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Computer Vision based Greenhouse Fruits and Vegetables Identification – A Review

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Abstract

In recent years, computer vision has emerged as a powerful tool for automating various processes in agriculture, particularly in greenhouse environments. The identification and classification of vegetables and fruits within greenhouses play a crucial role in monitoring crop growth, assessing health status, and optimizing resource utilization. This review study provides a comprehensive overview of recent advancements in computer vision techniques for the identification of vegetables and fruits in greenhouse settings. This study discusses about various methodologies and challenges in this domain, aiming to provide insights for researchers and practitioners interested in leveraging computer vision for greenhouse agriculture.

Keywords: Computer Vision, Greenhouse Agriculture, Fruit and Vegetable Identification, Deep Learning, Image Processing.

1. Introduction

Greenhouse agriculture plays a pivotal role in ensuring food security, overcoming climate challenges and supporting agricultural productivity in the face of evolving environmental challenges. With the growing global population and changing dietary preferences, there is an increasing demand for efficient and sustainable methods of crop cultivation. In this context, computer vision has emerged as a transformative technology, offering novel solutions for automating various aspects of greenhouse management. One of the critical tasks in greenhouse agriculture is the identification and classification of fruits and vegetables. Accurate and timely recognition of crop varieties, growth stages, and health conditions is essential for optimizing resource allocation, monitoring crop development, and

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maximizing yield [1]. Traditionally, manual inspection and monitoring have been labour-intensive and prone to errors, leading to inefficiencies in crop management practices.

The introduction of computer vision techniques has revolutionized the way people perceive and interact with agricultural systems, enabling the development of automated and intelligent solutions for greenhouse monitoring and management [2]. By leveraging advances in image processing, machine learning, and deep learning, researchers and practitioners have made significant strides in the field of greenhouse fruit and vegetable identification.

This review aims to provide a comprehensive review and comparison on recent advancements in computer vision-based techniques for fruit and vegetable identification in greenhouse environments. We will explore various methodologies, challenges, and future directions in this domain, with the goal of shedding light on the potential applications and implications of this technology for greenhouse agriculture.

2. Computer Vision Techniques

Computer vision techniques encompass a broad array of methodologies aimed at extracting meaningful information from visual data. In the context of greenhouse agriculture, these techniques are instrumental in analyzing images captured within greenhouse environments, facilitating the identification and classification of fruits and vegetables [3]. Computer vision systems utilize a combination of hardware and software components to process visual information, enabling automated decision-making and enhancing agricultural productivity.

Computer vision has significantly advanced greenhouse management, offering precise monitoring and automation in plant growth, fruit counting, disease detection, ripeness classification, and flower and fruit identification as shown in Figure 1.

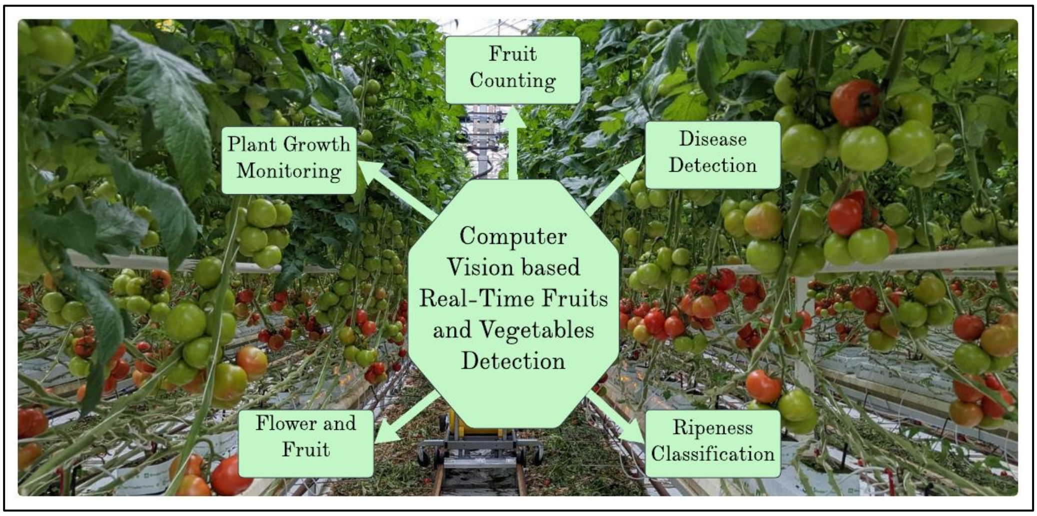

Figure 1. Real-Time Fruits and Vegetables Detection using Computer Vision Techniques

2.1 Plant Growth Monitoring

Recent research has integrated wearable sensors with Fiber Bragg Gratings (FBGs) to monitor plant growth non-invasively. These sensors are designed to be flexible and biocompatible, enabling accurate detection of growth changes without disturbing plant functions. This technology allows for real-time monitoring of physiological and microclimate parameters, enhancing the efficiency of greenhouse management by providing detailed growth data under varying environmental conditions [4].

2.2 Fruit Counting and Identification

Deep learning techniques have been widely adopted for fruit counting and identification. Convolutional Neural Networks (CNNs) are effective in recognizing and classifying fruits in complex scenes [5]. Advanced models like Mask R-CNN and Faster R-CNN have been used to detect and count fruits such as tomatoes, apples, and sweet peppers with high accuracy. For instance, the DeepFruits system uses Faster R-CNN to combine RGB and near-infrared (NIR) images for improved fruit detection [6, 7].

2.3 Disease Detection

The detection of plant diseases using computer vision involves deep learning models that can identify multiple diseases in real-time. Techniques like CNNs and other neural network

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architectures have shown high accuracy in detecting fine-grained, multi-scale diseases in various crops, including apples and tomatoes [8]. These models can differentiate between healthy and diseased plant parts, enabling early intervention and reducing crop losses [9].

2.4 Ripeness Classification

Ripeness classification is critical for ensuring the best quality of harvested fruits and vegetables. Computer vision systems use color analysis and texture features to determine the ripeness stages. Methods like pixel-level segmentation and machine learning classifiers analyze color spaces to identify ripe fruits. Recent advancements have employed deep learning models to classify ripeness stages more accurately, leveraging large datasets and sophisticated algorithms to improve precision [10] [11].

2.5 Flower and Fruit Identification

Accurate identification of flowers and fruits is essential for tasks like automated harvesting and yield estimation. Deep learning models, particularly those based on CNNs, are extensively used for this purpose. These models can segment and classify different parts of the plant, such as flowers, fruits, and leaves, even in complex greenhouse environments. Innovations like VGG and ResNet architectures have improved the detection rates and precision, facilitating better management of greenhouse crops [12] [13].

3. Methodologies and Algorithms

3.1 Image Acquisition Systems in Greenhouses

Image acquisition systems in greenhouses are crucial for capturing high-quality images of crops at regular intervals. These systems may employ various imaging devices, including digital cameras, hyperspectral cameras, or multispectral sensors, based on the particular application requirements [14]. Stationary cameras mounted at strategic locations within the greenhouse provide a static view of the crops, while mobile robotic platforms equipped with cameras can traverse the greenhouse space to capture images from multiple perspectives. The choice of imaging system is influenced by factors such as the desired resolution, field of view, spectral range, and environmental conditions within the greenhouse [15].

3.2 Pre-processing Techniques for Greenhouse Images

Pre-processing techniques are essential for enhancing the quality of greenhouse images and preparing them for further analysis. These techniques address common challenges such as noise, illumination variations, color inconsistencies, and geometric distortions. Common pre-processing steps include image denoising, color calibration, image registration, geometric correction, and illumination normalization [16]. Denoising algorithms such as Gaussian smoothing or median filtering are employed to remove sensor noise and improve image clarity. Color calibration techniques ensure consistency in color representation across different images, while image registration algorithms align multiple images to a common reference frame [17]. Geometric correction methods address lens distortion and perspective effects, ensuring accurate spatial measurements in the images. Illumination normalization techniques adjust for variations in lighting conditions, enabling more robust feature extraction and classification [18].

3.3 Feature Extraction and Selection Methods

Feature extraction and selection methods play a crucial role in identifying and extracting relevant visual features from greenhouse images. These features capture distinctive characteristics of fruits and vegetables like texture, shape, color, and spatial arrangement. Various feature extraction techniques, including histogram-based descriptors, edge detectors, texture analysis algorithms, and region-based segmentation methods, are employed to capture different aspects of the visual information [19]. Histogram-based descriptors, such as color histograms or gradient histograms, provide global statistics of pixel intensities or gradients within the image, capturing broad-scale color or texture information [20]. Edge detectors, such as the Canny edge detector or the Sobel operator, identify abrupt changes in pixel intensity, highlighting object boundaries and structural features. Texture analysis algorithms, such as Gabor filters or local binary patterns (LBP), characterize the spatial arrangement of pixel intensities, capturing fine-scale texture patterns [21]. Region-based segmentation methods, such as watershed segmentation or mean-shift clustering, partition the image into homogeneous regions based on pixel similarity, enabling the extraction of object-specific features [22].

Feature selection techniques aim to reduce the dimensionality of the feature space and focus on the most discriminative features for fruit and vegetable identification. Common feature selection methods include wrapper, filter and embedded methods. Filter methods analyse the relevance of each feature in a classification algorithm by considering statistical features such as correlation coefficients or mutual information scores to select the most informative features. Wrapper methods analyse feature subsets by training and also testing the classification performance of a specific classifier, iterating over different feature combinations to identify the optimal subset. Embedded methods integrate feature selection directly for optimizing feature weights or selection criteria during model training [23]. The comprehensive illustration of all the methods are given in Figure 2.

Figure 2. Comprehensive Overview of the Technologies used in Real-Time Fruits and Vegetables Monitoring

Overall, the integration of computer vision and deep learning in greenhouse management has revolutionized how we monitor and manage plant growth, classify ripeness, detect diseases, and identify flowers and fruits. These technologies not only enhance the efficiency of agricultural practices but also contribute to higher yield and better quality of produce.

3.4 Classification Algorithms for Fruit and Vegetable Identification

Classification algorithms are essential for assigning a label or category to greenhouse images based on the extracted features. These algorithms aim to learn discriminative patterns from the training data and generalize to classify unseen images accurately. In the context of fruit and vegetable identification, a variety of machine learning and deep learning algorithms are employed, ranging from traditional classifiers to sophisticated neural network architectures.

Traditional machine learning classifiers, such as Naive Bayes classifiers, Support Vector Machines (SVMs), and k-Nearest Neighbors (k-NN), have been widely used for fruit and vegetable identification tasks. These classifiers learn decision boundaries based on handcrafted features extracted from the image data, effectively separating different classes in the feature space. Support Vector Machines (SVMs) seek to find the hyperplane that maximally separates the classes in the feature space, while Random Forests construct an ensemble of decision trees to perform classification based on feature subsets. k-Nearest Neighbors (k-NN) classify a test sample by a majority vote of its k nearest neighbors in the feature space, while Naive Bayes classifiers model the conditional probability distribution of each class given the feature values.

Deep learning architectures have shown significant performance in fruits and vegetables identification tasks, leveraging hierarchical feature representations learned directly from raw image data. Convolutional Neural Networks (CNNs) consist of multiple layers of convolutional, pooling, and fully connected layers, enabling the automatic extraction of hierarchical features from input images. These architectures learn to capture complex spatial patterns and relationships within the image data, allowing for highly discriminative feature representations. Transfer learning techniques, such as fine-tuning pre-trained CNN models on domain-specific datasets, further enhance the performance of CNN-based classifiers, leveraging knowledge learned from large-scale image datasets. Other deep learning architectures, such as LSTM, RNN can also be employed for sequential data processing tasks, such as fruit ripeness prediction or disease progression tracking. These classification algorithms are trained on annotated datasets containing examples of different fruit and vegetable classes, enabling them to generalize and accurately classify unseen images. Evaluation metrics such as accuracy, recall and precision are used to assess the performance of the classification algorithms and compare different approaches. Additionally, techniques such as cross-validation and hyperparameter tuning are used to optimize the performance of the classifiers and ensure robustness to variations in the input data.

A range of machine learning and deep learning algorithms have been successfully applied to fruit and vegetable identification and classification. In [24], researchers have achieved high accuracy in classifying apple varieties using a combination of deep features and traditional machine learning models. Similarly, some researchers [25] have developed a deep learning-based system that accurately classified fruits and vegetables and assessed their ripeness. In [26], researchers have conducted a systematic literature review on the application of deep learning for fig fruit detection and counting, finding that deep learning algorithms consistently achieved high performance. The methodology proposed in [27] is a cost-effective method using a Vector Network Analyzer and machine learning for fruit identification and ripeness grading, achieving high classification accuracy. These studies collectively demonstrate the effectiveness of machine learning and deep learning in fruit and vegetable identification and classification as illustrated in Table 1. Figure 3 depicts the comparison of efficiency of different techniques for fruits and vegetables identification.

Table 1. Comparative Study

References	**Dataset Used**	**Algorithms Used**	**Main Findings**	**Limitations**
[24]	Manual dataset collected from the Ministry of Agriculture and Fruit Research Institute of the Republic of Turkey.	Transfer learning with seven popular CNN architectures, DenseNet201, deep features extraction, traditional ML models (SVM, RFC, MLP, KNN),	SVM has outperformed all other models with an accuracy of 98.28%	Variability within classes leads to misclassifications. The study has bot addressed ripening stage during data collection

		integration of deep features, MLP, PCA and SVM		
[25]	Includes 32 classes of fruits and vegetables. Datasets from Kaggle were utilized.	MobileNetV2	Attained classification accuracy of 96%	Limited data and inability to detect damaged, obstructed, or poorly illuminated fruits and vegetables.
[26]	The dataset includes public datasets like MS COCO, ImageNet, Kaggle dataset, and Roboflow, as well as personal datasets manually collected at the orchard.	Faster RCNN, Mask RCNN, YOLO, SSD	RCNN has attained a highest accuracy of 86%	Limited dataset availability. No proper datasets available for classifying fig fruits.
[27]	Used two different datasets of five types of fruits.	K-Nearest Neighbour (KNN) and Neural Network model	The model has achieved a classification accuracy of 94%	The model is not effective on a larger scale when considering more diverse types of fruits.
[28]	Dataset 1: 12,000 images of various fruits and vegetables; Dataset 2: 13,346 images of apple, orange, and banana; Dataset 3: 3,200 images of multiple fruit classes	Deep Convolution Neural Networks (DCNN), softmax classifier, AlexNet	The proposed model has achieved highly favorable results of about 92%, 93.5%, 97% on all three datasets.	Difficulty in fruit classification due to shape, color, and texture similarities among different fruit species, variations in fruit conditions, and maturity phases

[29]	The dataset used in the study includes 1200 images of six different types of fruits and vegetables: apple, banana, orange, tomato, capsicum, and bitter gourd	Yolov4 and Yolov5	A classification accuracy of 95.9% for Yolov4 and 99.9% for Yolov5 has been achieved.	The study only focused on six types of fruits and vegetables, limiting generalizability
[3]	The dataset is retrieved manually and collected from Kaggle Database	Deep learning model: Inception-ResNet-V2, Machine learning classifiers	ResNetV2 has achieved an accuracy of 94%.	The hybrid procedure increases the computing time

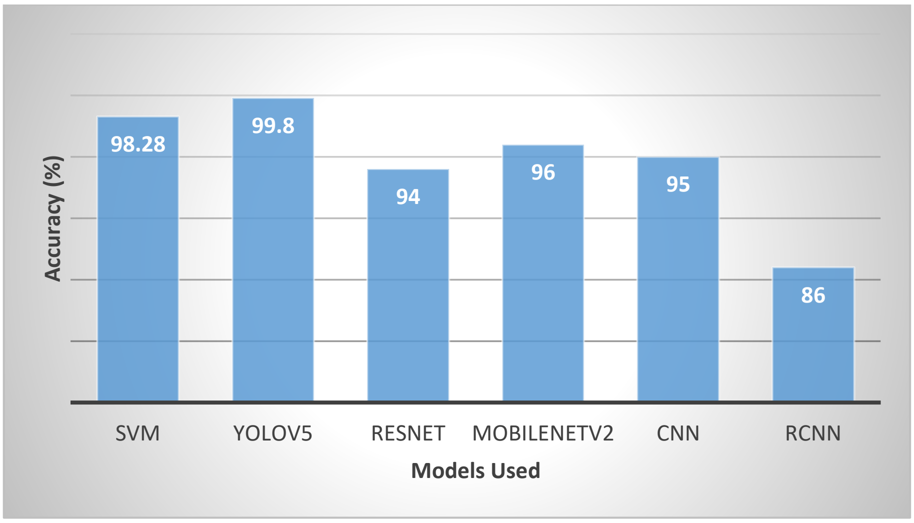

Figure 3. Efficiency of Different Techniques for Fruits and Vegetables Identification

4. Challenges

Greenhouse image acquisition systems face several challenges, primarily related to maintaining high-quality and consistent image capture amidst varying environmental conditions. Choosing the appropriate imaging device, whether digital, hyperspectral, or multispectral, is critical and depends on specific application requirements like resolution and spectral range. Moreover, ensuring comprehensive coverage necessitates a mix of stationary cameras and mobile robotic platforms, each with unique logistical challenges. Pre-processing techniques further add to the complexity by addressing noise, illumination variations, and geometric distortions. Effective image denoising, color calibration, image registration, and geometric correction are essential for enhancing image clarity and accuracy. Additionally, illumination normalization is crucial for consistent feature extraction and classification, demanding robust and adaptive pre-processing methods.

The extraction and selection of relevant features from greenhouse images involves balancing the comprehensive visual information and reducing redundancy. Techniques such as histogram-based descriptors, edge detectors, and texture analysis algorithms must be employed strategically to extract diverse features like shape, texture, and color. Dimensionality reduction through filter, wrapper, and embedded methods is necessary to focus on the most discriminative features for effective classification. The selection of traditional classifiers (e.g., SVM, Random Forest) and deep learning architectures (e.g., CNNs) depends on the dataset and specific use case. The algorithms developed should be generalized well to unseen images and optimizing them through cross-validation and hyperparameter tuning remains as significant challenges. Additionally, the limited dataset availability and class variability can delay model performance, emphasizing the need for scalable, efficient, and adaptable solutions in diverse greenhouse environments.

5. Conclusion

This study has the integration of advanced imaging systems and machine learning algorithms for the monitoring and management of crops in greenhouse environments. This comprehensive analysis covers the critical aspects of image acquisition, pre-processing, feature extraction, selection methods, and classification algorithms. The challenges identified highlight the complexity of maintaining high-quality image capture and the need for robust pre-processing techniques to handle environmental variations and distortions. Furthermore, the research investigation into feature extraction and classification reveals the importance of selecting appropriate methods to ensure accurate identification and classification of fruits and vegetables. While traditional machine learning models offer valuable insights, the performance of deep learning architectures, particularly Convolutional Neural Networks (CNNs) and object detection algorithms like YOLOv5 highlights their potential in revolutionizing greenhouse management.

The research findings reveal that, despite the significant advancements in technology, there remain considerable challenges related to data variability, algorithm optimization, and scalability. Addressing these challenges is crucial for the practical implementation of these technologies in real-time. Future research should focus on developing more adaptable and cost-effective solutions to enhance the efficiency and accuracy of greenhouse monitoring systems, ultimately contributing to higher yields and better-quality produce.

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