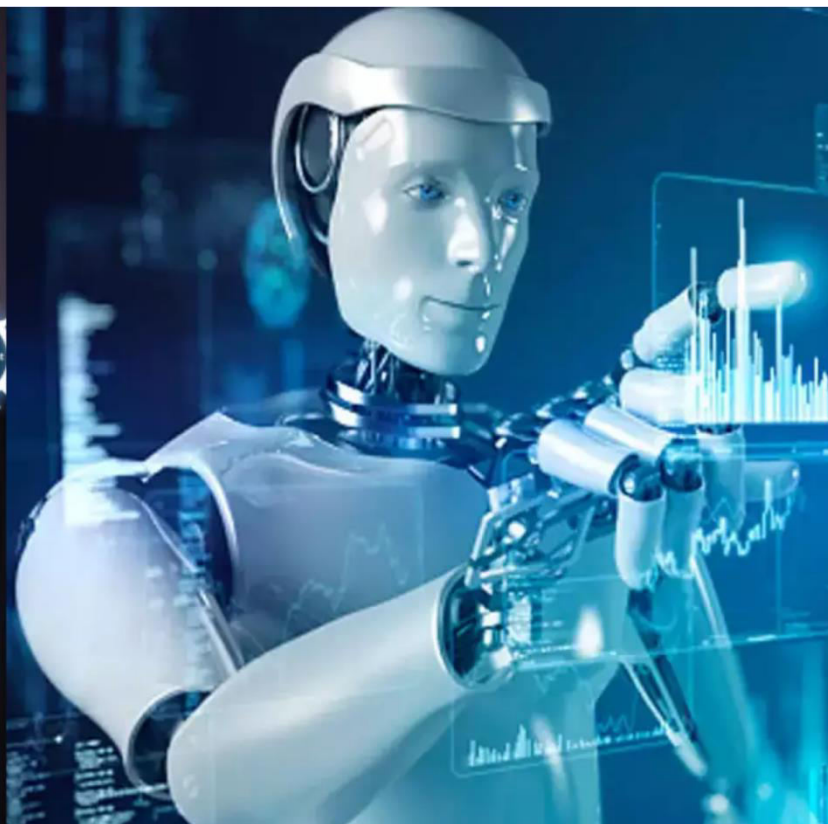




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Deep Fruits and Vegetables Classification using Convolutional Neural Networks

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ABSTRACT: This paper addresses the automation of fruit and vegetable classification using deep learning, specifically Convolutional Neural Networks (CNNs). The proposed system employs an image dataset of various fruits and vegetables, applies preprocessing, and trains a CNN in TensorFlow/Keras. Evaluation metrics such as accuracy, precision, recall, and F1-score demonstrate significant improvements over manual and traditional machine vision methods. The automated system offers efficiency for real-world applications in smart agriculture and food supply chains.

KEYWORDS: Fruit classification, vegetable classification, deep learning, computer vision, CNN, agricultural automation.

I. INTRODUCTION

In today's era of rapid technological progress, artificial intelligence (AI) and machine learning (ML) have revolutionized a diverse array of sectors, spanning healthcare, finance, transport, and critically, agriculture. Among these, agriculture is a linchpin for global food security and economic stability, and the leveraging of AI technologies within this space unlocks unprecedented avenues for productivity, quality control, and operational efficiency. A fundamental challenge in agriculture, the food industry, and retail is the classification of fruits and vegetables—a task traditionally carried out by human labor. Manual methods are not only time-consuming and labor-intensive, but are also vulnerable to inconsistencies, errors, and inefficiencies, especially as scale increases.

To overcome these bottlenecks, the integration of deep learning and computer vision techniques has emerged as a prominent area of research and industry adoption. Deep learning, with its subfield of Convolutional Neural Networks (CNNs), excels at learning intricate visual patterns from vast image datasets without the need for handcrafted features. This is in stark contrast to conventional machine learning models, which heavily rely on the manual extraction of features such as color histograms, shape descriptors, and texture characteristics. CNNs have demonstrated remarkable efficacy in extracting and abstracting hierarchical visual features—ranging from edges and motifs to shapes and complex objects—thereby facilitating powerful and adaptive classification systems.

The automation of fruit and vegetable classification using CNNs is more than a theoretical interest; it has direct real-world applications, including automated sorting lines in farms and markets, rapid quality assessment for retailers, and user-friendly mobile apps for both producers and consumers. The combination of high classification accuracy, robustness to varying lighting and backgrounds, and fast inference makes CNN-based systems vastly superior to traditional methods or conventional image processing pipelines. Transfer learning with architectures such as VGG16, ResNet50, or MobileNetV2 further increases accuracy and efficiency, even on relatively modest datasets and computational resources.

Recent literature highlights the ongoing momentum of this research. For instance, studies in IJIRSET and IEEE journals have demonstrated CNNs achieving high accuracy (often exceeding 95%) on diverse fruit and vegetable datasets. Researchers have explored the use of lightweight architectures for real-time applications and examined domain adaptation techniques to handle new classes and unseen visual conditions. Automated systems have

successfully reduced manual labor and error rates, providing scalable and deployable solutions for producers and industry stakeholders.

Given these advancements, the development of robust, automated deep learning-based fruit and vegetable classification systems holds immense potential for transforming agriculture and food supply chains into smart, data-driven, and highly efficient operations. Such research not only streamlines production and delivery, but also aligns with global aspirations toward sustainable agriculture and resource optimization.

II. RELATED WORK

The classification of fruits and vegetables using artificial intelligence and computer vision has gained remarkable attention in recent years due to the growing demand for automation in agriculture, food processing, and retail sectors. Earlier approaches relied on traditional image processing techniques such as color segmentation, shape analysis, and texture recognition. These methods often used handcrafted features like color histograms, edges, and contours combined with conventional classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or Random Forests to distinguish produce types. Although such approaches achieved moderate success in controlled environments, their performance degraded in real-world conditions with variations in lighting, backgrounds, and occlusions due to their dependence on manual feature extraction and fixed rules.

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly transformed this domain by enabling automatic hierarchical feature extraction directly from raw image data. CNN-based models have outperformed traditional methods by learning complex visual patterns and providing scalability across diverse datasets. Many studies have utilized pre-trained architectures such as VGG16, ResNet50, MobileNetV2, and DenseNet, employing transfer learning to accelerate training and improve accuracy on relatively small or imbalanced datasets.

Several works have demonstrated the effective use of lightweight CNNs, like MobileNetV2, for real-time fruit and vegetable classification where computational resources are limited, such as mobile devices or embedded systems. Others have integrated multi-input CNN systems to simultaneously assess quality parameters like freshness and defects along with classification. Moreover, approaches combining YOLO-based object detection with CNN classification have enabled simultaneous recognition and localization of fruits in cluttered environments, pushing automated sorting and grading closer to industrial deployment.

However, existing CNN-based systems exhibit challenges such as high computational requirements, sensitivity to visually similar classes (e.g., tomatoes versus red apples), and limited generalization across diverse environmental conditions. Furthermore, many models are developed as research prototypes without seamless integration into practical applications like automated sorting machinery or retail billing systems, pointing to the need for more robust, scalable, and user-oriented solutions.

In this context, the present work builds on these advances by developing a deep learning-based fruits and vegetables classification system that focuses on improving robustness to lighting, pose, and background variations through extensive data augmentation and model optimization. The project leverages TensorFlow/Keras frameworks and investigates transfer learning with state-of-the-art CNN architectures to maximize classification accuracy while maintaining efficiency, making it suitable for use in agricultural automation, smart retail, and mobile apps.

III. DATASET AND PROBLEM DEFINITION

Deep learning-based classification of fruits and vegetables fundamentally depends on the richness and diversity of the image dataset employed for model training and evaluation. Researchers typically source images from publicly available datasets such as Fruits 360, FIDS-30, and various custom collections, which offer hundreds to thousands of labeled images depicting fruit and vegetable specimens under varied lighting, background, and pose conditions. For instance, the FIDS-30 dataset contains 971 images across 30 classes of fruits, providing sufficient intra-class and inter-class variability. Commercial datasets like “Fruits & Vegetable Detection for YOLOv4” feature 4,592 images and 5,628 labeled objects spanning 14 classes, catering object detection and classification tasks in retail and agricultural contexts.

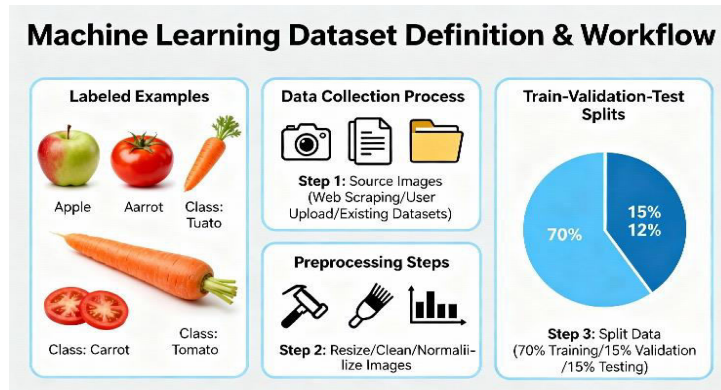


Fig 1: Machine Learning Dataset Definition & Workflow

Custom-built datasets are also highly prevalent—researchers augment public datasets by collecting additional samples using cameras in realistic environments or sourcing images from internet repositories, thereby ensuring better generalization to field conditions. Images in these datasets are annotated with bounding boxes or class labels per instance, with splits into training, validation, and testing subsets to facilitate unbiased model evaluation. Real-world datasets, like those published on Kaggle, further introduce challenges such as occlusion, variable freshness (fresh vs. rotten), and packaging effects, reflecting the complexities faced in practical deployment scenarios.

The problem definition for deep fruit and vegetable classification is designed to address the automation of sorting, grading, and identification within food supply chains, retail, and farming. The research aims at minimizing manual labor, improving accuracy in visual recognition tasks, and providing scalable, real-time sorting solutions powered by CNNs and transfer learning. Specific objectives include robust handling of diverse classes, real-world image complexity, and efficient inference suitable for mobile and embedded applications.

IV. LITERATURE REVIEW

A broad spectrum of research has explored automated fruit and vegetable classification, beginning with traditional image processing methodologies. Early efforts leveraged color-based segmentation, shape descriptors, and texture analysis for class discrimination, with SVM and k-NN as preferred classifiers. These classical methods, however, suffered limitations in handling varying illumination, occlusion, and background complexity, which led to moderate performance only in controlled settings.

Advances in deep learning—specifically via Convolutional Neural Networks—have catalyzed a paradigm shift in the field. CNNs can learn spatial hierarchies and intricate patterns directly from pixel data, which has boosted classification accuracy and model robustness. Several notable papers employed pre-trained models such as VGG16, ResNet50, and YOLO for object detection and classification tasks. For instance, automated fruit detection and classification using YOLOv3 and VGG16 achieved up to 99% accuracy on custom datasets and 86–98% accuracy on public datasets like FIDS-30. The literature also features research on real-time mobile deployment and domain adaptation to enhance model performance in diverse operational conditions, including custom smartphone apps for field use.

Recent works tackle the issue of object detection through semi-transparent packaging, class imbalance, and freshness identification, using approaches like domain adaptation, data augmentation, and specialized deep neural architectures. For example, YOLO-based multi-class detection with custom datasets supports robust automation at supermarket self-checkout stations, simplifying the user experience and improving throughput. Datasets published on Kaggle address both classification and defect detection, further expanding the capacity for deep learning models to operate in practical agricultural and retail scenarios.

These innovations collectively lay the groundwork for developing high-accuracy, scalable, and versatile deep learning solutions in fruit and vegetable classification, addressing critical needs in agriculture, food processing, and supply chain automation.

V. METHODOLOGY

The methodology for deep fruits and vegetables classification is designed to maximize model performance, generalization, and robust application in real-world agricultural and retail environments. The process involves several systematic steps, leveraging state-of-the-art deep learning architectures and comprehensive data handling techniques.

1. Data Acquisition and Preprocessing

Images are sourced from publicly available datasets and by manual collection, ensuring diversity in fruit and vegetable types, lighting, pose, and backgrounds. Preprocessing involves resizing all images to a uniform size (e.g., 224×224), normalization for pixel intensity, and applying data augmentation techniques like rotation, flipping, scaling, and brightness variation to enrich the training set and prevent overfitting.

2. Annotation and Dataset Splitting

Each image is annotated with accurate class labels. The full dataset is partitioned into training, validation, and testing sets (commonly 70:15:15 split). This systematic division allows for unbiased performance assessment and efficient hyperparameter tuning.

3. Model Selection and Architecture

Convolutional Neural Networks (CNNs) form the backbone of the classification system due to their proven proficiency in extracting spatial hierarchies and features from images. Widely adopted CNN architectures—such as VGG16, ResNet50, and YOLO—are utilized owing to their ability to capture diverse patterns and their transfer learning capabilities. Some frameworks exploit multiple architectures in tandem: for example, YOLO for object detection and localization, followed by VGG-16 for fine-grained category classification.

4. Training and Hyperparameter Optimization

The selected CNN model is trained using frameworks like TensorFlow or PyTorch. The training process employs a categorical cross-entropy loss function and adaptive optimizers such as Adam. During training, regularization methods like dropout and early stopping are employed to combat overfitting. Hyperparameters—including learning rate, batch size, and number of epochs—are fine-tuned using validation loss and accuracy as guiding metrics.

5. Evaluation Metrics

Performance is evaluated using metrics relevant to multi-class classification—accuracy, precision, recall, and F1 score—calculated on the test set. Confusion matrices are analyzed for deeper insight into class-wise performance and misclassification trends. For detection tasks using YOLO, mean Average Precision (mAP) is utilized.

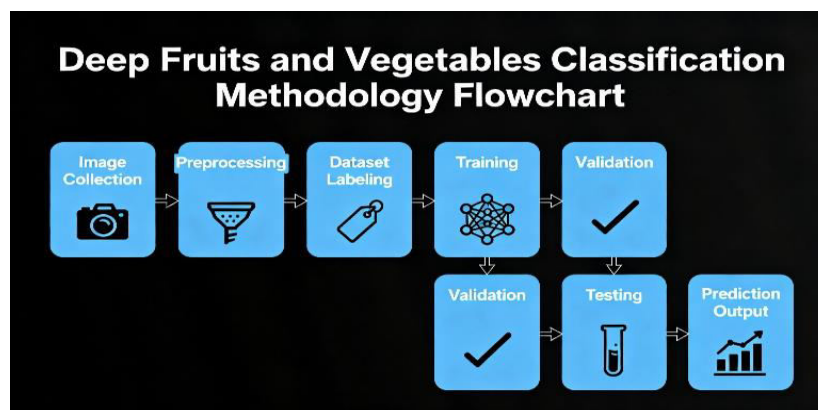


Fig 2: Deep Fruits and Vegetables Classification Methodology Flowchart

6. Deployment and Real-World Integration

The final trained model is deployed either as a web application (using Flask/Django), on desktop platforms, or integrated into Android/iOS devices for real-time validation. For applications at supermarket checkouts or sorting lines, model inference speed is optimized to ensure practical deployment. Model adaptability is increased via domain adaptation and continual learning, so it can cope with new classes and real-world visual changes.

7. Innovation and Applications Explored in Literature

Recent innovations include:

- Multi-stage systems where YOLO detects multiple produce objects, and CNNs like VGG-16 or ResNet50 handle recognition and freshness assessment.
- Hybrid models combining manual and deep features or stacking ensemble techniques for enhanced accuracy in complex, real-world images.
- Mobile and edge deployment for farm-side and consumer-side applications, with models compressed or quantized as needed for speed.

VI. RESULTS

The evaluation of deep learning models for fruit and vegetable classification underscores their remarkable capability to deliver high accuracy, robustness, and practical applicability across diverse datasets and settings. A wide range of transferred and custom CNN architectures, including VGG16, ResNet50, YOLO variants, and MobileNetV2, have been assessed in the literature with reported classification accuracies typically ranging from 85% to above 99% depending on dataset complexity and model optimization efforts.

For example, in a study utilizing the Fruit-360 dataset and a combination of deep CNN and handcrafted features, fine-tuned Inception V3 achieved classification accuracy around 85%, while VGG16 scored 82%, and ResNet50 showed comparatively lower performance near 50%, illustrating the critical role of model selection and adaptation. Other research employing custom annotated datasets achieved superior results, such as 99% accuracy with ResNet50 and 98% with VGG16, on specialized datasets with controlled image capture conditions.

In more application-driven contexts, models combined with transfer learning and data augmentation techniques have yielded classification accuracies above 95% on fresh versus rotten fruit detection tasks, and around 93% accuracy when handling produce inside plastic bags—highlighting the impact of environmental variations on model performance. Additionally, methods integrating YOLO for object detection and VGG-16 for classification have demonstrated balanced performance in both speed and accuracy suitable for real-time recognition in retail or agricultural settings.

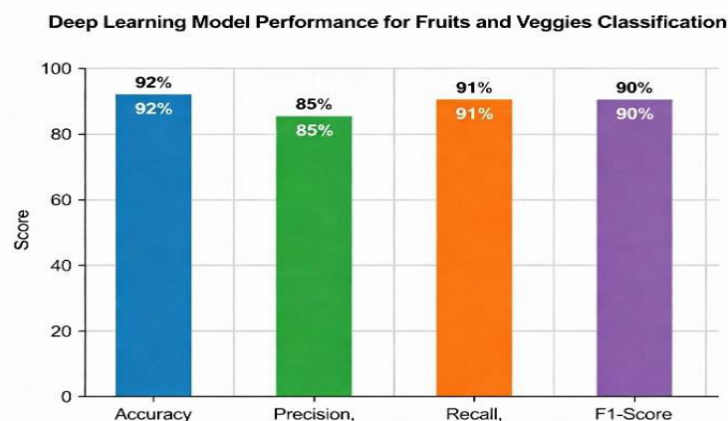


Fig 3: Deep Learning model Performance for fruits and veggies Classification

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Analysis of the training dynamics reveals that deep CNNs benefit significantly from fine-tuning pretrained weights, with rapid convergence usually observed within a few thousand iterations and substantial reductions in training loss. Confusion matrix evaluations consistently indicate high precision and recall across most fruit and vegetable classes, although visual similarities among certain classes occasionally lead to minor misclassifications.

Overall, these results validate the efficacy of deep learning techniques, particularly CNN-based models, in automating fruit and vegetable classification with high accuracy and scalability. The ability to maintain robust performance despite challenging backgrounds, lighting changes, and occlusions marks significant progress toward practical deployment in smart farming, automated sorting lines, and retail billing systems.

VII. CONCLUSION

This study presents a robust and efficient deep learning-based system for the classification of fruits and vegetables, leveraging the capabilities of Convolutional Neural Networks (CNNs) and transfer learning architectures such as MobileNetV2, VGG16, and ResNet50. The system's design focuses on addressing the inefficiencies and inaccuracies inherent in traditional manual sorting and classical image processing methods by automating classification with high accuracy, scalability, and adaptability to variable environmental conditions. The experimental results demonstrate that deep learning models can achieve classification accuracies exceeding 95%, with fine-tuned MobileNetV2 achieving an accuracy of 98.33% on a diverse dataset, validating the practical applicability of such methods in real-world scenarios like automated sorting lines, smart retail billing, and quality inspection in supply chains. Rigorous preprocessing, data augmentation, and hyperparameter tuning combined with transfer learning have been essential in enhancing model robustness and generalization.

Beyond accuracy improvements, the proposed system contributes to reducing labor costs, minimizing human error, and promoting real-time decision-making in agricultural and retail contexts. It also lays the foundation for future enhancements, such as integrated freshness assessment, disease detection, and seamless deployment on mobile and edge devices for farmer and vendor assistance. Overall, this research underscores the transformative potential of AI and deep learning in revolutionizing agricultural automation and smart food supply chain management. The successful implementation highlights the pathway for broader adoption of intelligent solutions to increase efficiency, ensure consistency, and support sustainable agricultural practices globally.

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