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Application status and challenges of machine vision in plant factory—A review

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A B S T R A C T

Plant factories have a great potential for mitigating the contradiction between the world's growing population and food scarcity. During the process of its automatic production, machine vision plays a significant role. This technique almost covers every production link from raising seedlings, transplanting, management, and harvesting to fruit grading. To provide references and a starting point for those who are committed to studying this issue. In this paper, the application prospects of machine vision in plant factories were analyzed, and the present researches were summarized from the fields of plant growth monitoring, robot operation assistance, and fruit grading. The results found that although the existing methods have solved some practical problems at low cost, high efficiency and precision, some challenges still are faced by machine vision. Firstly, the changing lighting, complex backgrounds, and color similarity within plant different parts cause the commonly used image segmentation algorithms to fail. The shortage of standard agricultural datasets also keeps deep learning and unsupervised classification algorithms from making progress. Secondly, there are some theoretical knowledge gaps for machine vision application in a particular environment of plant factories, which seriously contains its application effect. Thirdly, the lack of special image acquisition devices and supporting facilities resulted in poor image quality. All these factors hinder machine vision application in plant factories. Nevertheless, it is still a powerful tool and irreplaceable at present. We believed that this technique would promote plant factory development greatly with more robust, efficient, and reliable algorithms are developed in the future.

Contents

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1. Introduction

The world's population is growing and expected to exceed 9 billion by 2050, per capita arable land will be less than 0.1 ha at that time [1], food scarcity will become a primary factor threatening human survival, so "growing more with less" is what scientists concern most [2]. Plant factories are a promising option for solving these problems. Compared with traditional agriculture, the growing environment of plant factories is controllable, and crops grow in a vertical space, so that little land is required. It can produce more food due to its year-round production capacity. Plant factory buildings often are deployed next to consumers to save transportation costs [3–9]. However, building and labor costs contain plant factory development. In this context, automatic production is promising and sustainable.

Machine vision has received a spread wide use in the intelligent systems of plant factories recently [10–14]. This technology almost covers all production links from raising seedling, transplanting, management, and harvesting to fruit grading. It extracts information from images by simulating human vision, then analyzes them and guides practical production [15–17]. Machine vision collects plant information in a non-invasive way compared with the chemical and physical methods and has no damage to plants. It also works continually with high efficiency and low cost.

The classic machine vision system includes an image acquisition section, data processing section, and task execution section. The first one is used to capture images and pass them to the next part. This part includes light sources, optical systems, and image acquisition cards. The data processing part extracts and analyzes information from images and makes a decision based on learning results, finally gives orders to the last section. A computer system is a primary component in this section. The task execution section usually is a mechanical module, which performs tasks such as irrigation and fruit picking. Robots, environmental controlling systems, and nutrition supply systems are used commonly in this part.

Many reviews have reported machine vision application status in agriculture. They are mainly involved in field crops [18,19], and few of them refer to plant factories. The environments in a plant factory are complex and different from the outdoors. Besides the plant itself, there are irrigation pipes, hanging ropes, mechanical equipment, and other supporting facilities. The lighting condition also changes periodically according to the plant's needs, which brings some challenges to machine vision applications. In this paper, a comprehensive survey on this issue had developed from aspects of plant growth monitoring, robot operation assistance, and fruit grading, aiming at providing references and a starting point for researchers in this field. And the advantages and disadvantages of some methods are analyzed. Finally, the challenges that machine vision faced in plant factories have presented.

2. Plant growth monitoring

Information for plant health levels can support management decision-making. Rapid information acquisition and decision-making can often avoid risks and reduce economic losses. In a traditional greenhouse, environmental parameters, such as air temperature, relative humidity, and lighting intensity, were adjusted based on the grower's observation or a set threshold rather than the needs of plants [20,21], which is extensive management. The best way is that plants can get feeding based on growth information collected continuously, and on this issue, machine vision can help. At present, this technique is used in plant phenotype, pest and disease alert, and nutrient stress detection.

2.1. *Plant morphological characterization*

Plant phenotype parameters include color, size, texture, and shape for different plant organs such as flowers, leaf, stem, fruit, canopy, and roots (can be estimated indirectly) [22]. This information reflects the growth state and health levels of

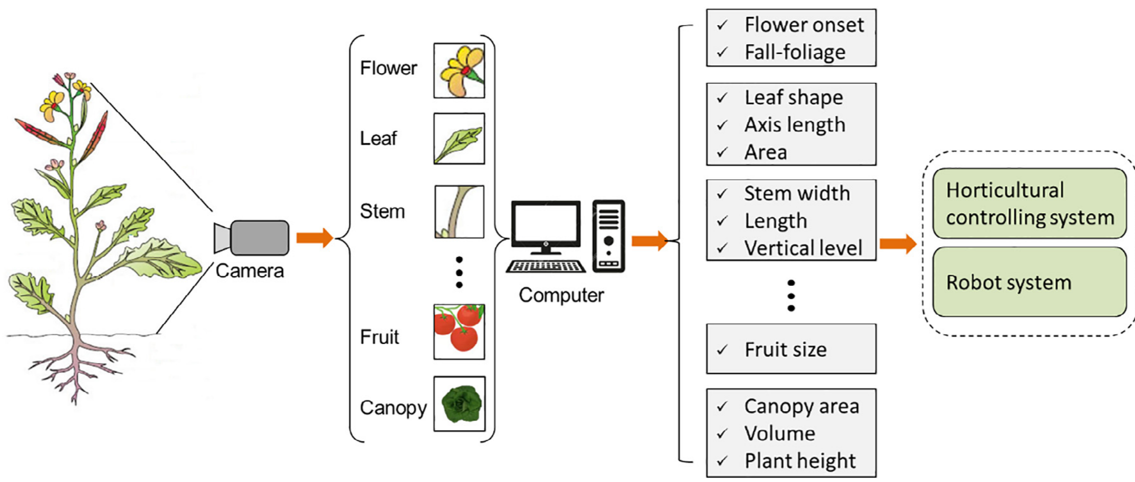

Fig.1 – Different parts of a plant for morphology information acquisition.

plants. It is helpful for the decision-making and management of horticultural systems. As shown in Fig. 1, the area and shape of the plant leaf can indicate its species. Plant height is a quantitative morphological parameter to ascertain the growth rate or annual growth cycle of plants grown in different/same weather or nutrient conditions [23,24]. Fall foliage is a qualitative feature to indicate the health levels of the plant [25]. The top canopy area could also be related to the plant's fresh and dry weight [26,27]. The information was obtained through physical measurement methods or observation by naked eyes in the past, which requires a high level of expertise for growers. It is also impossible to collect information in real time. Many reports introduced machine vision to solve problems, the results listed in Table 1.

The plant size can evaluate its growth rate and estimate yield. Before transplanting, it is necessary to measure the seedling size and judge whether it has grown to a suitable level. Yang Zhenyu [28] combined the S component in the HSI color model and the Otsu algorithm to segment seedlings from the background. The seedling height was extracted by the Vertex Chain Code (VCC) and the Minimum Bounding Rectangle (MBR), while the seedling skeleton was calculated as a parameter to describe vertical degree. These two parameters are combined to select the available seedlings. However, all images were taken manually. He Zili [17] designed an inspection robot. It can capture images of a single plant automatically and calculate its growth parameters. In addition to providing supporting information for the robot's application, plant growth parameters can also be input for environmental control systems. Sun Guoxiang [29] extracted the cucumber population canopy coverage and width through the Excess Green Minus Excess Red (MExg-ExR) algorithm, this information as a decision-making input along with air temperature, relative humidity, and soil moisture. Finally, an irrigation system was developed to apply water and fertilizer.

Researches mentioned above conduct in the sunlight greenhouse. However, the supplemental lighting system is used in most plant factories to improve light conditions indoors and help plants grow well. Artificial light radiates a narrow band of wavelength and produces monochromatic light to meet the plant's special lighting needs in different growing stages. Some algorithms have a good performance when dealing with images taken under sunlight but often fail to segment feature areas from the images captured under artificial light. It is difficult to separate the plant or its organs from the background. The study [30] tried to use the Kubelka-Musk theory to solve this problem, but there was an imperfect result. Image segmentation is the first step for image analysis, but artificial light brings challenges to it.

Plant phenotype accuracy is an issue worth noting. Few reports mentioned it. Large deviations will cause control systems to make wrong decisions, which routinely brings serious consequences. The plant parameters have variability even under the same growth conditions, so the single plant growth parameters are not representative, and they should not be a decision-making basis for control systems. Additionally, the accuracy of the phenotype model needs to be improved through physical and other methods constantly. At the same time, statistical methods need to be applied for sampling point deployment, ensuring the information collected can reflect all plant conditions.

2.2. *Pest and disease detection*

High humidity and air temperature in a plant factory provide a suitable living environment for crop pests and diseases, which always causes an irreversible economic loss if not receive in-time treatment. They are observed and alerted manually in traditional greenhouses. It is not only time-consuming but also labor-intensive. On the one hand, the observation results are easy to be affected by human subjective sense. Because each person has inconsistent definitions for infected levels [31–33]. On the other hand, the initial symptoms of pests and diseases are not obvious for human vision. The large areas of plants have infected with diseases before we found them. In the latest studies, machine vision is introduced to monitor plant health levels, the principle is as shown in Fig. 2, and the researches results were listed in Table 2.

Table 1 – Summary of machine vision used for plant phenotype.

Ref.	Task	Color model	Method	Advantages	Disadvantages
[22]	Extract plant outlines, stem width, and lengths	RGB	Least-squares threshold selection, Thinning algorithms	High accuracy of 0.025 mm	Analysis was not possible when leaves shaded the stem
[23]	Assess variations in plant parameters (such as area) over time	CIE, L*a*b*	Super pixel-based random forest, Simple linear iterative clustering (SLIC) algorithm, K-means	An automated, high-throughput pipeline to analyze large-scale image data	Poor performance when different color distribution, leaves overlapped
[24]	Extract leaf centroid, major axis length, minor axis length	RGB	K-NN, Decision tree, Multilayer perceptron, AdaBoost methodology	High precision rate of 95.42%	Any inclination or curling of the leaves will cause the morphological features extraction to fail
[25]	Extract leaf area, plant height, detection of the onset of flowers, fall-foliage condition	RBG	PIPME, Binary morphological operation, Threshold method, Linear spatial filtering	high level of accuracy, display the results on the user interface	The device was fixed and can't capture more images automatically
[26]	Extract plant top projected canopy area, plant perimeter, and weighted radius	RGB, HSL	Co-occurrence matrix and grey tone spatial dependence matrix, Bresenhams line algorithm	The user interface enabling the operator to visualize dynamic camera motion	The accuracy of plant parameters detected is unknown
[27]	Detect surface area and volume computations	None	Clustering algorithm, Expectation maximization algorithm, α-Shape triangulation	The system works continuously for the life-cycle of the plant	Can only scan a single plant at one time
[28]	Extract the vertical degree and height of pot seedlings	HSI	Otsu algorithm, Vertex chain code method, and MBR (Minimum Bounding Rectangle)	Improve the efficiency and robustness of the image segmentation	The image background needs to be processed manually
[17]	Estimate the leaf area	RGB	Threshold segmentation, Gaussian smoothing	Robot mobile platform makes image acquisition flexible	Only classify three different plants
[29]	Extract canopy coverage, width, and length	HIS, YCbCr	Retinex, MExg- ExR(excess green minus excess red)	With high accuracy of 98.31% under different light conditions	It is only suitable for vertical viewing angle conditions

2.2.1. *Disease detection*

The process of disease diagnosis through machine vision includes (i) image pre-processing, (ii) lesion area segmentation, (iii) features-searching (color, shape, and texture) of the lesion area, (iv) model training, and (v) disease recognition.

Mi Yating [34] labeled foreground and background of tomato leaves by Sobel operator and used Watershed algorithm to segment disease spots, a diseases recognition model based on the BP and GA-BP neural networks was built. The recognition rate of the early blight, late blight, and leaf mold reached 100%, 98%, and 96%, respectively. But there were less than 100 images were tested in this research. Ma Juncheng [35] used the Conditional Random Fields (CRF) and Decision Tree model to segment cucumber downy mildew. The Rough Sets were adopted to select classification features. Finally, SVM was used to diagnose cucumber downy mildew. The accuracy rate was 90%. To improve recognition accuracy, Refs. [36,37] had trained an SVM model based on the color and shape of powdery mildew, brown spot, and anthracnose spots of cucumber leaves. This SVM model combined several features and improved the average identification accuracy of lesions to 96.39%. But these methods are time-consuming and cannot meet real-time work requirements. The Hough Transform and Random Forest algorithm were used in Ehsan Kiani's research [38], detection and segmentation accuracy of the plant diseases reached 97%, and the processing time was 1.2 s. A system based on Color Processing Detection Algorithm (CPDA) and fuzzy logic classification algorithm (FLCA) even shortened the working time to 0.06 s [39]. In a plant factory, the changing lighting and complex background always cause a poor image segmentation effect. Ali [40] used Random Forest and Hough Transform algorithms to extract the area of the lesions. The learning characteristics of the Random Forest and the detection characteristics of the Hough Transform were well combined so that the recognition rate improved obviously. These researches showed that machine vision has great potential for disease detection. However, SVM was adopted to classify lesions widely in these reports. It consumed a large amount of machine memory and time.

The existing researches focus on the evident disease lesion areas. In this case, the disease has caused irreversible damage to the quality and yield of the crop. Therefore, predicting disease in advance is a promising study field. Leaf Wetness Dura-

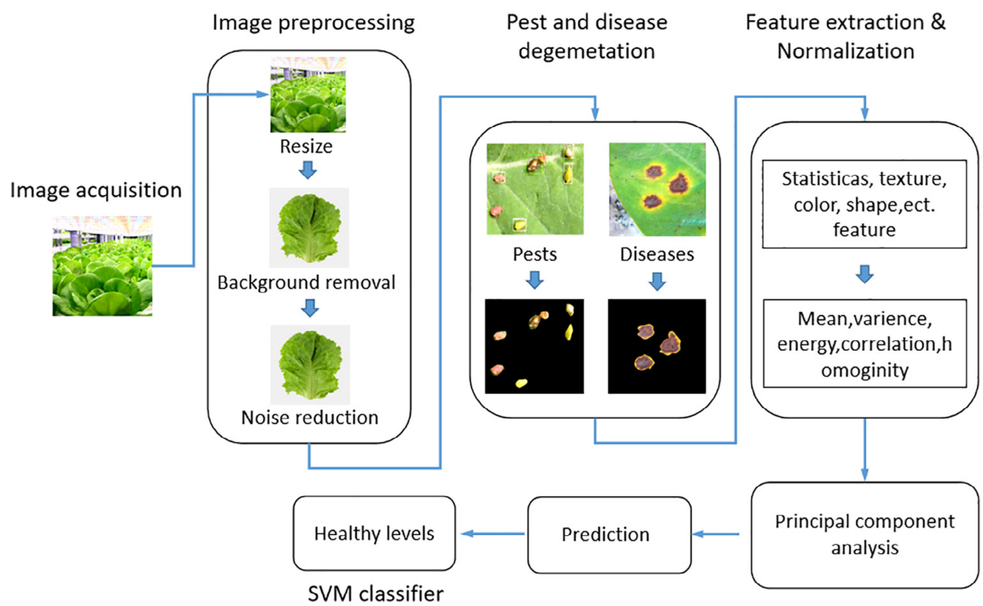

Fig. 2 – Principle of pest and disease detection through machine vision.

Table 2 – Summary of machine vision used on plant disease detection.

Ref.	Plant type	Task	Color model	Method	Advantages	Disadvantages
[34]	Tomato	Identify and grade tomato early blight, late blight, leaf mold	RGB, HIS, LAB	Divide and conquer median filter, Sobel-Watershed, GA-BP	High denoising efficiency, BP neural network optimized by genetic algorithm converges faster	A small number of images leads to incomplete test results
[35]	Cucumber	Diagnosing cucumber downy mildew	HSV	Rough set method, SVM based RBF, image segmentation based on conditional random fields	The algorithm has high computational efficiency and high accuracy of lesion segmentation	Different lighting conditions will affect the results
[36]	Cucumber	Detection of powdery mildew on cucumber leaves	HIS	Threshold segmentation, SVM classifier based on the radial basis kernel function	The system mounted on the disease warning robot to collect images autonomously	Time-consuming
[37]	Cucumber	Detection of brown spot, downy mildew, and anthracnose of cucumber	HIS	Histogram threshold segmentation, Gray level co-occurrence matrix	The average recognition rate of the three diseases reached 96.39%	Algorithm running is time-consuming
[38]	Greenhouse plant	Powdery mildew recognition	RGB	Hough transform, Random forest	High speed and detection accuracy of 97%	The result will be affected by shadows
[39]	Strawberry	Detect healthy and disease infected strawberry leaves	RGB	Color processing detection algorithm (CPDA), Fuzzy logic classification algorithm (FLCA)	Fast running speed (0.06 s) and have a very minimal computational load	It is only suitable for the images under outdoor sun illumination condition
[40]	Tomato, Bell pepper	Powdery mildew of bell pepper plants and spotted wilt virus of tomato	RGB	Random Forest and Hough Transform algorithms	High accuracy of mold recognition	Low running speed
[41]	Cucumber	Detect LWD (leaf wetness duration) to warn the occurrence of diseases	L*a*b*	K-means	Innovatively use image processing to estimate the wetting time of cucumber leaves	Compared with manual detecting, the monitoring error within 1 h

tion (LWD) is related to the infection and prevalence of many leaf diseases. There is the high relative humidity in plant factories due to plant transpiration and evaporation of a nutrient fluid, which causes plant leaves to be moist for a long time, and eventually induces downy mildew and other diseases. However, the leaf wetness level is a changing process. It is difficult to observe through naked eyes. Sun Wenjuan [41] tracked the ratio of the wetness area to the whole cucumber leaf area dynamically based on the L*a*b color model and K-means algorithm, then LWD was calculated. Compared with the manual observation, the monitoring error was within 1 h.

2.2.2. Pest detection

The pests in plant factories include aphids, whiteflies, and thrips. They are small, migratory, and concealed (often located on the backside of leaves). Periodically checking plants and searching for pests is challenging for greenhouse staff. Some studies have proposed an automatic monitoring system based on machine vision (Listed in Table 3). In these systems, the features of pest shape, color, texture, and number were extracted to build species identification models based on ANN and SVM [42].

Li Y identified and located the pest on the plant directly by image segmentation and binocular stereo vision technique [43]. To evaluate the infected level of whitefly, S. R. Pokharkar [44] calculated the percentage of the infected area of leaf and the size of pests. This system only focused on adult whitefly detection. Rupesh G. Mundada [45] proposed a new method for early whitefly detection and achieved an accuracy of 100%. But the pest eggs did not be taken into account. In Zhibin Wang [46] research, a cognitive segmentation approach was used, and the whitefly and its eggs can be segmented accurately from leaf images.

Pests have a migratory characteristic. It implies the severely infected situation when they can be captured by camera easily on plant leaves. Counting pests on the trap board is a commonly used statistical method [47]. Trap board attracts pests and catches them based on their biological habits, the pests on trap boards is denser than that on the leaf. Liu Mengmeng [48] used Prewitt and Canny operators to detect a single pest edge in the HIS and L*a*b color model, and fused the two images to extract the pest area. Finally, 9 color characteristics and 5 morphological characteristics of pests were selected to train SVM, the average recognition accuracy of the model reached 93.5%. But his method was easy to be affected by lighting and had a higher requirement for image acquisition. To solve this problem, reference [49] proposed a method based on Two-Dimensional Fourier Transform (2DFT), in which the pests on the trap board were regarded as the noise of the image, the 2DFT was used as a noise collector. Finally, spectral analysis was used to count the number of pests. The Correlation coefficient of the result between the system and the manual counting method reached 0.99, and the relative error was within ±4%. In practical application, the trap boards need to be replaced manually after they were scrapped. It is inefficient and breaks the

Table 3 – Summary of machine vision used on plant pest detection.

Ref.	Task	Color Model	Method	Result	Advantages	Disadvantages
[43]	Identify and locate pests on the plant	HSV	Centroid-matching, Sum of Squared Differences (SSD)	Pest error focused on the range of 20 mm when the depth measurement is less than a range of 500 mm	This system can locate pests	The illumination conditions, size, and color of pests lead to measurement errors.
[44]	Detection and calculating area of infection on leaves of a whitefly	RGB	Linear spatial filtering, Sobel operator	The percentage of the infected area and the size of each pest was calculated	High calculation accuracy of whitefly size and leaf infection area	Only for whitefly adult detection
[45]	Early whitefly detection	RGB	Smoothening filter, SVM	SVM is done with 100% accuracy	High detection accuracy for early pest	High image acquisition requirements
[46]	Whitefly detection	CIE L*a*b*	K-means Clustering Algorithm, Initial cluster centers self-learning algorithm	The new method can accurately segment whiteflies from crop leaf images	High accuracy and good robustness for both egg and pest detection	The result is easily affected by light conditions
[48]	Detect whitefly and thrips of cucumber	HIS L*a*b*	Prewitt and canny operator, SVM, BP	The recognition rates of whiteflies and thrips are 91.0% and 96.0%	SVM classification performance based on linear kernel function is good and stable	The method was greatly affected by light and has high requirements for image acquisition
[49]	Count whiteflies and thrips	RGB	Two-dimensional Fourier transform (2DFT)	The correlation coefficient R^2 was above 0.99 compared with the human counting results	High counting accuracy and little influence by light	Only two pests were detected and tested

automation of the entire monitoring system. Chen Meixiang [50] designed a pest monitoring system that can replace trap boards automatically.

Pesticide application is not the best strategy to control pests. The most environmentally friendly approach is prevention and comprehensive management before pest infection. Their occurrence is related to environmental situations closely. So, building an early warning model is promising through collecting, analyzing, and excavating information such as plant's nutritional status, environment data, and pest levels.

2.3. *Nutrient stress detection*

Plants are supplied with nutrients by hydroponic technology in a plant factory. When the nutrient supply is insufficient or excessive, it will inhibit plant growth, this phenomenon is named nutrient stress. Nutrient stress is the most information used to assess nutritional balance. However, there is no sensor commercially available for real-time detection of plant stress conditions [51]. Machine vision may bridge the gap. It can "let the plant speak", and helps growers to feed nutrients according to the plant's own needs. The latest research results in this field are listed in Table 4.

Zhang Yan'e [52] extracted the color and texture features of cucumber leaves and growing points to build a model describing the relationship between them and plant nutrient levels. Hendrawan Yusuf [53] combined the N-DHRIO algorithm and ANN to detect the moisture of moss and designed an automatic irrigation system. In this study, the color and texture of the lettuce canopy were also extracted to analyze the light requirements in different parts of lettuce and to feed suitable light intensity. In David's research, the top canopy area of lettuce was taken as morphological characteristics [4]. Hue, saturation, and brightness were used as color characteristics. Entropy, energy, contrast, and homogeneity were used as texture characteristics, these features were combined to evaluate the calcium deficiency of early lettuce. The method can identify whether plants are calcium-deficient one day in advance compared with human vision. The studies mentioned above used RGB cameras to capture plant images, the information contained in an RGB image was limited. Three different cameras were used in the reference of [54]. The image from an RGB camera covers the information of color, shape, and texture of lettuce, the one from a NIR camera infers the vegetation index, and the thermal image can be used to measure plant temperature. Three images were fused to diagnose the health level and growth of a plant in real-time. To improve the water stress detection accuracy, Stephen N [55] tested different color models and found the texture classification efficiency in the HIS color model achieved 99.45%. Experiments also showed that the system can recognize plant water stress 2 h before the human visual inspection. Plant morphology changing is also a signal for water stress. For instance, the plants under water stress generally have drooping leaves, they are wilted because of the imbalance between the water demand and water supply [56]. Therefore, detecting water stress by observing plant morphology is an interesting exploration.

The accuracy of this method still needs to be improved, although machine vision can monitor plant nutrient stress ahead of human vision. Gong Zhen [57] took the tomato and sweet pepper as the object, collected the characteristic spectra of nitrogen, phosphorus, and water, and extracted the canopy width, height, and stalk thickness of the plant through machine vision, these data were combined with the chemical analysis results and plant growth data. Finally, a prediction model of nutritional stress and growth was built. Compared with the model based on single data, this model performed better.

3. Robot operation assistance

To reduce labor costs and improve production efficiency, robots received widespread use in plant factories. They are mainly responsible for food production such as seedling, transplanting, picking, etc. Machine vision is as important to robots as eyes are to humans. It is helpful to navigate, recognize, and locate targets. The application process of machine vision on robots is as shown in Fig. 3. Next, a computer would analyze them to get the information such as path, target and its spatial coordinate from the image. And finally, the data is integrated to guide the robot behaviors.

3.1. *Visual navigation*

The navigation and localization system indoors include (i) map-based navigation systems, (ii) map-building-based navigation systems, and (iii) mapless navigation systems. The first method needs to build a robust and reliable map by sensors ahead of time, it is time-consuming and labor-intensive. On the other hand, the map built before is easy to be break due to the environment changing in plant factories, because other robots and equipment need to be introduced according to crop growth stages, they change space distributions. The second one requires more computational resources, time, and storage capability. So, a mapless navigation system based on machine vision is a potential technique [58–59]. This navigation method has the advantages of low cost, high accuracy, and rich information. It is suitable for robot navigation indoors.

Many researchers have proposed a path detection algorithm based on machine vision (Table 5), in which the most famous ones were Hough Transform, Least-Square Method (LSM), and Binocular Stereo Vision (BSV). Hough Transform has a good performance of anti-interference, it reduces the influence of navigation point errors and improves the fitting accuracy of navigation routes, but the algorithms run slowly and cannot meet the real-time requirements. LSM is a mathematical optimization technique. It selects the best function to match the path by minimizing the sum of squares of deviations. This is a commonly used method for crop row extraction, but the returned result is inaccurate when there are many error points. BSV is a technology that obtains the parallax of two images through two cameras and generates 3D information of the target image through a series of inverse projection transformations. It is difficult to synchronize two cameras that the stereo vision algorithm is usually more com-

Table 4 – Summary of machine vision used on plant stress detection.

Ref.	Plant type	Task	Color Model	Method	Result	Advantages	Disadvantages
[52]	Cucumber	Nutrient stress	RGB	Threshold segmentation, Gray level co-occurrence matrix	The correlation coefficient between G component and leaf nitrogen content and chlorophyll reached 0.88.	High prediction accuracy of the model	Only for cucumbers at a certain growth stage
[53]	Lettuce	The relationship between light intensity and color characteristics	RGB	Neural-Discrete Hungry Roach Infestation Optimization (N-DHRIO), ANN	Adjust light intensity automatically according to the needs of different parts of the lettuce	High detection accuracy, accurate and stable controlling result	Light control only for individual lettuce
[4]	Lettuce	Calcium deficiency	RGB, SHL	Gray-level co-occurrence matrix, Dual-segmented regression analysis	Identify calcium-deficient 1 day earlier than human vision	High detection sensitivity	The variable nature of lighting is problematic
[54]	Lettuce	Water stress detection	RGB, SHL	HSL filtering,	Able to detect the water stress 2 h before human visual	Combine RGB image, NIR image, and thermal image	Slow running speed, the whole process took about 11.2 min
[55]	Moss	Water stress detection	RGB, HIS, CIE, LAB, XYZ	Color Co-occurrence Matrix (CCM)	The HSI texture features achieved 99.45% water stress classification efficiency	Good detection result under varying light intensities	Some errors still need to be corrected
[56]	Impatiens	Identify plant water stress	RGB	Typical gray–level histogram segmentation	5 to 45 h earlier stress detection compared to human visual	Establish a water stress index using the plant movement information	Only one type of plant has been tested
[57]	Tomato, pepper	Nutrient stress	None	Median Filter	Established a spectral prediction model for crop nutrition	Fusion of hyperspectral, image, and chemical detection results	The accuracy of nutrient stress prediction has not been verified

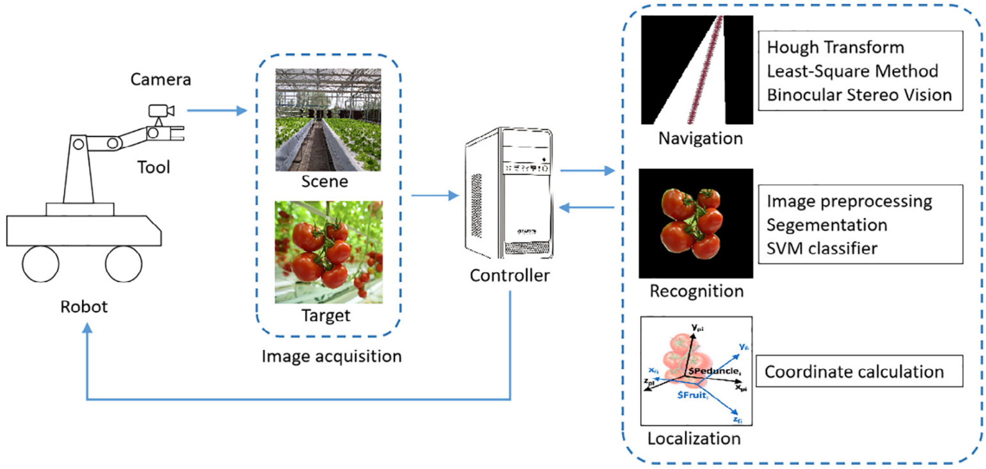

Fig. 3 – Application of machine vision on robot operating assistance.

Table 5 – Summary of machine vision used on navigation system.

Ref.	Color Model	Method	Result	Advantages	Disadvantages
[62]	RGB	Chromatic aberration operator (2G-R-B, Improved Hough transform	The average time of this method is less than 150 ms, and the maximum error is less than 5 cm when the path is tracked at 0.3 m/s.	The method of path extraction is more reliable	The method is time-consuming and the robot moves slowly
[63]	RGB	Improved grayscale factor, Otsu, Median point Hough transformation	The maximum error of the navigation path was 0.5° and the time taken was 7.13 ms, which is 45. 24 ms faster than the traditional Hough transform and on average 5.1° more accurate than the least-squares method	Faster running speed and more accurate	Easy to be affected by shadows and light
[64]	HIS	K-means, Morphological corrosion, Canny	Compared with common threshold segmentation methods, the road extraction rate can reach 95%, and the average single image processing time is reduced by 53.26%.	The algorithm is not interfered with by light, high road recognition rate faster calculation speed	The shelter will affect path recognition result
[65]	HIS	K-means, Improved Hough transform, Canny	It takes an average of 12.36 ms to extract the centerline of the crop row and the maximum lateral deviation within 5 cm.	Can effectively adapt to different light conditions	Low running speed
[66]	RGB	KLT algorithm	The vehicle demonstrated the ability to follow the center of a 61 cm wide path	The vehicle demonstrated the ability to turn at intersections, as well as drive through them	Low speed at intersections
[68]	RGB	Multi-Scale retinex, Improved Hough transform, QR code	The maximum lateral position deviation is 3.9 cm, the average heading angle deviation is 2.1°, and the average steering angle deviation is 5.6°	High accurate navigation by QR code	Robot speed is slower at corners

plicated and has a poor real-time performance [60–62]. Aiming at the existing problems, Chen Jiqing [63] proposed a midpoint Hough Transform algorithm based on an optical system. This method used an improved gray factor and Otsu algorithm to segment soil and plants, then extracted navigation points by relative coordinate centers in the binary image. Finally, the navigation path was fitted through the midpoint Hough Transform. Compared with the traditional Hough Transform (52.37 ms), the improved method only requires 7.13 ms, and its average accuracy is 5.1° higher than that of the LSM.

Different lighting conditions and shadows often bring challenges to robot navigation. In the researches of [64,65], the K-means algorithm was used to cluster and segment images, then the redundant and interfering information was removed by morphological corrosion method, the Canny operator was used to detect the edge of the road. This method performed better under different light conditions and has a higher road extraction rate with less time.

However, when the robot turns at the end of the road, the visual navigation has problems of low efficiency and a large deviation [66,67]. Wang Peng [68] designed a QR code navigation system. There was a QR code attached at the end of the road, and the navigation information has been stored in it ahead of time. The robot can accurately turn a corner by recognizing the QR code. The test results showed that the maximum navigation deviation was 3.9 cm when the robot traveled at 2 $m \cdot s^{-1}$.

3.2. *Target recognition and location*

Target recognition is the process of separating the plant from the background or fruit from the rest of the plant. It is a prerequisite for robots to complete tasks automatically, such as fruit picking and seedling transplanting. At the same time, the calculation is conducted between the global, camera, and image coordinates to obtain the spatial coordinate of the target, then the robot's manipulator moves to that location and takes action [69].

To make the transplanting robot works accurately and reliably, Ren Ye [15] used the Single-Connected Domain Analysis algorithm to extract the leaf area of seedlings and located them, then judged the seedling whether suitable for transplanting according to leaf area. The recognition accuracy rate reached more than 98%. Sometimes, there are empty holes in the seedling tray because of seed quality and mechanical damage. To replant the holes automatically, Zhang Xiao [70] segmented the seedling tray into the grids, then calculated the leaf area of the seedling and set a threshold to detect and locate the empty holes. The system has high recognition accuracy and a good replenishing effect. To make the picking robot works stably, Pulse Coupled Neural Network (PCNN) was used in the reference [71] to segment and recognize cucumber based on Least-Squares Support Vector Machine (LS-SVM). The 70 images were tested and found the correct recognition rate was 82.9%.

In practical applications, targets are not always segmented smoothly. The process becomes more difficult when the target colors change due to lighting conditions, or they are similar to the background. Some researchers tried to segment the target based on its texture and shape features, but a threshold defining the features needs to be given, the calculation results are greatly affected by the threshold. Using a statistical method to extract image features is a practical technique. Firstly, modeling the image from the statistical perspective. Secondly, finding the set of pixels with the greatest probability. Zhang Ping [72] proposed an Unsupervised Conditional Random Field Image segmentation algorithm (ULCRF) by combining the Conditional Random Field (CRF) and Latent Dirichlet Allocation (LDA) algorithm. The LDA's segmentation result was used as the initial mark of CRF, then CRF was used to reflect the difference of pixels. This algorithm can segment the plant from the background or the organ (fruit, leaf, and stem) from plants quickly with higher accuracy. Many of the researches just focused on the scenario of daytime, but operating at nighttime can overcome the problem of low work efficiency. Longsheng Fu [73] recognized kiwifruit at nighttime based on machine vision with the help of artificial lighting. Firstly, an RGB camera was placed underneath the canopy so that clusters of kiwifruits could be included in the images. Next, the images were segmented in an R-G color model. Finally, a group of image processing conventional methods such as the Canny operator was applied to detect the fruits. The developed algorithm recognized 88.3% of the fruits successfully.

4. Fruit grading

Machine vision also has been applied widely in the field of fruit grading. It promoted the automatic development of the food processing industry. In these researches, the SVM and ANN were used to define fruit maturity or quality. Their accuracy depends on whether there is a large number of reliable data sets to train them. As shown in Fig. 4, this technology plays a part in these scenes.

4.1. *Maturity grading*

Vegetables such as tomatoes and cucumbers have different flowering and fruiting times. The maturity degree varies with the individual. One-time harvesting cannot meet the requirements of maturity, quality, and marketing standards, so it needs to detect and select ripe fruits before picking.

Zhang Jingqi [74] adopted the GrabCut algorithm to segment the tomatoes from the background, and the K-means clustering operation was carried out to divide them into green, half-ripe and mature in the HSV color model. Finally, the SVM classifier classifies different fruits, the accuracy rate of classification reached more than 92%. To solve the problems that plant stems and hanging ropes shelter tomato fruits and cause interference to machine recognition, Wang Xinzhong [75] used color features to segment fruit-sensitive areas and removed background noises such as leaves, stems, and facilities in plant factories through morphological calculation. The regional hole-filling algorithm was used to eliminate the bright holes formed by sunlight, and finally, the sequential method was used to track and segment the boundary of the multi-fruit area. In this study, the tomatoes were classified into five mature degrees. To improve classification

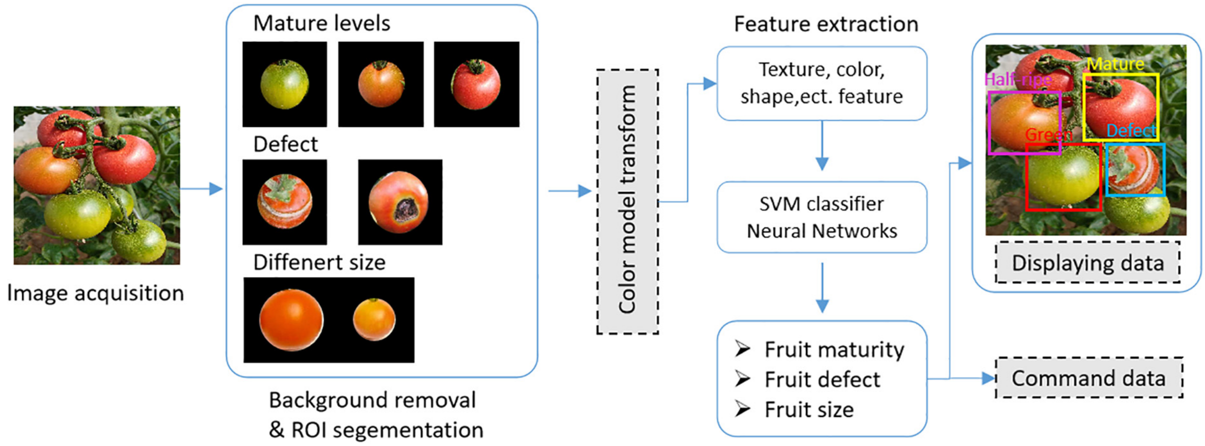

Fig. 4 – Application process of machine vision on fruit grading.

efficiency, reference [76] combined Neural Network, Regression Model, and Extreme Learning Machine (ELM), and proposed a Deep Stacking Sparse Auto-Encoder (DSSAE) to grade tomato maturity by image data directly. This method was fast because it didn't need to extract features from the image.

Most reports regarded red as the symbol of ripe tomato. However, to reduce the damage during transportation and make sure the fruits at a perfect level when they are shipped to retailers, the grower demands to pick the ripe fruit with the green color and hardness appearance. These kinds of fruits remain fresh and good-looking when be delivered to retailers. These particular demands raise a new problem. The green tomato is similar to the leaves and stems in color, which brings challenges to separate fruits from the background. Li Han [77] used the Fast Normalized Cross-Correlation function (FNCC) to detect the potential area of the fruit, then separated the potential fruit area and removed the non-fruit area based on the histogram information. The Hough Transform circle was used to extract the position of green fruit. The two results were fused to recognize the green tomatoes. The recognition rate for 83 images was 89.2%. Different varieties of tomatoes have different colors when they are mature. Harvest time judgment based on color is limited. Takuya Fujinaga [78] explained a method of generating a map of the tomato growth states to monitor the various stages of tomato and decide a harvesting timing for robots. The tomato growth state map visualized the relationship between the maturity stage, harvest time, and yield. The present tomato picking system uses multi-spectral sensors, color, and other passive sensors for tomato detection and recognition. There is a narrow detection range and poor anti-interference ability, and detecting cannot be performed accurately in real-time. Jun Liu [79] proposed an improved DenseNet Deep Neural Network architecture and the Focal Loss function to enhance the accuracy of feature propagation and reduce the amount of stored data. Experiments showed that the improved network was superior to other existing deep models in terms of detection rate and FPPI, and its computational complexity is lower than that of the DenseNet algorithm 18% under the same hardware and software configuration.

Additionally, some researchers suggested maturity grading of other fruits based on machine vision. The results proved pretty good. The research [80] introduced two approaches based on machine learning and transfer learning on the classification of papaya maturity. Among these approaches, VGG19 performed better with 100% accuracy and 112 s training time, which is 6% more than the existing method. In [81] investigation, maturity levels of bell peppers were judged by measuring Total Soluble Solids (TSS), Brix, and refractometry. The maturity classifier based on the neural networks (RBF-ANN) and Fuzzy Logic models (ANFIS) were tested, respectively, and the accuracy was 100% and 88%. The absorbance data was used in Yue Xiaoqin's research to establish three maturity recognition models (multivariate linear, multivariate nonlinear, and SoftMax regression classifier). Then strawberry maturity was divided into three levels, and the results showed that the Multivariate Nonlinear model gives the highest identification rate (over 94%) in greenhouses [82]. These research results confirm the advantages of machine vision in fruit maturity grading.

4.2. *Quality classification*

In other researches, people tried to grade fruit by detecting quality. It is a meaningful thing. For example, if there have one tomato cracked, the quality of all tomatoes in the box decreases during transportation, which would cause an economic loss. Kick-out cracked one early could avoid such things from happening.

Liu Hongfei [83] fitted the contour of a single tomato through the improved Hough Transform based on the Least-Squares Method, and the 2D Gabor wavelet operator was used to extract the texture of the fitted image and judge the cracking fruit. The correct recognition rate of fruit was 91.41%, while the correct recognition rate of cracking fruit was 97.14%. Xie Weijun [84] extracted carrot features such as the green shoulder, bending, fibrous root, surface cracking, and fracture to classify them. The green shoulder was identified by binarizing the image under the H component of the color model, the bending characteristics were obtained by extracting carrot skeleton, the fibrous roots were determined by the slope of the carrot edge under the S component, the surface cracking was obtained by binarizing the G and B components, and the fracture was judged by the slope of the carrot tip under the H component. Longsheng Fu [85] demonstrated the feasibility of classifying kiwifruit into different grades by calculating fruit length, the maximum diameter of an equatorial section, and projected area. Results showed that fruit classification based on the estimated minimum diameter of the equatorial section achieved a success rate of 84.6%. This number can be improved to 98.3% when a linear combination of the length/maximum diameter of the equatorial section and projected area/length ratios were used. Table 6 compares some methods and results. The sample for model training in most existing researches does not exceed 100 images.

5. The application of deep learning in a plant factory

Machine vision application in plant factories includes but is not limited to the aspects mentioned above. Image analysis is an important research area in these applications. The most methods for image analysis in our survey consist of K-means, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and other basic image processing algorithms, such as Ostu, Decision Tree, Random Forest, Threshold Segmentation, and Hough Transform. Features must be hand-crafted to suit the particular object in these classical machine-vision approaches. Decision-making is dependent on hand-crafted methods or learning-based classifiers such as SVM and Decision Tree. So, hand-crafted features play an important role [86]. The uncertainty of factors such as lighting conditions, crop growth conditions, and viewing distance increases the difficulty of feature selection and design, which affects the robustness and generalization of algorithms.

In recent years, computer vision based on deep learning has proven promising for real-time applications. Based on the massive original data and the neural network structure with multiple hidden layers, this technique realizes autonomous learning and is faster, which avoids the interference caused by hand-craft features [87,88]. The highly hierarchical structure and large learning capacity make them flexible and adaptable for highly complex challenges when performing classification and predictions. Deep learning is popular now in the precision manufacturing industry. It helps manufacturing transform into highly optimized smart facilities by finishing the descriptive-analytic, diagnostic-analytic, predictive-analytic, and prescriptive-analytic tasks. The application reduces operating costs, keeps up with changing consumer demand, improves productivity, and reduces downtime [89]. In the references of [90,91], the technique does a one-shot recognition for defects on the steel surface and detects surface anomalies of products. The results showed that deep learning could significantly reduce the requirements of data training and have a good performance.

What is used in the manufacturing industry also allows used in precision agriculture and plant factory. However, the image acquisition process in agriculture is difficult, as there are complex crop features and backgrounds. Additionally, image acquisition must be timed and synchronized to the crop growth cycle (only once a year for many crops). Zhao Qihui proposed a kind of method for classifying leaf water stress degrees based on R-CNN and Dense Net169, and the classification accuracy of the model on the test set was 94.68% [92]. Wang Tiewei proposed an approach based on data-balanced Faster R CNN for ripe degree recognition of winter jujube. The average recognition accuracy was 98.50%, which was higher than YOLOv3 [93]. In some reports, deep learning is a tool to classify the different fruits [94], organs of plants

Table 6 – Comparison of grading methods and results in different studies.

Ref.	Plant	Task	Color model	Method	Sample number	Results
[74]	Tomato	Maturity classification, divided into green ripe, half-ripe, and mature	HSV	K-means, SVM	65	The maturity classification accuracy rate in 100 images can reach more than 92%
[75]	Tomato	Maturity classification, divided into green ripeness, ripening, half ripening, ripe, and perfectly ripe	HIS, RGB	BPNN	70	The correct grading rate in 100 images reaches 93%
[76]	Tomato	The quality is divided into 5 levels from good to bad	RGB	ANN, ELM	840	The grading accuracy rate in 126 images is 95.5%
[77]	Tomato	Detect the potential area of the fruit	HSV, RGB	FNCC, Hough Transform circle	Not mentioned	Recognition accuracy for 83 images was 89.2%
[83]	Tomato	Cracking fruit detection	RGB	SVM	50	The correct recognition rate of 35 images is 97.14%
[84]	Carrot	Classification based on the green shoulder, bending, root, cracked, broken	HSV, RGB	Feature extraction in different color model components	Not mentioned	The total recognition rate among 720 images is 90.9%

[95], and small sample data [96], it was proven faster, and better in real-time performance.

Nevertheless, while visual pattern recognition based on deep learning carries enormous economic value in agriculture, little progress has been made to merge computer vision and crop sciences due to the lack of suitable agricultural image datasets. Most existing datasets primarily focus on objects or street views, such as Pascal VOC, MS-COCO, and ADE20K segmentation datasets [97]. In the study [98], benchmark dataset for crop/weed discrimination, a single plant phenotype was proposed. There were 60 images with annotations in the datasets. For each picture, there has a ground truth vegetation segmentation mask and manual annotation of the plant type (crop vs. weed) supplied. To improve the detection accuracy and efficiency, Liu Liu constructed the standard pest detection datasets of MPD2018 and AgriPest based on the accumulation of the past five years. 88 K pest images and 582 K pest annotations are contained in MPD2018, while the 49 K pest images and 264 K pest annotations are included in AgriPest [99]. However, these datasets are not available in a plant factory. It is urgent to collect and construct the plant factory datasets for deep learning techniques in the future.

6. Challenges faced by machine vision in a plant factory

In plant factories, machine vision application covers nearly all production links, from plant seedling, transplanting, cultivation, and harvesting to quality inspection [100]. This technology has a great potential for promoting the development of intelligent plant factories. Some challenges still are faced by it, although the existing methods have solved some practical problems at low cost, high efficiency, and high precision.

6.1. *Failure of image processing algorithms*

Artificial light (LED) usually can provide plants indoors with suitable lighting [101,102]. The two light sources used most are red light (660 nm) and blue light (460 nm). They are turned on at the same time to improve the photosynthetic rate of plants. It appears to be purple after the lights are combined [103]. Images captured under these lighting conditions bring some challenges for segmentation algorithms. We took a healthy green plant (Epipremnum aureum) from the office as an object to have a test. Images were taken under the sunlight and artificial light lighted (red and blue), respectively. The background color of the two images was white, and only the lighting conditions were different. The common segmentation algorithms were used and to extract the canopy of the Epipremnum aureum. The results showed in Fig. 5. For the images taken under sunlight, every algorithm can separate plant canopy from the background except for some noises for some algorithms. The watershed algorithm had the best performance among them. For the image took under the LED lights, all algorithms failed to separate the canopy area of the plant, and it did not work even for the watershed algorithm.

Segmentation is the first step for image processing, and it is the premise of feature extraction and image analysis [104,105]. However, under the different lighting conditions of the plant factory, the usual algorithms often fail. There is a particular and complex environment indoors due to many supporting facilities, such as irrigation pipes, hanging ropes, monitoring equipment, mechanical devices, etc. The plant itself contains fruits, leaves, and stems. The color of fruits is similar to the color of leaves for some plants like cucumber. The targets also are easy to be sheltered by leaves. All these factors have posed new challenges to the existing segmentation algorithms.

In the surveyed researches, the SVM and ANNs with a supervised learning process were the widely used methods. The results of these methods are dependent on whether there are a large number of standard datasets to train it. The number of images for classifier training in many references did not exceed 100, so the classification accuracy varies with studies greatly. On the other hand, it takes a lot of time and computer memory from model training to model use. Unsupervised grading algorithms can support classify tasks without training samples, these methods are the best choice when dealing

Fig. 5 – Comparison of plant segmentation results of different algorithms under sunlight and artificial light.

with unstructured image repositories [106], and they are more efficient [107]. Recently, deep learning was also proven promising in precision agriculture, but the progress of this technique in the plant factory is relatively slow. It is partially due to the lack of relevant datasets that encourage the studies on agricultural imagery and visual patterns. Therefore, developing unsupervised grading algorithms and constructing the standard datasets for agricultural image analysis is urgent works to do in the future. On the other hand, developing robust algorithms for scenarios in greenhouses and plant factories is a study trend.

6.2. *Gaps in basic theoretical knowledge*

Undoubtedly, machine vision technology has significant advantages when applied in a plant factory. It works in a non-invasive way and is more timely, accurate, and efficient [108]. Different plants have different parameters even under the same growth conditions, so the information from a single plant is not representative and cannot be used as a basis for decision-making. But it is not realistic to collect all plant information in a limited time. The planting architectures (vertical or plane planting) and environmental unevenness (air temperature, humidity, flow speed) will also lead to different plant growth conditions in different areas. How to take all of these factors into account and form a standard, to guide the inspection points deployment of machine vision, and indicate the real growth status of plants precisely, is meaningful work to do. Additionally, the detection accuracy of plant nutrition stress lacks verification [109]. Much deviation would cause the excessive or insufficient response of control systems. What is the relationship between the environmental parameters, nutritional conditions, plant growth, and the diseases and pests in plant factories? Can they be predicted accurately to reduce economic loss? They are not involved in recent researches.

The gap in theoretical knowledge will seriously affect the application effect of machine vision in plant factories. Therefore, mathematical models can be built to predict plant growth, nutrient needs, and health levels through deep learning technology. With the progress of information technology, big data has become an unavoidable topic. It is promising to combine big data with machine vision to promote plant factory development in the future.

6.3. *Lack of image acquisition hardware*

Image quality hurts image processing. Most of the images in surveyed references were taken by digital cameras manually, which inevitably causes uneven image quality. A few people used industrial cameras mounted on a robot to take images, but there was a poor anti-shake effect. Besides, there is limited scope for cameras. It is incapable of capturing plants growing in the vertical space through the cameras in the market. In the long-term, as a vision sensor, image acquisition equipment should be the same as other sensors. Some products with high accuracy, strong applicability, and low cost need to be created. It is also necessary to design some supporting equipment in the plant factory to meet its application scenarios, such as slide rails, short-range or long-range shooting cameras, and mounting bases.

7. Conclusions

Machine vision is vital in promoting plant factory development. The recent research results of this technique are reviewed and analyzed in this paper. Specifically, we focused on fields of plant growth monitoring, robot operation assistance, and fruit grading. Based on the latest references, the challenges that machine vision faced in plant factories are analyzed. Firstly, the changing lighting conditions and the complicated background indoors make the existing algorithms fail to segment feature areas from images. The datasets for deep learning are not available in plant factories. Secondly, there are theoretical knowledge gaps about machine vision's application in the specific scenarios indoors, which affect the application effect of the technique. Thirdly, the camera's anti-shake function is not good, and the captured scope is limited. It is incapable of taking images of plants growing in the vertical space, and the supporting equipment for image acquisition is still insufficient. These problems hinder the further application of machine vision in plant factories. Nevertheless, machine vision still is a powerful tool to promote plant factory development at present. It has irreplaceable advantages in precision agriculture. We believed that this technology would become more robust, efficient, and reliable with the progress of information technology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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