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Review

Object Detection and Recognition Techniques Based on Digital Image Processing and Traditional Machine Learning for Fruit and Vegetable Harvesting Robots: An Overview and Review

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Abstract: The accuracy, speed, and robustness of object detection and recognition are directly related to the harvesting efficiency, quality, and speed of fruit and vegetable harvesting robots. In order to explore the development status of object detection and recognition techniques for fruit and vegetable harvesting robots based on digital image processing and traditional machine learning, this article summarizes and analyzes some representative methods. This article also demonstrates the current challenges and future potential developments. This work aims to provide a reference for future research on object detection and recognition techniques for fruit and vegetable harvesting robots based on digital image processing and traditional machine learning.

Keywords: digital image processing; traditional machine learning; harvesting robot; computer vision; object detection; object recognition; research overview; research review

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1. Introduction

Fruit harvesting is an important aspect of farming. It directly affects the yield and profitability of cultivation. With the increasing scale of global cultivation (e.g., global annual production of fruits and vegetables such as tomato, citrus, apple, and strawberry, has reached 182 million tons [1], 89 million tons [2], 86 million tons [3], and 9 million tons [4], respectively), the contradiction between the large amount of labor used in traditional production methods and labor shortages has become increasingly prominent. The labor cost of fruit and vegetable harvesting has reached 30–50% of the total production cost [5–9]. Fruit and vegetable harvesting robots have attracted broad attention in the agricultural field (as shown in Figure 1) because of their high productivity and low production cost [10,11]. As shown in Figure 2, taking typical fruits and vegetables such as plums [12], apples [13–16], sweet peppers [17–19], strawberries [6,7,20], litchis [21], tomatoes [22,23], and kiwifruits [24] as objects, a series of harvesting robots have been developed and applied in greenhouses and orchards. Fruit and vegetable harvesting robots have entered a critical period in the progression from laboratory research to industrial applications.

As an important part of vision systems of fruit and vegetable harvesting robots, the accuracy, speed, and robustness of object detection and recognition are directly related to the harvesting efficiency, quality, and speed. Vision systems of harvesting robots vary for different picking targets. Their characteristics mainly include the imaging sensor and the specific content of crop visual information. Black/white, RGB, spectral, and thermal cameras (as shown in Table 1) are widely used in harvesting robots to obtain color, shape, texture, and size information of fruits in a specific operational area. Different processes of object detection and recognition of fruits and vegetables are shown in Figure 3. Many researchers have conducted extensive and in-depth research on object detection and recognition techniques for fruit and vegetable harvesting robots based on digital image processing and traditional machine learning. The research can be subdivided into the following aspects:

(1) Techniques based on digital image processing, such as color features (RGB (Red, Green, Blue) [25–28], HSV (Hue, Saturation, Value) [29–31], HSI (Hue, Saturation Intensity) [32–34], Lab (Lightness, Green to Red and Blue to Yellow) [33,35,36], HSB (Hue, Saturation, Brightness), YCbCr)-based methods, shape feature-based methods [37–46], texture feature-based methods [44,47–52], and multi-feature fusion-based methods [17,28,39,52–67].

(2) Image segmentation and classifiers based on traditional machine learning, such as K-means clustering algorithm-based methods [68–75], SVM (Support Vector Machine) algorithm-based methods [54,57,69,73,76–84], KNN (K Nearest Neighbor) clustering algorithm-based methods [36,85–91], AdaBoost (Adaptive Boosting) algorithm-based methods [62,92–99], decision tree algorithm-based methods [100–107], and Bayesian algorithm-based methods [108–113].

Figure 1. Digital farming with agricultural robotics (source: www.AdaptiveAgroTech.com (accessed on 1 October 2022)).

Table 1. Comparison of frequently used sensors for fruit and vegetable recognition.

Sensors	Features Exploited	Advantages	Disadvantages
Black/white camera	Shape and texture features	A negligible effect on changing lighting conditions	Lack of color information of target objects
RGB camera	Color, shape, and texture features	Exploits all the basic features of target objects	Highly sensitive to changing lighting conditions
Spectral camera	Color features and spectral information	Provides more information about reflectance	Computationally expensive for complete spectrum analysis
Thermal camera	Thermal signatures	Color Invariant	Dependency on minute thermal difference

This article provides an overview and review of the progress in object detection and recognition techniques for fruit and vegetable harvesting robots based on digital image processing and traditional machine learning. Although there have been some reviews of techniques for object detection and recognition of fruits and vegetables [114–135], the contributions of this work are to: (1) systematically summarize object detection and recognition techniques of fruit and vegetable harvesting robots based on digital image processing and traditional machine learning in recent years; (2) systematically analyze the advantages, disadvantages, and applicability of various techniques; and (3) demonstrate the current challenges and future potential developments. Through this clearer and more comprehensive overview and review, we aim to provide a reference for future research on object detection and recognition techniques of fruit and vegetable harvesting robots based on digital image processing and traditional machine learning.

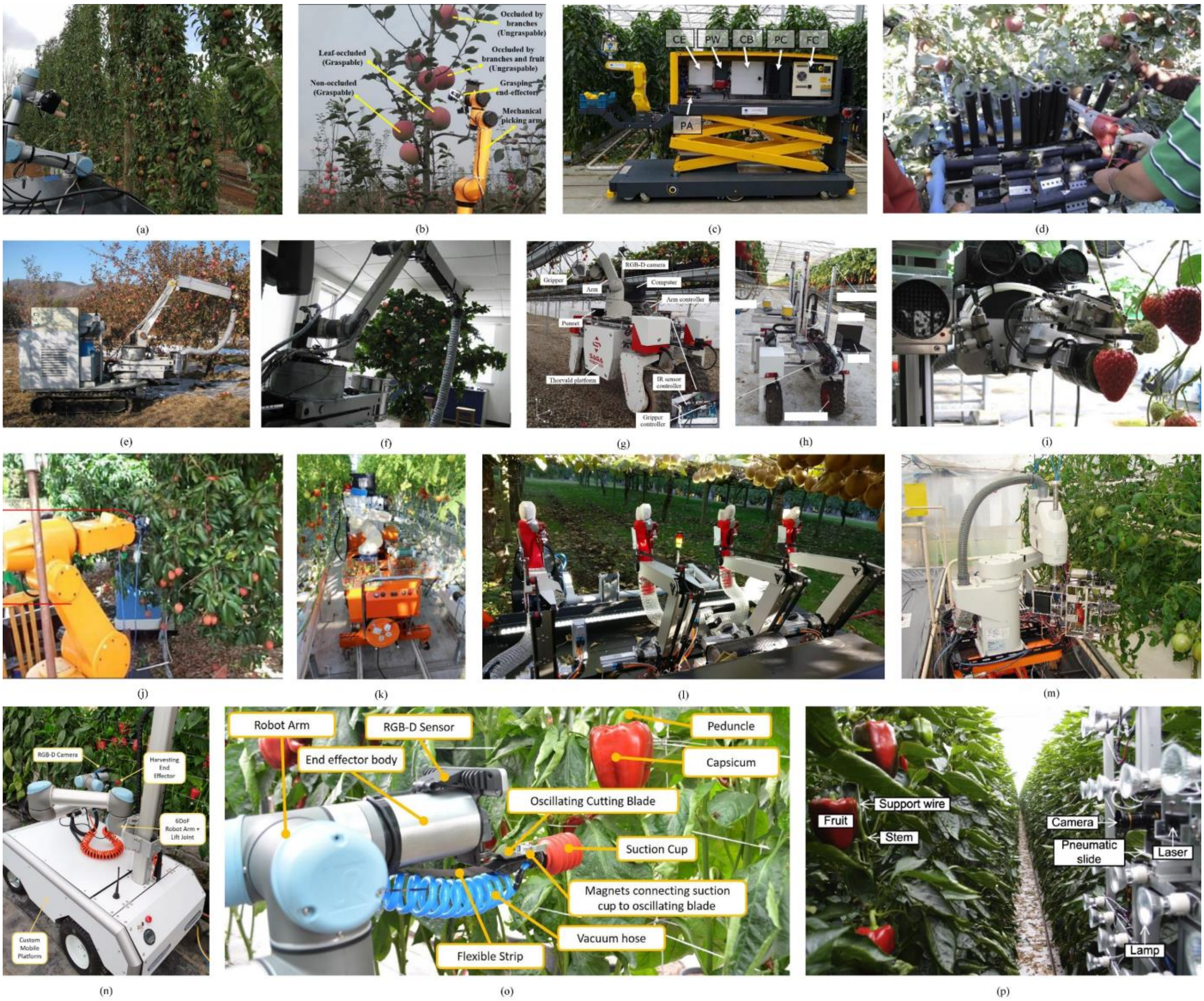


Figure 2. Typical harvesting robots: (**a**) a plum harvesting robot (Photo: Reprinted with permission from Ref. [12]. 2021, Brown, J.); (**b**,**d**–**f**) apple harvesting robots (Photo: Reprinted with permission from Ref. [13]. 2021, Yan, B.; Ref. [14]. 2017, He, L.; Ref. [15]. 2012, Ji, W.; Ref. [16]. 2011, Zhao, D.); (**c**,**n**–**p**) sweet pepper harvesting robots (Photo: Reprinted with permission from Ref. [17]. 2020, Arad, B.; Ref. [18]. 2017, Lehnert, C.; Ref. [19]. 2014, Bac, C.W.); (**g**–**i**) strawberry harvesting robots (Photo: Reprinted with permission from Ref. [6]. 2020, Xiong, Y.; Ref. [7]. 2019, Xiong, Y.; Ref. [20]. 2010, Hayashi, S.); (**j**) a litchi harvesting robot (Photo: Reprinted with permission from Ref. [21]. 2018, Xiong, J.); (**k**,**m**) tomato harvesting robots (Photo: Reprinted with permission from Ref. [22]. 2018, Feng, Q.; Ref. [23]. 2010, Kondo, N.); (**l**) a kiwifruit harvesting robot (Photo: Reprinted with permission from Ref. [24]. 2019, Williams, H.A.M.).

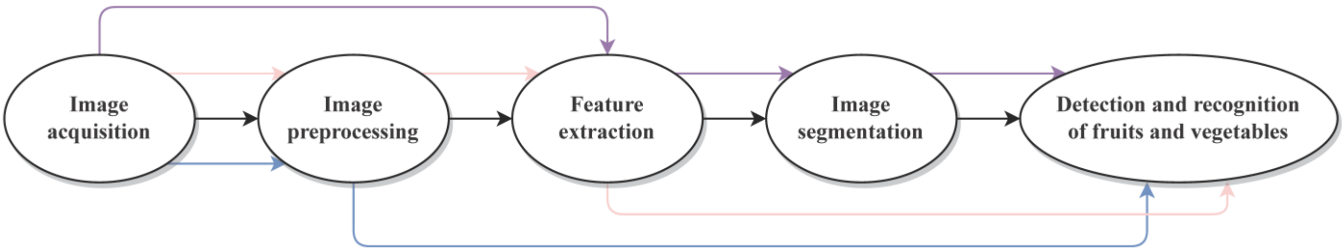


Figure 3. Different processes of object detection and recognition of fruits and vegetables.

The outline of this overview and review is shown in Figure 4. The organization of this paper is as follow: in Section 2, we provide an overview and review of the research and development in object detection and recognition techniques of fruits and vegetables based on digital image processing. We present separate discussions focused on color, shape, texture features, and multi-feature fusion-based methods.

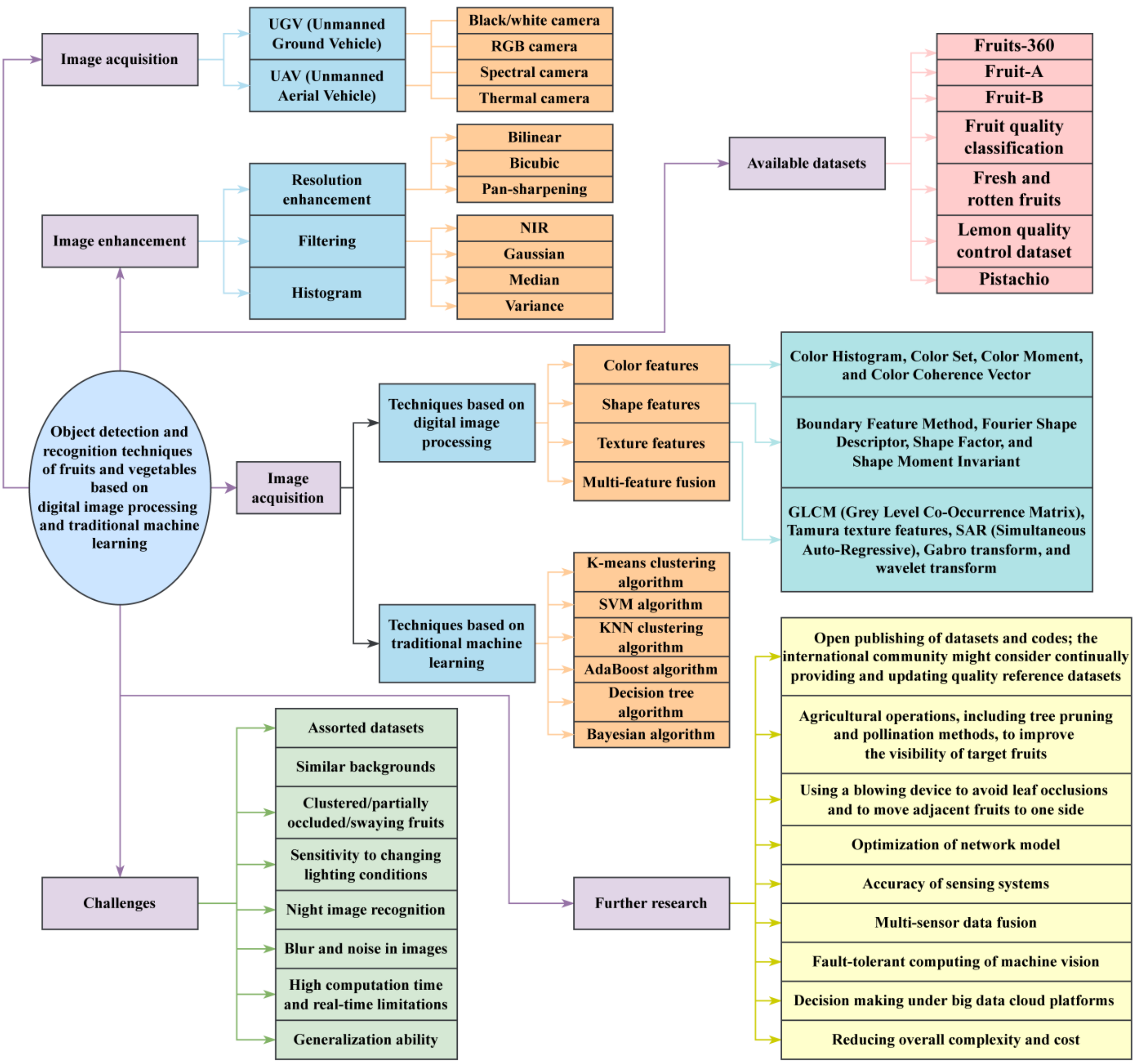


Figure 4. The outline of this overview and review.

In Section 3, we provide an overview and review of the research and development in object detection and recognition techniques of fruits and vegetables based on traditional machine learning. We present separate discussions focused on K-means clustering, SVM, KNN clustering, AdaBoost, decision tree, and Bayesian algorithm-based methods.

Section 4 extends our discussions to the challenges and further research of object detection and recognition techniques of fruits and vegetables. A summary of findings and conclusions are presented in Section 5.

2. Techniques Based on Digital Image Processing

Colors, shapes, and textures are important features used by fruit and vegetable harvesting robots for detecting and recognizing target objects. Many researchers have conducted extensive and in-depth research on object detection and recognition techniques of fruits and vegetables based on color features (RGB [25–28], HSV [29–31], HIS [32–34], Lab [33,35,36], HSB, YCbCr), shape features [37–46], texture features [44,47–52], and multi-feature fusion [17,28,39,52–67] (as shown in Figure 5). Table 2 compares the results of different techniques by different researchers, and presents analysis of the advantages, disadvantages, and applicability of various techniques.

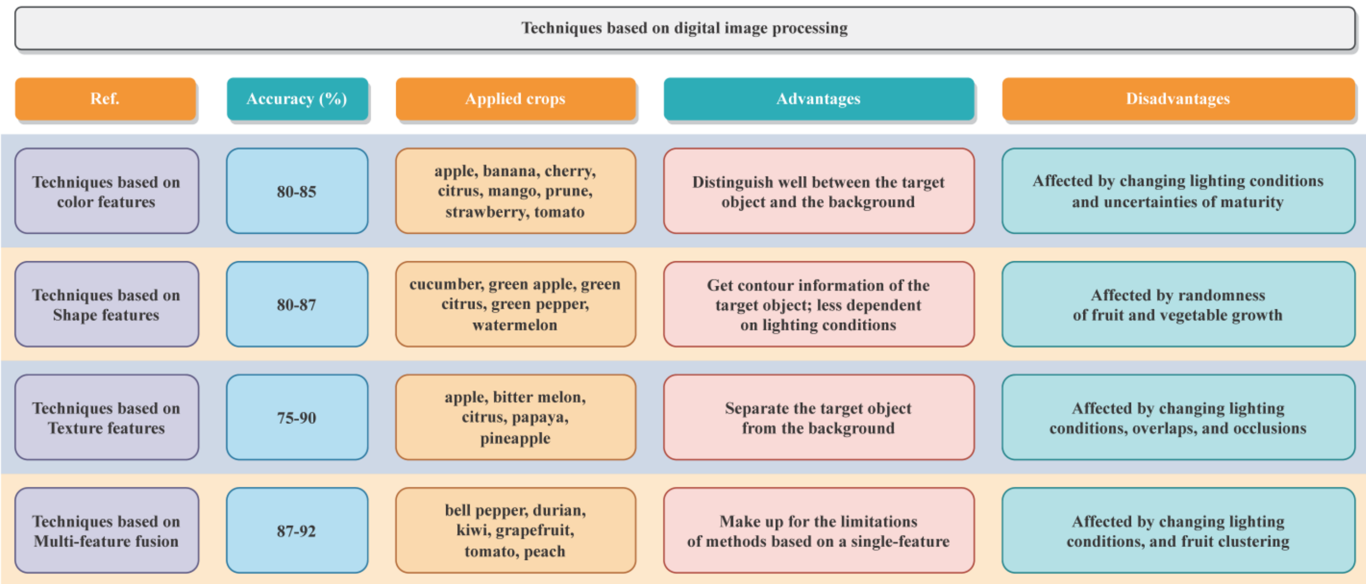


Figure 5. Techniques based on digital image processing.

Table 2. Comparison of techniques based on digital image processing.

Applied Crops	Description	Sensors	Advantages	Improvements	Value of Metrics Used %	Ref.
Apple	The near-large fruit from the apple image in orchards should be obtained	RGB camera	The R-channel and G-channel images of orchard apple RGB images are operated by the Adaptive Gamma Correction method	Future work may include improving the detection rate	70	[27]
Tomato	A new mature tomato detection algorithm based on the improved HSV color space and the improved watershed segmentation	RGB camera	Mature red tomatoes are detected successfully even with light effect	The accuracy of recognition needs to be improved	81.6	[31]
Apple	The potential use of close-range and low-cost terrestrial RGB imaging sensors for fruit detection in a high-density apple orchard	RGB camera	Band combinations are generated as additional parameters for fruit detection	Unripe fruits with poor lighting are not detected in the methodology	75	[35]
Blueberry	Recognizing blueberry fruit of different maturity using histogram-oriented gradients and color features in outdoor scenes	RGB camera	Using a* and b* features in the L*a*b* color space to discard non-fruit regions	The speed of detection needs to be improved	mature fruit: 96.1 intermediate fruit: 94.2 young fruit: 86	[36]
Apple	The Hough Circle Transformation algorithm is proposed to fit and extract apple shapes	RGB camera	In order to overcome the problem of Global Hough Transform, a local parameter Adaptive Hough Transform is used	When the recognition algorithm is faced with multiple overlapping apples, if the apples are not arranged in a straight line, it is easy to obtain recognition errors	91.3 (72 ms)	[25]

Table 2. *Cont.*

Applied Crops	Description	Sensors	Advantages	Improvements	Value of Metrics Used %	Ref.
Citrus, tomato, pumpkin, bitter gourd, towel gourd, and mango	Fruit detection in natural environments using Partial Shape Matching and Probabilistic Hough Transform	RGB camera	PSM and PHT are used for sub-fragment detection and aggregation without necessitating the painstaking design of specific features for each type of fruit. This makes the proposed algorithm a generalized method	PHT utilizes a scale-variant dissimilarity metric to determine the probability value of a vote. So, it may fail to detect fruits with large scale changes	78.3; 84.8; 74.5; 76.2; 80.7; 91.9	[37]
Orange	A machine vision algorithm combining adaptive segmentation and shape analysis for orange fruit detection	RGB camera	In the segmentation of the fruit, the orange is enhanced by using the red chromaticity coefficient, which enables adaptive segmentation under variable outdoor illumination	The speed of detection needs to be improved	93	[45]
Green fruits	A technique based on texture analysis is proposed for detecting green fruits	RGB camera	The method is sufficiently accurate for precise location and monitoring of textured fruit in the field	The method needs to be improved to better handle some disadvantageous conditions such as strong sunlight and occlusions	pineapple: 85 bitter melon: 100	[51]
Green apple	Detection of green apples in hyperspectral images of apple-tree foliage using machine vision	Spectral camera	The method uses several techniques, such as extraction and classification of homogenous objects for analyzing hyperspectral data	Independent studies need to be conducted in a variety of conditions and with a number of crop varieties to verify the robustness of the method	88.1	[46]
Green citrus	Green citrus detection using 'eigenfruit', color and circular Gabor texture features under natural outdoor conditions	RGB camera	The method proposes the use of color, shape, and texture features together to detect immature green citrus fruits, including scanning an image using a sub-window, and merging results of different classifiers with majority voting	Future work may include improving the detection rate, reducing the processing time, and accommodating more varied outdoor conditions	75.3	[44]

Table 2. *Cont.*

Applied Crops	Description	Sensors	Advantages	Improvements	Value of Metrics Used %	Ref.
Immature citrus	Immature citrus fruit detection based on local binary pattern features and hierarchical contour analysis	RGB camera	The good performance of occlusion tolerance of the proposed method is mainly due to the robust LBP texture descriptor and hierarchical contour analysis which uses the pattern of light intensity distribution on the fruit surface	The fruit occluded very seriously or even completely by leaves and other fruits couldn't be detected by the proposed method	82.3	[39]
Litchi	A method of ripe litchi recognition for two varieties of litchis using RGB-D images is proposed	RGB-D camera	The random forest binary classification model is trained employing color and texture features to recognize litchi fruits	Depth segmentation can effectively reduce the false positive rate of litchi recognition	green litchi: 89.92 red litchi: 94.5	[55]
Oil palm fresh fruit bunch	The maturity classification of oil palm fresh fruit bunches based on color and texture features	RGB camera	Forty features are extracted from several color spaces, which were reduced to five features using the PCA method to optimize the computation time	The speed of detection needs to be improved	98.3	[53]
Strawberry	A simple color thresholding algorithm based on the RGB channels for detecting strawberries	RGB-D camera	The vision system uses color thresholding combined with screening of the object area and the depth range to select ripe and reachable strawberries, which is fast for processing	Future work could merge the detection from multiple frames so that occluded strawberries can be visible from a different view	isolated strawberry:96.8 occluded strawberry:53.6	[18]

2.1. Techniques Based on Color Features

Mature fruits and vegetables usually have significant and stable color features. Color features provide a set of indicators for the detection and recognition of fruits and vegetables. Object detection and recognition techniques of fruits and vegetables based on color features, extract color features through Color Histogram, Color Set, Color Moment, and Color Coherence Vector. The techniques based on color features are mainly applicable to cases where the colors of fruits and vegetables are significantly different from the backgrounds (branches, leaves, trunks), such as tomatoes [28,31], apples [29,35], mangoes [34], bananas, cherries, citrus, prunes, and strawberries.

Goel and Sehgal [28] detected and recognized several ripening stages of tomatoes using RGB image information. This research has a positive implication for selecting the best ripening stage of fruits and vegetables. For example, fruits and vegetables that need to be transported over long distances can be harvested at an early stage of ripeness.

Zemmour et al. [26] analyzed different color spaces. The research results showed that evaluating different color spaces is very important, because for different kinds of fruits and vegetables, a different color space might be superior to the others. In order to improve the accuracy of the detection and recognition of tomatoes, marigold flowers, and apples, Malik et al. [31], Sethy et al. [30], Yu et al. [29], respectively, converted RGB images into HSV color space, and then separated the image luminance channels. Ratprakhon et al. [34] converted RGB images into HIS color space to detect and recognize the ripeness of mangoes. Tan et al. [36] and Biffi et al. [35], respectively, converted RGB images into Lab color space to detect and recognize blueberries and apples. Zemmour et al. [26] suggested that Lab color space could be used more for low quality images because it is more robust to noise in images. In challenging color conditions (for example, where fruit and vegetable colors are similar to the backgrounds), other features could be considered to improve the effectiveness of object detection and recognition for fruit and vegetable harvesting robots.

The detection and recognition time of fruits and vegetables based on color features is relatively long. In order to shorten the detection and recognition time, Yang et al. [25] proposed an Otsu's thresholding method based on the two times Red minus Green minus Blue (2R-G-B) color feature to segment images. Lv et al. [27] operated the R-channel and G-channel images of orchard apple RGB images using the Adaptive Gamma Correction method. This method not only shortened the detection and recognition time, but also overcame the influence of changing lighting conditions. Zemmour et al. [26] proposed an automatic parameter tuning procedure specially developed for the dynamic adaptive thresholding algorithm for object detection and recognition of fruits and vegetables. The thresholds were selected by quantifying the required relationship between the true and false positive rates.

In general, techniques for object detection and recognition of fruits and vegetables based on color features are less dependent on image size. However, the variability and uncertainty of fruit and vegetable maturity can affect the accuracy, speed, and robustness of detection and recognition. These techniques are mainly applicable to structured environments such as greenhouses.

2.2. Techniques Based on Shape Features

Mature fruits and vegetables usually have significant and stable shape features. Geometric shape features provide another set of indicators for the detection and recognition of fruits and vegetables. Techniques for object detection and recognition of fruits and vegetables based on shape features, extract shape features using the Boundary Feature Method, Fourier Shape Descriptor, Shape Factor, and Shape Moment Invariant. These techniques are mainly applied to cases where the shapes of fruits and vegetables are significantly different from the backgrounds. For example, the shapes of apples and citrus are usually rounded compared to the branches and leaves, and a cucumber shows an elongated fruit shape (as shown in Figure 6).

Figure 6. Samples of cucumbers in a natural complex environment (Photo: Reprinted with permission from Ref. [136]. 2020, Mao S.).

For round fruits, Hannan et al. [45] detected and recognized fruits in clusters by shape analysis. This method can better detect and recognize target objects in changing lighting conditions. Jana and Parekh [42] proposed a shape-based fruit detection and recognition method. It involves a pre-processing step to normalize a fruit image with respect to variations in translation, rotation, and scaling, and utilizes features that do not change due to varying distances, growth stages, or surface appearances of fruits. The method was applied to 210 images of 7 fruit classes. The overall recognition accuracy ranged from 88 to 95%. Lu et al. [39] proposed a new shape analysis method called Hierarchical Contour Analysis (HCA). The hierarchical contour maps around each local maximum were extracted and fitted with Circular Hough Transform, and the fitted circles were predicted as fruit targets if their radii were in a predetermined range. The HCA can effectively utilize shape information, and does not need to extract and analyze the edge in an image. Therefore, it is efficient and robust under various lighting conditions and occlusions in natural environments. Lin et al. [37] also proposed a method for the detection and recognition of fruits and vegetables based on shape features. The research results showed that the method is competitive for detecting most kinds (such as green, orange, circular, and non-circular) of fruits and vegetables in natural environments.

Since the shapes of fruits and vegetables are usually not affected by the colors, object detection and recognition techniques of fruits and vegetables based on shape features are more effective for cases where the colors of fruits and vegetables are similar to the backgrounds, while the shapes of fruits and vegetables are significantly different from the backgrounds, such as green citrus [37,40,44], green apples [38,43,46], cucumbers, green peppers, and watermelons.

In general, techniques for object detection and recognition of fruits and vegetables based on shape features are less dependent on lighting conditions. However, in unstructured environments, the randomness of fruit and vegetable growth can affect the accuracy, speed, and robustness of detection and recognition of fruits and vegetables. These techniques are mainly applicable to natural orchards with certain agricultural operations.

2.3. Techniques Based on Texture Features

Mature fruits and vegetables usually have significant and stable texture features, and the surface textures of fruits and vegetables are usually smoother than the backgrounds. Texture features provide another set of indicators for the detection and recognition of fruits and vegetables. Techniques for object detection and recognition of fruits and vegetables based on texture features, extract texture features through the GLCM (Grey Level Co-Occurrence Matrix), Tamura texture features, SAR (Simultaneous Auto-Regression), Gabro transform, and Wavelet transform. These techniques are mainly applicable to cases where the textures of fruits and vegetables are significantly different from the backgrounds, such as apples [52], bitter melons [51], citrus [44], papayas [110], and pineapples [51].

Trey et al. [49] used leaf texture features as parameters for plant family detection and recognition. The research results showed that the method gives a perfect classification of three plant families of the Ivorian flora. Rahman et al. [47] detected and recognized tomato leaf diseases through 13 different statistical features calculated from tomato leaves using the GLCM algorithm. The method was implemented in the form of a cell phone application. The research results showed that the method provides excellent annotation with an accuracy of 100% for healthy leaf, 95% for early blight, 90% for Septoria leaf spot, and 85% for late blight.

Since the surface textures of fruits and vegetables are usually not affected by the colors and shapes, techniques for object detection and recognition of fruits and vegetables based on texture features are more effective for cases where the colors and shapes of fruits and vegetables are similar to the backgrounds, while the textures of fruits and vegetables are significantly different from the backgrounds. Kurtulmus et al. [44] used circular Gabor texture analysis for the detection and recognition of green citrus. The method detected and recognized target fruits by scanning the whole image, but the correct rate was only 75.3%. To improve the accuracy of detection and recognition of fruits and vegetables, Chaivivatrakul and Dailey [51] proposed a texture-based feature detection and recognition method for green fruits. The method involves interest point feature extraction and descriptor computation, interest point classification using support vector machines, candidate fruit point mapping, and morphological closing and fruit region extraction. This approach can effectively improve the correct rate of detection and recognition of green fruits (more than 85%). In addition, Hameed et al. [48] proposed a texture-based latent space disentanglement method to enhance the learning of representations for novel data samples.

In general, the main problem of techniques for object detection and recognition of fruits and vegetables based on texture features is that changing lighting conditions and complex backgrounds can affect the accuracy, speed, and robustness of detection and recognition. These techniques are mainly applicable to greenhouse environments.

2.4. Techniques Based on Multi-Feature Fusion

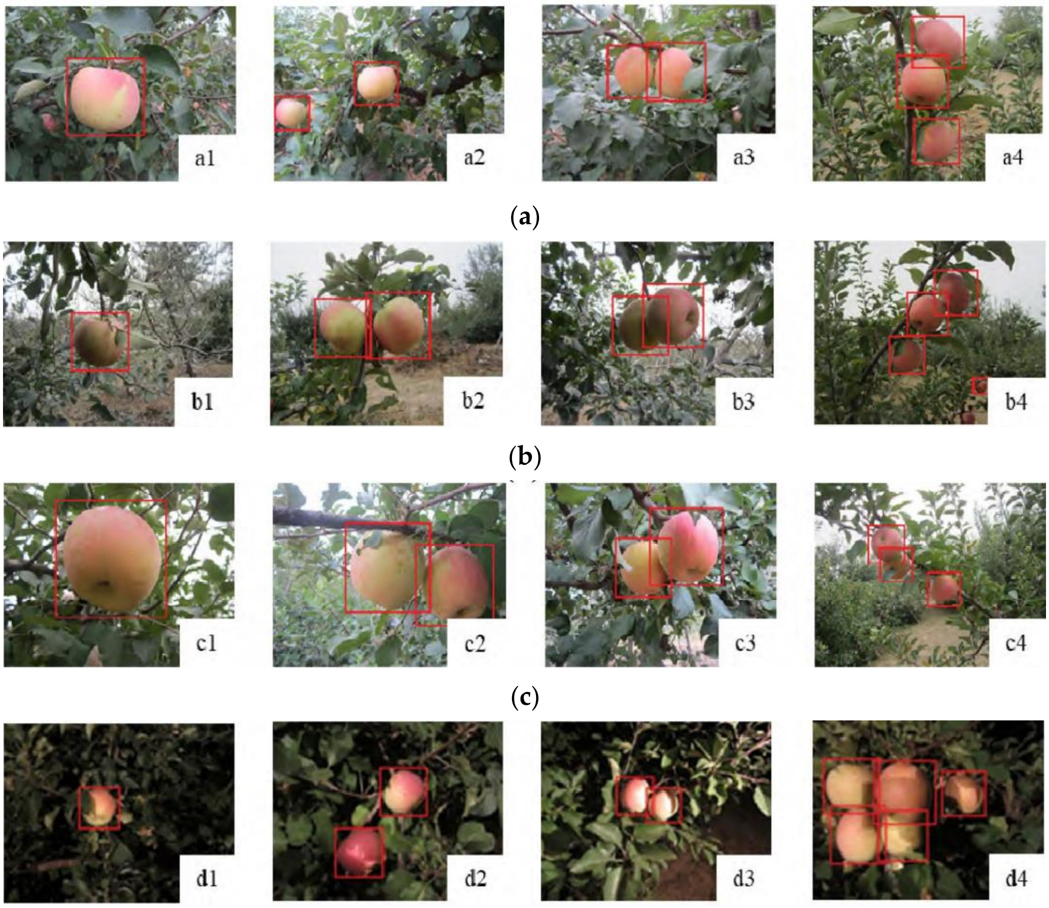
Techniques for object detection and recognition of fruits and vegetables based on a kind of feature can recognize fruits from natural environments, but they usually have certain limitations. Techniques for object detection and recognition of fruits and vegetables that integrate two or more features to form multi-feature fusion can effectively improve the accuracy, speed, and robustness of detection and recognition [59,92,95,136–139].

In terms of color and shape features, Liu et al. [60] proposed a method for the detection and recognition of incomplete red apples (as shown in Figure 7). The research results are shown in Figure 8. The method can be used to detect not only apples, but can also be used to detect other fruits that have different colors from the backgrounds, such as oranges, kiwifruits, and tomatoes. However, the method only detects fruits using rectangular boxes. Pixel-wise segmentation is more accurate than detection boxes. Recognizing fruits at the pixel level could be the focus of further work. Arad et al. [17], and Liu et al. [58] extracted color features from RGB color channels of fruit and vegetable images, and morphological features were extracted from the images with detected fruit and vegetable borders using morphological operations. Then, they detected and recognized bell peppers, grapefruits, and peaches.

In terms of color and texture features, to solve segmentation problems, Lin and Zou [62] proposed a new segmentation method using color and texture features. This method incorporates HSV color features and Leung–Malik texture features to detect citrus using fixed-size sub-windows. Madgi and Danti [63] classified fruits and vegetables based on color features and GLCM texture features. The research results showed that the combination of color with GLCM texture features is more effective than combined color and LBP texture features.

(**a**) (**b**)

Figure 7. Two kinds of apple fruits: (**a**) completely red fruits; (**b**) incompletely red fruits (Photo: Reprinted with permission from Ref. [60]. 2019, Liu X.).



(**a**)

(**b**)

(**c**)

(**d**)

Figure 8. Detection results of different images: (**a1**–**a4**) images taken under front light; (**b1**–**b4**) images taken under backlight; (**c1**–**c4**) images taken under side light; (**d1**–**d4**) images taken under artificial light (Photo: Reprinted with permission from Ref. [60]. 2019, Liu X.).

In terms of shape and texture features, Lu et al. [39], Mustaffa et al. [61], and Bhargava and Bansal [54] recognized fruits and vegetables by shape features including area, perimeter, and roundness, and constructed fruit and vegetable textures based on local binary patterns. Finally, they classified green citrus, multi-species durians, and multi-species apples.

In terms of color, shape, and texture features, Rakun et al. [52] achieved apple detection and recognition under uneven lighting conditions, partial fruit shading, and a similar background by combining color, shape, and texture features. Basavaiah and Anthony [56] proposed a detection and recognition method based on color, shape, and texture features for a variety of tomato diseases. Azarmdel et al. [57] and Septiarini et al. [53], respectively, achieved the detection and recognition of mulberries and oil palms based on multiple features such as color, shape, and texture features.

Currently, digital image processing techniques used by researchers for the detection and recognition of fruits and vegetables always require setting thresholds such as color, shape, and texture features, but the optimal thresholds often vary with images. In order to address this problem, Payne et al. [66] proposed using RGB and YCbCr color segmentation and texture segmentation based on the variability of neighboring pixels to divide pixels into target fruit and background pixels for high-accuracy detection and recognition. However, this method relies too much on the color features of images, and the recognition accuracy is low when the color features are not obvious. For this reason, Payne et al. [65], based on the previously proposed algorithm, reduced the reliance on color features by setting the boundary-constrained mean and edge detection filters, and increased the use of texture filtering. The research results showed that the recognition accuracy is significantly improved compared with before the improvement. Yamamoto et al. [64] used a multi-feature fusion method to simplify the tedious steps of setting thresholds for each image and improve the accuracy of detection and recognition.

3. Image Segmentation and Classifiers Based on Machine Learning

Since machine learning can derive laws from sample data that can hardly be summarized by theoretical analysis, many researchers have conducted extensive and in-depth research on techniques for object detection and recognition of fruits and vegetables based on the K-means clustering algorithm [68–75], SVM algorithm [54,57,69,73,76–84], KNN clustering algorithm [36,85–91], AdaBoost algorithm [62,92–99], decision tree algorithm [100–107], and Bayesian algorithm [108–113] (as shown in Figures 9 and 10). Table 3 compares the results of different techniques of different researchers, and presents analysis of the advantages, disadvantages, and applicability of various techniques.

Table 3. Comparison of techniques based on traditional machine learning.

Applied Crops	Description	Sensors	Advantages	Improvements	Value of Metric Used %	Ref.
Litchi	A litchi recognition algorithm based on K-means clustering is presented to separate litchi from leaves, branches and background	Two CCD color cameras	The method can be robust against the influences of varying illumination and precisely recognize litchi	Future research could improve the localization accuracy of litchi via hardware and software improvements	unoccluded: 98.8; partially occluded: 97.5	[75]
Apple	The development of a real-time machine vision recognition system to guide a harvesting robotic for picking apples in different conditions	CCD camera	The segmentation method based on seeded region growing methods and color features is applied, and color and shape features of color images are extracted	Reducing the recognition execution time is still a challenge	89 (352 ms)	[14]
Aubergine	To detect and locate the aubergines automatically, an algorithm based on SVM classifier is implemented	TOF camera	The occlusion algorithm is applied to aubergines that have low visibility due to leaf occlusions by planning a collaborative behavior between the arms to solve the problem of occlusion and proceed with dual-arm harvesting	Most of the failures are related to changing lighting conditions. So, future work to enhance the harvester robot should prioritize improvements to image acquisition	91.67 (26 ms)	[77]
Citrus	Identification of fruits and branches in natural scenes for a citrus harvesting robot using machine vision and support vector machine	Color CCD camera	A multi-class support vector machine, which succeeds by morphological operation, was used to simultaneously segment the fruits and branches	The effect on feature extraction, and real-time response of the identification method, have to be further optimized	92.4	[73]
Tomato	An algorithm is proposed for tomato detection in regular color images to reduce the influence of illumination and occlusion	RGB camera	The proposed method used a combination of shape, texture, and color information. HOG descriptors are adopted in this work. An SVM classifier is used to implement the classification task	Future research could focus on further improving the detection accuracy and extension to other stages of tomatoes	94.41 (950 ms)	[83]
Green pepper	A green pepper recognition method based on least-squares support vector machine optimized by improved particle swarm optimization	RGB camera	In order to reduce the complexity of data calculations and improve the efficiency, the extracted feature vectors are normalized. The feature vector is used as the input eigenvector of the least-squares support vector machine (LSSVM).	Due to the high rate of leak recognition, the correct recognition rate of green pepper needs to be improved	89.04 (320 ms)	[81]

Table 3. *Cont.*

Applied Crops	Description	Sensors	Advantages	Improvements	Value of Metric Used %	Ref.
Tomato	A dual-arm cooperative approach for a tomato harvesting robot using a binocular vision sensor	Stereo camera	A tomato detection algorithm combining an AdaBoost classifier and color analysis is proposed and employed by the harvesting robot	Future work could focus on the improvement in the successful harvesting rate under uncertain conditions	96	[93]
Tomato	Detecting tomatoes in greenhouse scenes by combining an AdaBoost classifier and color analysis	RGB camera	To use shape, texture, and color information, Haar-like features, an AdaBoost algorithm, and APV-based color analysis are implemented	Future work could include enhanced detection rates, reducing the processing time, and various cultivars of tomatoes, and accommodate more varied unstructured environments	96	[99]
Immature green citrus	Used only regular RGB images of the citrus canopy to detect immature green citrus fruit in natural environments	RGB camera	A local binary patterns feature-based Adaptive Boosting (AdaBoost) classifier is built to remove false positives. A sub-window is used to scan the difference image between the illumination-normalized image and the resulting image from CHT detection in order to detect small areas and partially occluded fruit	It can improve image processing speed by decreasing false positive removal time	85.6	[96]
Grain impurity of rice	Real-time grain impurity sensing for rice combines harvesters using image processing and decision tree algorithm	CMOS camera	The illumination method is optimized by histogram equalization. Decision tree classification is used	Future work may include improving the detection rate, reducing the processing time, and accommodating more varied outdoor conditions	76	[102]

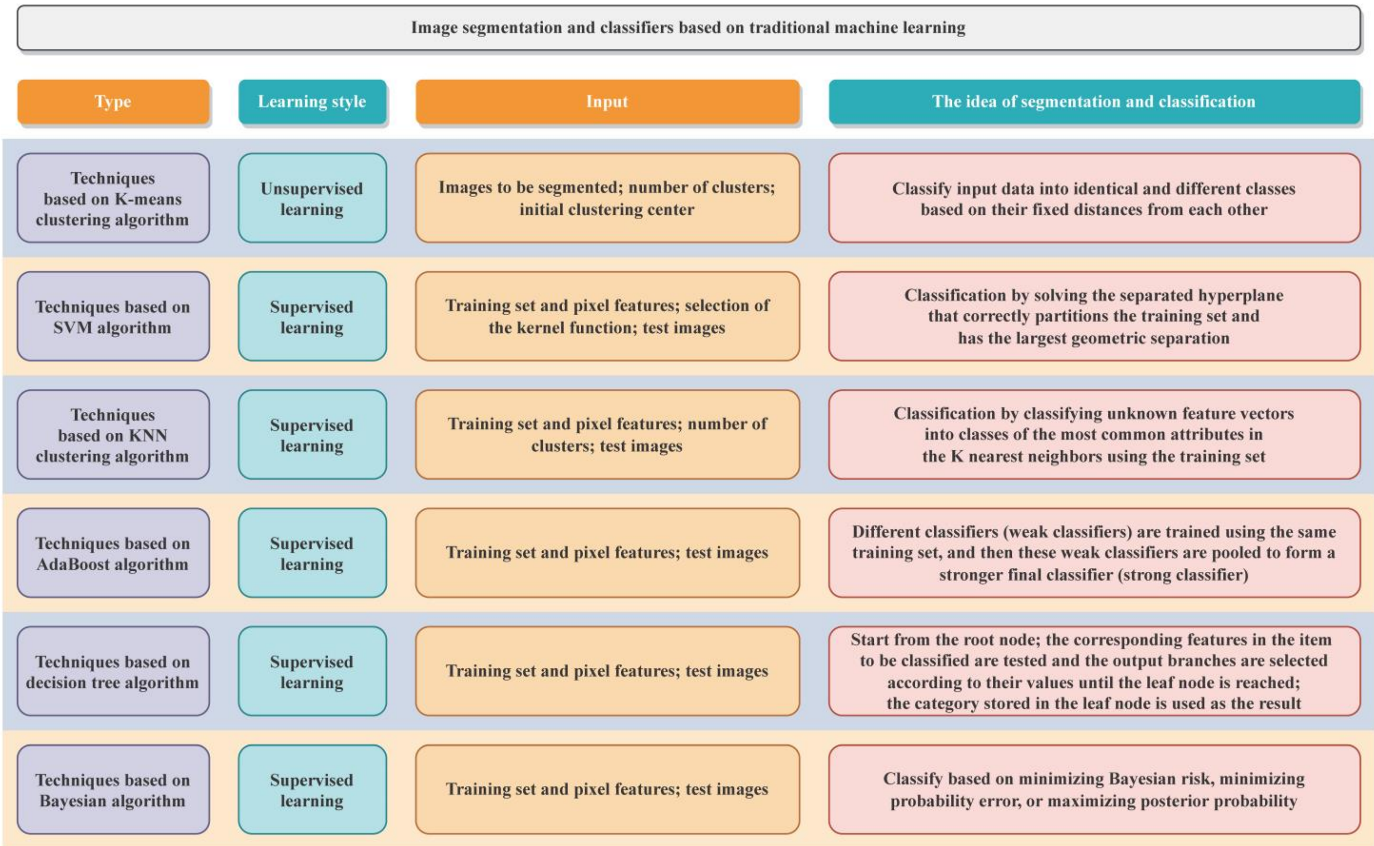


Image segmentation and classifiers based on traditional machine learning

Type	Learning style	Input	The idea of segmentation and classification
Techniques based on K-means clustering algorithm	Unsupervised learning	Images to be segmented; number of clusters; initial clustering center	Classify input data into identical and different classes based on their fixed distances from each other
Techniques based on SVM algorithm	Supervised learning	Training set and pixel features; selection of the kernel function; test images	Classification by solving the separated hyperplane that correctly partitions the training set and has the largest geometric separation
Techniques based on KNN clustering algorithm	Supervised learning	Training set and pixel features; number of clusters; test images	Classification by classifying unknown feature vectors into classes of the most common attributes in the K nearest neighbors using the training set
Techniques based on AdaBoost algorithm	Supervised learning	Training set and pixel features; test images	Different classifiers (weak classifiers) are trained using the same training set, and then these weak classifiers are pooled to form a stronger final classifier (strong classifier)
Techniques based on decision tree algorithm	Supervised learning	Training set and pixel features; test images	Start from the root node; the corresponding features in the item to be classified are tested and the output branches are selected according to their values until the leaf node is reached; the category stored in the leaf node is used as the result
Techniques based on Bayesian algorithm	Supervised learning	Training set and pixel features; test images	Classify based on minimizing Bayesian risk, minimizing probability error, or maximizing posterior probability

Figure 9. The idea of image segmentation and classifiers based on traditional machine learning.

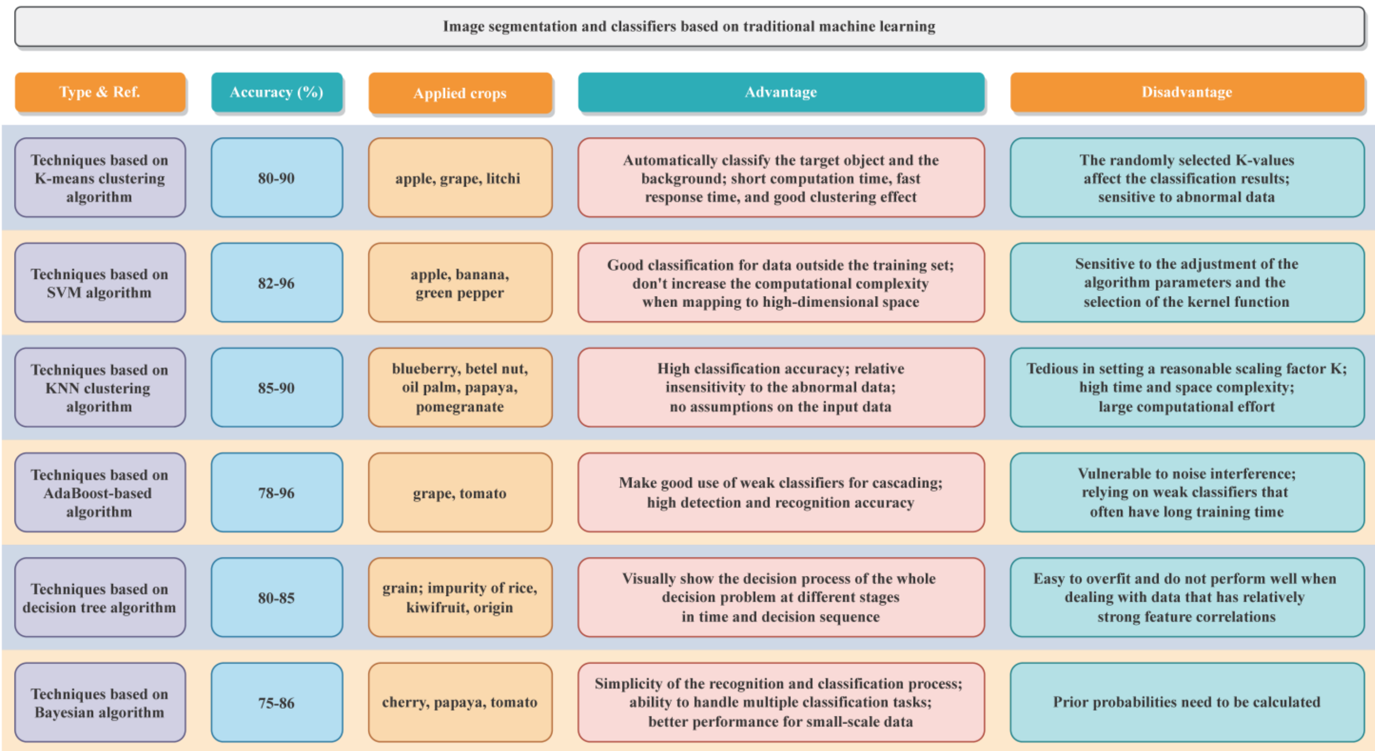


Image segmentation and classifiers based on traditional machine learning

Type & Ref.	Accuracy (%)	Applied crops	Advantage	Disadvantage
Techniques based on K-means clustering algorithm	80-90	apple, grape, litchi	Automatically classify the target object and the background; short computation time, fast response time, and good clustering effect	The randomly selected K-values affect the classification results; sensitive to abnormal data
Techniques based on SVM algorithm	82-96	apple, banana, green pepper	Good classification for data outside the training set; don't increase the computational complexity when mapping to high-dimensional space	Sensitive to the adjustment of the algorithm parameters and the selection of the kernel function
Techniques based on KNN clustering algorithm	85-90	blueberry, betel nut, oil palm, papaya, pomegranate	High classification accuracy; relative insensitivity to the abnormal data; no assumptions on the input data	Tedious in setting a reasonable scaling factor K; high time and space complexity; large computational effort
Techniques based on AdaBoost-based algorithm	78-96	grape, tomato	Make good use of weak classifiers for cascading; high detection and recognition accuracy	Vulnerable to noise interference; relying on weak classifiers that often have long training time
Techniques based on decision tree algorithm	80-85	grain; impurity of rice, kiwifruit, origin	Visually show the decision process of the whole decision problem at different stages in time and decision sequence	Easy to overfit and do not perform well when dealing with data that has relatively strong feature correlations
Techniques based on Bayesian algorithm	75-86	cherry, papaya, tomato	Simplicity of the recognition and classification process; ability to handle multiple classification tasks; better performance for small-scale data	Prior probabilities need to be calculated

Figure 10. Techniques based on traditional machine learning.

In general, compared to techniques based on digital image processing, techniques based on traditional machine learning have improved the speed, accuracy, and robustness of the detection and recognition of fruits and vegetables to different degrees. However, techniques based on traditional machine learning are sensitive to the inputs of abnormal data. Various parameters need to be set in advance before training, and the final classification effect is related to the setting of various parameters. Some parameters are also affected by changing lighting conditions, which make the tuning processes more complicated. At the same time, the current mainstream image segmentation and classifiers based on traditional machine learning are often solutions for specific scenes, so they usually lack generality. They are less effective for multiple classification problems, and are mainly applicable to the detection and recognition of a single species in greenhouse environments.

3.1. Techniques Based on K-Means Clustering Algorithm

The K-means clustering algorithm is a widely used unsupervised learning method. It can automatically classify input data into identical and different classes based on their fixed distances from each other. Techniques for object detection and recognition of fruits and vegetables based on the K-means clustering algorithm are widely used. Wang et al. [75] proposed a litchi detection and recognition algorithm based on K-means clustering. The research results showed that the method can be robust against the influence of changing lighting conditions. The highest average recognition rates of un-occluded and partially occluded litchi were 98.8% and 97.5%, respectively. Luo et al. [72] proposed a K-means clustering algorithm-based detection and recognition method for cutting points of double-overlapping grape clusters for harvesting robots in a complex vineyard environment. The recognition accuracy of the overlapping grape clusters was 88.33%. The success detection rate of the cutting points on the peduncles of double-overlapping grape clusters was 81.66%. Jiao et al. [70] also proposed a fast detection and localization method for overlapping apples based on K-means clustering and a local maximum algorithm.

In order to further resist the effect of changing lighting conditions, Wang et al. [74] improved the wavelet transform and used the K-means clustering algorithm to segment target images. The method not only accurately segments fruits with different colors, but also maintains high accuracy for the detection and recognition of fruits under changing lighting conditions.

In order to exclude the interference information in images as much as possible, Luo et al. [72] used the K-means clustering algorithm to obtain a complete closed target image region after segmentation, denoising, and filling operations on the captured image. To obtain more feature information of target fruits, Moallem et al. [73] applied the K-means clustering algorithm to the Cb component in YCbCr color space, and the defect segmentation was achieved using a Multi-Layer Perceptron (MLP) neural network. Then, statistical, textural, and geometric features from refined defected regions were extracted. Although the classification accuracy of this method is high, the weaknesses are obvious. First, the K-value must be given in advance, but it is difficult to do so. Second, the randomly selected K-centroids will have a large impact on the classification results.

In general, these techniques do not need to give labels, and can automatically classify target objects and backgrounds according to the fixed values between input data. Therefore, the advantages of techniques for object detection and recognition of fruits and vegetables based on the K-means clustering algorithm are short computation time, fast response time, and good clustering effect (especially when the clusters are dense and the differences are obvious). The disadvantages are that they are sensitive to abnormal data, and the randomly selected K-values have a large impact on the classification results.

3.2. Techniques Based on SVM Algorithm

The SVM algorithm is a widely used supervised learning method. It is commonly used in linear/nonlinear regression analysis and pattern classification. It achieves classification by solving the separated hyperplane that correctly partitions the training set and has the largest geometric separation. Techniques for object detection and recognition of fruits and vegetables based on the SVM algorithm are widely used. Bhargava1 and Bansal [54], Patel and Chaudhari [78], Singh and Singh [82], and Moallem et al. [73] compared the performance of different classifiers (SVM, KNN, etc.) for the detection and recognition of different fruits and vegetables. The research results showed that, in their studies, the SVM classifier performs better than the other classifiers.

To improve the cooperative capability of fruit and vegetable harvesting robots, Sepúlveda et al. [77] implemented a cooperative operation between the arms of a two-armed eggplant harvesting robot based on the SVM algorithm. To address the problems of local occlusions, irregular shapes, and high similarity to backgrounds, Ji et al. [81] proposed a green pepper recognition method based on a least-squares support vector machine optimized by the improved particle swarm optimization (IPSO-LSSVM). The research results showed that the recognition rate of green peppers was 89.04%, and the average recognition time was 320 ms. This approach meets the requirements of accuracy and time of greenhouse green pepper harvesting robots.

To further improve the accuracy, speed, and robustness of detection and recognition of fruits and vegetables, Yang et al. [80] also proposed an image segmentation method for Hangzhou white chrysanthemum based on the least-square support vector machine (LS-SVM). The research results showed that the trained LS-SVM model and SVM model could effectively segment the images of Hangzhou white chrysanthemum from complicated backgrounds under three lighting conditions, namely, front lighting, back lighting, and overshadowing, with an accuracy of above 90%. When segmenting an image, the SVM algorithm required 1.3 s, while the proposed LS-SVM algorithm needed just 0.7 s. In addition, the implementation of the proposed segmentation algorithm on the harvesting robot achieved an 81% harvesting success rate.

In general, the advantages of techniques for object detection and recognition of fruits and vegetables based on SVM algorithm are that they simplify classification and regression problems, and can achieve good classification for the data outside the training set. At the same time, they can solve the problem of small samples of target fruits in natural environments, and do not increase the computational complexity when mapping to high-dimensional space. Therefore, the segmentation of fruit and vegetable images containing many high light points can be effectively realized by these techniques. The disadvantages are that they are too sensitive to the adjustment of the algorithm parameters and the selection of the kernel function. The kernel function and its parameters must be reselected for a new dataset. In addition, the accuracy is only high for binary classification tasks, but less effective for multi-classification problems.

3.3. Technique Based on KNN Clustering Algorithm

The KNN clustering algorithm is a widely used supervised learning method. It is commonly used in classification and regression models. It achieves classification by classifying unknown feature vectors into classes of the most common attributes of the K nearest neighbors using the training set. Techniques for object detection and recognition of fruits and vegetables based on the KNN clustering algorithm are more widely used. Based on the KNN clustering algorithm, Tan et al. [36], Astuti et al. [90], Suban et al. [89], Sarimole and Rosiana [85], and Sarimole and Fadillah [86] detected and recognized the ripeness of blueberries, oil palms, papayas, betel nuts, and pomegranates, respectively.

Tanco et al. [91] studied the detection and recognition of fruits and vegetables using three types of classifiers (SVM, KNN, and decision tree). The research results showed that the KNN clustering algorithm produced the best detection and recognition results. Ghazal et al. [88] trained and tested six supervised machine learning methods (SVM, KNN, decision tree, Bayesian, Linear Discriminant Analysis, and feed-forward back propagation neural network) on a publicly available Fruits 360 dataset. The research results showed that the methods based on the KNN clustering algorithm achieve relatively high classification accuracy.

In general, techniques based on the KNN clustering algorithm are able to classify the K nearest neighbors using functions to measure the distance between different eigenvalues. The advantages of techniques based on the KNN clustering algorithm are high classification accuracy, relative insensitivity to abnormal data, and no assumptions about input data. However, it is tedious to set a reasonable scaling factor of K in these methods. With a small value of K, the model complexity is high, overfitting is likely to occur, the estimation error of learning increases, and the prediction results are very sensitive to the instance points of the nearest neighbors. With a larger value of K, the complexity of the model and the estimation error of learning decreases, which is suitable for classification of a small dataset, but the approximation error of learning increases. The disadvantages are large computational effort, and high time and space complexity. Moreover, the detection and recognition accuracy of fruits and vegetables are easily affected by the growth environments and lighting conditions.

3.4. Techniques Based on AdaBoost Algorithm

The AdaBoost algorithm is a widely used supervised learning method. It is commonly used in two-class problems, multi-class single-label problems, multi-class multi-label problems, large-class single-label problems, and regression problems. Different classifiers (weak classifiers) are trained using the same training set, and then these weak classifiers are pooled to form a stronger final classifier (strong classifier). Techniques for object detection and recognition of fruits and vegetables based on the AdaBoost algorithm are widely used. Kumar et al. [93] introduced a novel plant species classifier based on the extraction of morphological features using a Multilayer Perceptron with the AdaBoost algorithm. In addition, they tested the classification accuracy of different classifiers, such as KNN, decision tree, and the Multilayer Perceptron. The research results showed that a precision rate of 95.42% was achieved using the proposed machine learning classifier, which is one of the state-of-the-art algorithms.

Ling et al. [94] proposed a tomato detection method combining an AdaBoost classifier and color analysis, and applied them to the harvesting robot. The research results showed that the ripe tomato detection success rate was about 95%., and 5% of the ripe tomatoes missed detection because of the occluding leaves. When the leaf occlusion area is more than 50% of the tomato area, the target tomato might not be detected. The method also has good robustness, and can meet the challenges of environmental factors such as changing lighting conditions and partial occlusions and overlaps. The speed of the method is about 10 fps, which is enough for the harvesting robot to operate in real time.

To further cope with challenges such as changing lighting conditions, cluttered backgrounds, and cluster occlusions, Lin and Zou [62] also proposed a novel segmentation method using the AdaBoost classifier and texture–color features. The research results showed that the method achieved a precision of 0.867 and recall of 0.768. However, the method may over-segment images because the LM filter bank tends to be influenced by illumination changes. A possible solution is to investigate an illumination invariant version of an LM filter bank.

In general, the advantages of techniques for object detection and recognition of fruits and vegetables based on the AdaBoost algorithm are that they can use different classification algorithms as weak classifiers and make good use of weak classifiers for cascading, with high detection and recognition accuracy. The disadvantages are that during the training process, the AdaBoost algorithm will cause the weight of difficult samples to exponentially increase, and the training will be biased towards such difficult samples, which makes the AdaBoost algorithm vulnerable to noise interference. In addition, the AdaBoost algorithm relies on weak classifiers, which often have a long training time.

3.5. Techniques Based on Decision Tree Algorithm

The decision tree algorithm is a widely used supervised learning method. It is commonly used in decision-making problems. It starts from the root node. Then, the corresponding features in the item to be classified are tested and the output branches are selected according to their values until the leaf node is reached. Finally, the category stored in the leaf node is used as the decision result. Wajid et al. [105] investigated the applicability and performance of various classification algorithms including Naïve Bayes, Artificial Neural Networks, and decision trees. The research results showed that the decision tree classification method performs better than the other methods for orange detection. The results recorded for the accuracy, precision, and sensitivity using this method were 93.13%, 93.45%, and 93.24%, respectively. In addition, in order to investigate the cost of implementation relative to the classification performance, Kuang, et al. [103] compared two types of machine learning algorithms (the multivariate alternating decision tree and the deep-learning-based kiwifruit classifiers). The research results showed that traditional decision tree classifiers can achieve comparable classification performance at a fraction of the cost.

Ma et al. [104] proposed a segmentation method based on a decision tree which is constructed by a two-step coarse-to-fine procedure. Firstly, a coarse decision tree is built by the CART (Classification and Regression Tree) algorithm with a feature subset. The feature subset consists of color features that are selected by Pearson's Rank correlations. Then, the coarse decision tree is optimized by pruning. Using the optimized decision tree, segmentation of images is achieved by conducting pixel-wise classification. Abd al karim and Karim [100] also proposed a decision tree classifier to classify fruit types. The Fruits 360 dataset was used, where 70% of the dataset was used in the training phase and 30% was used in the testing phase. Chen et al. [102] proposed a classification method for kernel and impurity particles using the decision tree algorithm.

In general, the advantages of techniques for object detection and recognition of fruits and vegetables based on the decision tree algorithm are that they enumerate the full range of feasible solutions to the decision problem, and the expected values of each feasible solution in various states. They can visually show the decision process of the whole decision problem at different stages in time and in the decision sequence. When applied to a complex multi-stage decision-making problem, the stages are obvious and the hierarchy is clear, so that various factors can be thoughtfully considered, which is conducive to making the right decision. The disadvantages are that they are easy to overfit and do not perform well when dealing with data that has relatively strong feature correlations. In addition, for data with an inconsistent number of samples in each category, the result gained in the decision tree is biased towards those features with more values.

3.6. Techniques Based on Bayesian Algorithm

The Bayesian algorithm is a widely used supervised learning method. It classifies based on minimizing Bayesian risk, minimizing probability of error, or maximizing posterior probability. It is commonly used in large-scale databases. The Bayesian algorithm was proposed because it has high accuracy and computational speed when applied to a large number of databases, is robust to isolated noise points, and only requires a small training set to estimate the parameters needed for classification.

Kusuma and Setiadi [113] proposed a classification method using feature histogram extraction and a Naïve Bayes Classifier for tomato recognition. In addition, Sari, et al. [110] proposed a classification method for papaya types based on leaf images using a Naive Bayes classifier and LBP feature extraction. In the research of Reyes et al. [108], the method based on the Bayesian algorithm, along with the off-the-shelf hardware, made it possible to perform an optimal classification of cherries in real time to meet international fruit quality standards.

In general, the advantages of techniques for object detection and recognition of fruits and vegetables based on Bayesian algorithms are the simplicity of recognition and classification processes, the fast response time, the better performance for small-scale data, the ability to handle multiple classification tasks, and the suitability for incremental training. The disadvantage is that the prior probabilities need to be calculated. Furthermore, the recognition performance is affected by the fact that the prior probabilities depend on the target image features. In addition, the recognition function may fail for data (variable features) that do not appear in the training set.

4. Challenges and Further Research

As summarized and reviewed in this article, various techniques for object detection and recognition of fruits and vegetables, each with their own pros and cons, have been investigated in the past. However, it is difficult to find studies reporting the absolute accuracy of each technique and comparisons of performance between those techniques in the same environment.

Therefore, open publishing of all reference datasets and all code is necessary. Some frequently used image databases of fruits and vegetables are shown in Table 4. As much as possible, further research should be carried out based on these open datasets to help compare different techniques. Moreover, the international community might consider continually providing and updating quality reference datasets.

Table 4. Some frequently used image databases of crops: fruits and vegetables.

Datasets	Total	Samples Training Sets	Testing Sets	Species	Web-Link	Year
Fruits-360	90,380	67,692	22,688	131 (100 × 100 pixels)	https://www.kaggle.com/datasets/moltean/fruits (accessed on 16 February 2023)	2020
Fruit-A	22,495	16,854	5641	33 (100 × 100 pixels)	https://www.kaggle.com/datasets/sshikamaru/fruit-recognition (accessed on 16 February 2023)	2022
Fruit-B	21,000	15,000	vail: 3000 text: 3000	15 (224 × 224 pixels)	https://www.kaggle.com/datasets/misrakahmed/vegetable-image-dataset (accessed on 16 February 2023)	2021
Fruit quality classification	19,526	-	-	18 (256 × 256/192 pixels)	https://www.kaggle.com/datasets/ryandpark/fruit-quality-classification (accessed on 16 February 2023)	2022
Fresh and rotten fruits	13,599	10,901	2698	6	https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification (accessed on 16 February 2023)	2019
Lemon quality control dataset	2533	-	-	3 (256 × 256 pixels)	https://github.com/robotduinom/lemon_dataset (accessed on 16 February 2023)	2022
Pistachio	2148	-	-	2	https://www.muratkoklu.com/datasets/ (accessed on 16 February 2023)	2022
Grapevine leaves dataset	500	-	-	5		2022
Apple	1300	1000	300	2	https://data.nal.usda.gov/search/type/dataset (accessed on 16 February 2023)	2020
Cauliflower	656	-	-	4	https://www.kaggle.com/datasets/noamaanabdulazeem/cauliflower-dataset (accessed on 16 February 2023)	2022
Sweet pepper and peduncle segmentation	620	-	-	8	https://www.kaggle.com/datasets/lemontyc/sweet-pepper (accessed on 16 February 2023)	2021

In addition, there are many factors leading to the low accuracy, slow speed, and poor robustness of object detection and recognition of fruit and vegetable harvesting robots. They can be summarized into the following aspects: (1) similar backgrounds; (2) clustered/partially occluded/swaying fruits; (3) sensitivity to changing lighting conditions; (4) night image recognition; (5) blur and noise in images; (6) high computation time and real-time limitations; and (7) generalization ability. To be more specific:

(1) Object detection and recognition of fruits and vegetables require fast response capability to improve the harvesting efficiency. The current mainstream object detection

and recognition techniques based on digital image processing and traditional machine learning have certain limitations, although they may have good accuracy performance. In complex environments, influenced by many factors such as changing lighting conditions and growth states of fruits, the more factors the method considers, the more complex the method, and the longer the running computation time. This will lead to low real-time performance for vision systems.

(2) When fruit and vegetable harvesting robots work, they can only detect and recognize the target objects according to the pre-trained model. In the actual harvesting process, there is often more than one kind of target object that needs to be harvested. In addition, the harvesting robots are only used during the harvesting season of the year, and are idle for the rest of the year, due to the obvious seasonality and timeliness of fruit harvesting, thus leading to the relatively poorer economics of harvesting robots. Therefore, the generalization ability of the algorithms still needs to be enhanced to achieve the detection and recognition of multiple kinds of fruits and vegetables. Future research could make the algorithms generalizable (i.e., derive the ability to recognize fruits with similar characteristics based on a kind of target object). In addition, the night image recognition algorithm could be required for vision systems, where the harvesting robots can work during the day, and then continue at night.

(3) Object detection and recognition of fruits and vegetables require the detection and recognition of clustered/partially occluded/swaying fruits. However, the presence of clustered/partially occluded/swaying parts may cause confusion in images, which is currently a greater challenge for detection and recognition in unstructured environments. A popular method is the Circular Hough Transform, which is more effective for round objects such as apples, oranges, and tomatoes. However, research results showed that this method is not only prone to false positives generated by the contours of other objects, such as leaves, but also has a long computation time. Another popular method is to use a blowing device to avoid leaf occlusions and to move adjacent fruits to one side. However, this method will increase the weight of end-effectors of harvesting robots, and may not be applicable to all kinds of crops. Future research could focus on agricultural operations, including tree pruning and pollination methods, to improve the visibility of target fruits, which may help to improve detection and recognition accuracy.

As summarized and reviewed in this article, methods based on multi-feature fusion and the SVM algorithm achieve a better accuracy rate in addressing these challenges. Furthermore, methods based on multi-algorithm fusion should be paid more attention. In addition, further research should focus on solving these challenges and improving the accuracy, speed, robustness, and generalization of vision systems, while reducing the overall complexity and cost. The optimization of network models, the accuracy of sensing systems, multi-sensor data fusion, fault-tolerant computing of machine vision, and decision making using a big data cloud platform may be key breakthroughs for further techniques for object detection and recognition of fruits and vegetables.

5. Conclusions

The intelligent harvesting robot is one of the most important artificial intelligence (AI) robots used for fruit and vegetable harvesting in modern agriculture. The excellent vision system can greatly promote the environmental perception ability of the harvesting robot. However, current visual systems of harvesting robots still cannot fully meet the requirements of commercialization. This article summarizes and reviews the progress in developing techniques for object detection and recognition of fruit and vegetable harvesting robots based on digital image processing and traditional machine learning. Although there previous reviews of techniques for object detection and recognition of fruits and vegetables have been published, the contributions of this work are: (1) systematic summary of the techniques developed in recent years for object detection and recognition of fruit and vegetable harvesting robots based on digital image processing and traditional machine learning; (2) systematic analysis of the advantages, disadvantages, and applicability of various techniques; and (3) demonstration of the current challenges and future potential developments. Through this clearer and more comprehensive overview and review, we aim to provide a reference for future research on techniques for object detection and recognition of fruit and vegetable harvesting robots based on digital image processing and traditional machine learning.

The current challenges of techniques for object detection and recognition of fruits and vegetables are mainly the similar backgrounds, clustered/partially occluded/swaying fruits, sensitivity to changing lighting conditions, night image recognition, blur and noise in images, high computation time and real-time limitations, and generalization ability.

Techniques for object detection and recognition of fruit and vegetable harvesting robots based on digital image processing can be subdivided into color feature (RGB, HSV, HSI, Lab, HSB, YCbCr)-based methods, shape feature-based methods, texture feature-based methods, and multi-feature fusion-based methods.

As summarized and reviewed in this article, techniques based on digital image processing require precise information about the target fruit features, which are usually used for object detection and recognition of fruits and vegetables based on features such as colors, shapes, and textures. However, in complex environments, these features of the target objects are affected by non-controllable factors, resulting in low accuracy, slow speed, and poor robustness of object detection and recognition of fruits and vegetables. Methods based on multi-feature fusion can improve the accuracy and robustness of object detection and recognition of fruits and vegetables. However, it is important to determine which features to integrate; for example, Lab color space could be used more for low-quality images because it is more robust to noise in images. In addition, the combination of color with GLCM texture features has proven to be more effective than combined color and LBP texture features.

Object detection and recognition techniques of fruit and vegetable harvesting robots based on traditional machine learning can be subdivided into K-means clustering algorithm-based methods, SVM algorithm-based methods, KNN clustering algorithm-based methods, AdaBoost algorithm-based methods, decision tree algorithm-based methods, and Bayesian algorithm-based methods.

In general, techniques based on traditional machine learning have good performance, but they require various parameters to be set in advance, where the parameters set in advance have a large impact on recognition accuracy. For classifiers, prior probabilities from the training set need to be obtained in advance, and the classification accuracy is affected by the weights of difficult to classify samples. As summarized and reviewed in this article, methods based on the SVM algorithm achieve a better accuracy rate. However, the current mainstream image segmentation approaches and classifiers based on traditional machine learning are often solutions for specific scenes. They usually lack generality and are less effective for multiple classification problems. They are mainly applicable to the detection and recognition of a single species in greenhouse environments. Methods based on multi-algorithm fusion should be paid more attention. This may be a breakthrough for future techniques for object detection and recognition of fruits and vegetables.

Further research into and development of techniques for object detection and recognition for fruit and vegetable harvesting robots are necessary. Commercial applications of harvesting robots need to be further addressed through integrated horticultural and engineering approaches for improved image segmentation, and for increased overall performance of crop detection and recognition.

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