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INFORMATION PROCESSING IN AGRICULTURE 7 (2020) 1–19

journal homepage: www.elsevier.com/locate/inpa

Computer vision technology in agricultural automation —A review

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A R T I C L E I N F O

Article history:
Received 10 June 2019
Received in revised form
24 September 2019
Accepted 27 September 2019
Available online 27 September 2019

Keywords:
Computer vision
Image processing
Agricultural automation
Intelligent detection

A B S T R A C T

Computer vision is a field that involves making a machine “see”. This technology uses a camera and computer instead of the human eye to identify, track and measure targets for further image processing. With the development of computer vision, such technology has been widely used in the field of agricultural automation and plays a key role in its development. This review systematically summarizes and analyzes the technologies and challenges over the past three years and explores future opportunities and prospects to form the latest reference for researchers. Through the analyses, it is found that the existing technology can help the development of agricultural automation for small field farming to achieve the advantages of low cost, high efficiency and high precision. However, there are still major challenges. First, the technology will continue to expand into new application areas in the future, and there will be more technological issues that need to be overcome. It is essential to build large-scale data sets. Second, with the rapid development of agricultural automation, the demand for professionals will continue to grow. Finally, the robust performance of related technologies in various complex environments will also face challenges. Through analysis and discussion, we believe that in the future, computer vision technology will be combined with intelligent technology such as deep learning technology, be applied to every aspect of agricultural production management based on large-scale datasets, be more widely used to solve the current agricultural problems, and better improve the economic, general and robust performance of agricultural automation systems, thus promoting the development of agricultural automation equipment and systems in a more intelligent direction.

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Peer review under responsibility of China Agricultural University.
https://doi.org/10.1016/j.inpa.2019.09.006
2214-3173

Contents

1. Introduction

In recent years, agriculture has played a key role in the global economy. As the population continues to expand, urbanization will lead to a gradual reduction in the area of cultivated land, and the pressure on the agricultural system will continue to increase [1,2]. The demand for effective and safe agricultural food production methods is growing [3–5]. Traditional agricultural management methods must be complemented by innovative sensing and driving technologies and improved information and communication technologies [6] to accelerate the increase in agricultural productivity in a more accurate manner, thereby promoting the development of high-quality and high-yield agriculture [7]. In the past few decades, computer vision inspection systems have become important tools in agricultural operations [8], and their use has greatly increased [9]. Expert and intelligent systems based on computer vision algorithms are becoming a common part of agricultural production management, and computer vision-based agricultural automation technology is increasingly used in agriculture to increase productivity and efficiency [10]. With the development of technologies such as GPUs (Graphics Processing Units) and DBNs (Deep Belief Networks) and the rapid development of artificial intelligence [11], the ability of computer vision technology has been greatly improved, and the improvements in resource efficiency [12] have provided many suggestions and insights for decision support and practices for farmers [13], ensuring the efficiency of agricultural production [14]. Therefore, computer vision technology will be increasingly applied to the field of agricultural automation and will steadily promote the development of agriculture to the era of intelligent agriculture 4.0 [15] (see Tables 2-1–2-6)

This review systematically summarizes the articles and findings from 2017 to 2019, analyzes the existing technologies and challenges, and explores the future opportunities and prospects to develop a current reference for researchers. Chapter 2 of this review introduces the developments and applications of computer vision technology in the field of agricultural automation. Six areas are involved in this section, including monitoring of crop growth, disease prevention, automatic harvesting, quality testing, automated management of modern farms and the monitoring of farmland information with Unmanned Aerial Vehicle (UAV). Chapter 3 analyzes the serious challenges faced in applying computer vision technology in the field of agricultural automation. Chapter 4 discusses the application prospects of computer vision technology in the field of agricultural automation. Finally, the conclusions are discussed.

2. The development status of computer vision technology in agricultural automation

2.1. *The monitoring of the healthy growth of crops*

The healthy growth of crops determines the yield, quality, resource utilization and ultimate economic benefits of agricultural production. However, there are a total of 17 essential elements that are needed for the growth of crops [16], including macronutrients, secondary nutrients and micronutrients. Traditionally, the monitoring of crop growth mainly relies on subjective human judgment and is not timely or accurate. Crop monitoring is an essential aspect of precision agriculture that captures information at different crop growth stages. Having an accurate understanding of the growth environment to make appropriate adjustments and optimize the growth environment of crops is greatly helpful in improving the production efficiency [17]. Compared with manual operations, the real-time monitoring of crop growth by applying computer vision technology can detect the subtle changes in crops due to malnutrition much earlier than human monitoring and can provide a reliable and accurate basis for timely regulation [18].

Dóra Faragó et al. [19] measured the basic morphology and physiological parameters of plants grown in vitro based on a noninvasive method. The images were comprehensively analyzed according to plant-size using MATLAB, and the main parameters, such as the plant size, convex ratio and chlorophyll content, were calculated. This method has the charac-

Table 2-1 – . Summary of methods used for crop health growth monitoring.

Author and year	Application goals and scenarios	Method adopted	Types of sensors	The results obtained	Advantages and disadvantages
Farago et al. [19]	Measurement of plant morphology and parameters	A noninvasive method	Canon PowerShot SX20	Parameters such as the chlorophyll content of plants were obtained.	Strong versatility, low cost and relatively simple
Rico-Fernández et al. [8]	Measurement of plant growth indicators, etc.	Threshold segmentation, machine learning, CIE Luv color space, etc.	A camera mounted to Bonirob Canon PowerShot S95 Canon EOS REBEL T2i	A very good result was achieved.	Ability to work in a variety of crops and environments Analysis of images with backlight is still very challenging.
Pérez-Zavala et al. [20]	Monitoring of grape growth	A method based on shape and texture information and clustering pixels	Visible spectrum cameras	Grape bunches and individual berries were accurately detected.	It operates reliably under different lighting and occlusion conditions.
Fahmi et al. [21]	Monitoring of palm oil plantations	Gray level cooccurrence matrix (GLCM) method	Drone type DJI 3 type Phantom	The accuracy of the system was achieved.	UAV-based monitoring can obtain information more quickly and accurately.
Yuanyuan Sun et al. [23]	Diagnosis of nitrogen content in rice leaves	A method for extracting features of different locations using MATLAB	A high-resolution camera	The blade change process was quantified.	Continuous and dynamic analysis can be performed without damage.
Zhu et al. [24]	Observation of the heading date of wheat	An automatic observation system based on computer vision	E450 Olympus	The absolute error of the method is 1.14 days compared to other methods.	The method has small error and good robustness.
Sadeghi-Tehran et al. [25]	Determination of the growth stage during the heading and flowering periods	A method for automatically detecting wheat heading and flowering	8 MP camera	The proposed method is robust enough and the flowering detection accuracy is 85.45%.	Heading and flowering can be monitored at the same time, with high detection accuracy and robustness.

Table 2-2 – . Summary of methods for the prevention and control of crop diseases, pests and weeds.

Author and year	Application goals and scenarios	Method adopted	Types of sensors	The results obtained	Advantages and disadvantages
Maharlooei et al. [30]	Detection and counting of soybean aphids	Image processing technology	Canon EOS Rebel T2i Sony DSC-W80 Panasonic DMC-ZS20 Canon EOS Rebel T2i DSLR Canon power shot G11	The image processing toolbox enables the identification and enumeration of mites.	Lower cost and ideal accuracy in high light conditions. However, there are some differences in low light.
Liu and Chahl, [31]	Detection of common invertebrate pests in farmland	A multispectral 3D MVS	Foral reflectance database	Acceptable accuracy	The precision is high, and the robot system can be optimized in real time.
Zhong et al. [32]	Fast counting and identification of flying insects	Raspberry PI	Raspberry Pi Camera Module v2	Average counting accuracy is 92.50% and average classification accuracy is 90.18%.	Easy to use, real-time intelligent monitoring is possible.
Xiaolong et al. [33]	Automatic counting of stripe rust spores	Automatic counting system based on image processing	An inverted microscope	The accuracy rate is over 95%.	Accuracy is high, but further exploration is needed in the natural and other environments.
Wang et al. [34]	Identification of apple black rot	Deep convolutional neural network	PlantVillage dataset	Produced 90.4% accuracy on the test set.	Innovative application of a deep learning model.
Toseef and Khan [35]	Diagnosis of diseases in wheat and cotton crops	Fuzzy inference system	Websites of agriculture departments of governments Websites of agriculture universities Online literature Field surveys Agriculture experts	Accuracy is as high as 99%.	The invention realizes the establishment of a small data set innovatively and can simultaneously detect wheat and cotton, is convenient to use and has great potential.
Sabzi et al. [36]	Identification of potato plants and three different weeds	Computer vision expert system based on a neural network	DFK 23GM021	Recognition accuracy of 98.38% and average PC execution time of less than 0.8 s.	Achieves high accuracy and high efficiency. However, if the density of the plants is very high, they cannot be separated independently.
Zhai et al. [37]	Precise spraying of pesticides	Genetic algorithm and particle swarm optimization algorithm	Six unmanned aerial vehicles	Able to effectively plan tasks and allocate scarce resources.	Can effectively plan tasks and allocate scarce resources.
Chang and Lin [38]	Automatic weeding and variable irrigation	Combines computer vision and multitasking	Logitech digital webcam	Average herbicidal rate of 90% and average classification rate of 90% or higher.	High accuracy, saves resources and good prospects.

Table 2-3 – . Summary of applications to the automatic harvesting of crops.

Author and year	Application goals and scenarios	Method adopted	Types of sensors	The results obtained	Advantages and disadvantages
Yuan Ting [43]	Picking cucumbers automatically in a greenhouse environment	Cucumber recognition and feature acquisition based on near infrared imaging	Hyper HAD CCD	The success rate of the extraction of the grab area is 83.3%.	The method uses spectroscopy innovatively, but the recognition accuracy needs to be improved.
Zhang et al. [44]	Automatic identification of cherries in a natural environment	A robot vision system identification method	0.9R-G Otsu algorithm Canny operator Hough transform	The recognition success rate of cherries is over 96%.	Reduce the difficulty and cost of picking and improve efficiency
Christopher McCool [45]	Accurate identification of sweet pepper crops	A new type of sweet pepper (chili) vision-based detection system	JAI AD-130GE	The LBP feature is used to realize ideal recognition.	The features are very novel and close to the human eye recognition effect, but the accuracy still needs to be improved.
Joseph R. Davidson[47]	Automated harvesting of apples.	The machine vision system combines a circular Hough transform and speckle analysis to achieve detection	Prosilica GC1290C Camcube 3.0	The collection rate is 95%, and the average positioning and picking time are 1.2 and 6.8 s, respectively.	The robot demonstrates the advantages of low cost and high efficiency.
Ji Wei [48]	Improve the efficiency of robotic apple picking	A retinex algorithm based on a guided filter	UniflyM216	Real-time and more efficient than traditional algorithms and continuous operation at night can be achieved	Compared with traditional algorithms, the accuracy and efficiency of nighttime operation are greatly improved.

Table 2-4 – . Summary of agricultural product quality testing.

Author and year	Application goals and scenarios	Method adopted	Types of sensors	The results obtained	Advantages and disadvantages
Deng [56]	Automatic carrot grading	An automatic carrot sorting system using machine vision technology	MV-VDM033SM/SC	The detection accuracy of each part is 95.5%, 98% and 88.3% respectively.	The method has high precision and high efficiency. However, the detection accuracy of the crack portion has yet to be improved.
Firouzjaei et al. [57]	Rapid nondestructive testing of sweet lemon damage	A method for rapid detection using an image processing technology	Canon powershot-SX30 IS	The method has an accuracy rate of 100% for damaged and undamaged fruits.	The quality detection and classification accuracy is high.
Kim et al. [58]	Nondestructive testing of potatoes	Nondestructive testing system based on machine vision technology	Monochrome CCD camera	Achieved a higher accuracy.	Nondestructive, high accuracy.
Iraji [59]	Tomato inspection and quality processing	A deep stack sparse autoencoder (DSSAEs) method	A data set from a farm in Toskola	The sensitivity of the method is 83.2% and the accuracy is 95.5%.	The system can classify data directly from the dataset without image processing technology to extract features.
Wang et al. [60]	Fruit quality testing	A portable near infrared (NIR) system called “SeeFruits”	ImSpectorV17E C8484-05	The system has a score of 0.89 in qualitative tasks and 0.83 in quantitative tasks.	The system is fast, flexible and friendly. However, the detection error still needs to be reduced.
Wang et al. [61]	Detection of internal damage to blueberries	A method combining a CNN structure and hyperspectral transmittance data	Isuzu Optics Corp., Taiwan	The experiments show that the two deep learning models have better classification performance than the traditional methods.	The combination of a CNN structure and hyperspectral transmittance data has a very strong development potential.

Table 2-5 – . Summary of modern farm automation management.

Author and year	Application goals and scenarios	Method adopted	Types of sensors	The results obtained	Advantages and disadvantages
Sudarsan et al. [66]	Estimation of soil texture and SOM	A new cost-effective in situ computer vision sensor system	AD 7013MT	This method shows low cost and portability.	It is low cost and portable. However, the robustness is further tested in different environments.
González-Esquiva et al. [68]	Management of irrigation water balance	A novel use of low-cost cameras and client-server architecture systems	A set low cost camera modules	High precision with an average error of less than 5%	High precision, low time, integration and scalability
Michael Halstead [70]	Accurately estimate the maturity of sweet pepper	Efficient detection using the FRCNN framework	Cheap off-the-shelf cameras	The system can accurately estimate the number of sweet peppers that appear.	The cost is low and relatively stable.
Wan et al. [71]	Detect tomato maturity	Technique combines characteristic color values with a back propagation neural network (BPNN).	SONY NEX5N	The average accuracy of the method for detecting tomato maturity is 99.31%.	Excellent precision and high satisfaction
Maldonado and Barbosa [72]	Estimation of citrus crop yield	A green fruit feature extraction method and a technique for estimating the citrus crop yield.	SONY DSC-W530	The false positive rate in the images obtained under good conditions is 3%.	High efficiency and small error
Gutiérrez et al. [73]	Estimation of mango crop yield	Line scan HIS technology.	Resonon Pika II Vis-NIR Prosilica GT3300C	The yield can be estimated more accurately.	Compatible with the most advanced RGB technology.

Table 2-6 – . Summary of the monitoring of farmland information with UAV.

Author and year	Application goals and scenarios	Method adopted	Types of sensors	Results obtained	Advantages and disadvantages
Guilherme Martineli Sanches et al., 2018 [84]	Prediction of yield from sugarcane field	Evaluation indexes: LAI and GRVI	12.4 megapixel 1/2.3-inch CMOS RGB camera	Approximately 10% can be added to output by both indices.	How to improve the yield model to extract plant height remains to be explored.
Victor P. Rueda-Ayala2019 [85]	Study on plant height and biomass on grassland	Digital grassland model	UAV with geolocation and RGB cameras	UAV shows great consistency.	UAV systems are cheaper, more stable and easier to operate.
Liang Han et al., 2019 [86]	Investigation of maize biomass	A machine learning method for modeling aboveground corn biomass	An Octocopter DJI Spreading Wings S1000 UAV platform equipped with two cameras	The combination of machine learning with UAV is promising.	It works well with machine learning.
Yaxiao Niu et al., 2019 [87]	Estimation of corn biomass	A machine learning method	Quadrotor UAV-RGB remote sensing system DJI Phantom 4 Pro	The effect is ideal.	It works well with machine learning.
Pedro Marques et al., 2019 [93]	Automatic monitoring of chestnut trees	A combined RGB and NIR model based on VI calculation.	senseFly eBee with RGB and CIR	It can manage chestnut plantations in a faster and more sustainable way.	Fast and stable
Juan Enciso et al., 2019 [94]	Growth monitoring of tomato	A measurement method based on UAV	DJI Phantom 4 Pro platform	No significant difference was observed between UAV and manual test results.	Some errors still need to be corrected.
Carlos Henrique Wachholz de Souza et al., 2017 [95]	Monitoring sugarcane field	An object-based UAV image analysis (OBIA) method	eBee Ag with a Canon PowerShot S110 compact camera	OBIA exhibits a high degree of automation and adaptability.	It can contribute to decision-making and agricultural monitoring.
Xiang Shi et al., 2019 [96]	Making irrigation decisions	Decision support system for irrigation based on multispectral UAV spectrum.	UAV infrared multispectral platform	It shows strong rationality, consistent with expected results	Reliability needs to be further improved.
Luxon Nhamo et al., 2018 [97]	Improving irrigation accuracy	A method to enhance the post-classification capability of UAV	Phantom 4 Pro drone with built-in camera	The accuracy of irrigation to the area increased from 71% to 95%.	It has certain feasibility and applicability.

teristics of strong versatility and low cost and is relatively simple. M.P. Rico-Fernández et al. [8] conducted further research; they studied the effects of botanical indicators and the color space using different machine learning algorithms and observed the changes in crop types, leaf color, and so on. They compared existing methods such as threshold processing and machine learning. On the basis of the analysis, a new formula, including the CIE Luv color space and a support vector machine, was proposed, and it has achieved good results in crop monitoring. This method can be applied to a variety of environments and crop species. However, it is still very challenging to analyze the images and improve the efficiency and accuracy of an analysis under backlight conditions.

Researchers have developed relevant monitoring methods for different plants with the aim of making monitoring faster and more accurate. Rodrigo Pérez-Zavala et al. [20] used a visible spectrum camera for robust grape berry recognition and grape bunch detection. The method they proposed relies on the shape, texture information, and segmentation of aggregated pixel regions. The evaluation results show that the grape monitoring accuracy was improved. This method works reliably under different lighting and occlusion conditions. In the same year, F Fahmi et al. [21] performed orthophoto processing on palm oil plantations based on the MATLAB image processing algorithm in a UAV. They used a GLCM (Grayscale Cooccurrence Matrix) method to classify fertile, sterile, and dead palm oil plants and developed parameters based on four directions and specific degrees of 0°, 45°, 90°, and 135°. The experiments showed that UAV-based monitoring can obtain information more quickly and accurately than traditional methods.

The yield and quality of important crops such as rice and wheat [22] determine the stability of food security, so it is essential to be able to continuously and nondestructively monitor plant growth and the response to nutrient requirements. Yuanyuan Sun et al. [23] analyzed the dynamic characteristics of rice leaves to diagnose nitrogen levels and used MATLAB to extract the leaf characteristics of different leaf positions. Newly developed features such as the yellowing area (EA), degree of yellowing (ED), and shape (area and perimeter), as well as color characteristics (green, standardized red index, etc.) are used to quantify the blade variation process. The advantage of this method is that it can be performed continuously and dynamically without damaging the plants. The heading date of wheat is one of the most important parameters for wheat crops. To accurately capture the heading date of wheat, Zhu et al. [24] studied an automatic computer vision observation system for the wheat heading period. The detection system was divided into rough detection and fine detection. They collected images under natural conditions, changed the lighting conditions frequently and conducted a series of experiments. The experimental results showed that the method was obviously superior to the existing method, and the absolute error of the test dataset was 1.14 days. The method had small errors and good robustness, but it was limited to monitoring the heading period. For the purpose of simultaneously monitoring the growth stage of the heading and flowering stages of wheat, Sadeghi Tehran P et al. [25] conducted further research and developed an automated method for monitoring both the wheat heading and flowering. The method has better detection accuracy than other methods, and the method is robust enough to be used for complex environmental changes such as illumination and occlusion.

The existing computer vision technologies can address the deficiencies of traditional monitoring and reduce the difficulty of traditional growth monitoring in terms of time, continuity and cost. Computer vision technology has the advantages of low cost, small error, high efficiency and good robustness and can be dynamically and continuously analyzed. However, the related methods still have limitations, achieving versatility and stability in various complicated situations is still challenging and extensive work will be required in the future in this regard.

2.2. *The prevention and control of crop diseases, insect pests and weeds*

The prevention and control of crop diseases, insects and weeds are the key steps in producing high-quality and pollution-free agricultural products and achieving high yields. Making full use of comprehensive agricultural measures to quickly and accurately diagnose the occurrence of pests and diseases [26] in farmland and to automatically and accurately estimate the severity of diseases is critical in crop disease prevention and control and the reduction of yield losses [27]. In the traditional management methods for agricultural plant protection, there are problems such as a lack of relative attention, poor accuracy and poor timeliness [28]. Currently, these methods rely more on manual management. For practitioners, there are higher requirements for professionalism. It is difficult for these methods to achieve universalization, and it is impossible for them to be implemented in real time. It is challenging to minimize the crop damage caused by disease, but through the application of computer vision technology, the timeliness and accuracy of prevention and control measures have been greatly improved, and the ability to control crop diseases, pests and weeds has been greatly improved. Prevention and control at critical times can reduce losses, increase efficiency and promote sustainable agricultural development [29].

The detection and identification of pests in farmland is a necessary condition for integrated pest management (IPM). Currently, farmers must first sample the pests and then manually count and identify them in a time-consuming manner that is labor intensive and error prone. Computer vision technology does some of this work in a more efficient and accurate manner. Researchers have made many efforts to this end. To monitor the status and count the number of aphids on soybean leaves, Mohammadmehdi Maharlooei et al. [30] used image processing techniques to perform many tests on soybean plants grown in a greenhouse. The acquired images were processed using MATLAB R2014a software to identify and calculate the number of mites. The method is low cost and has been experimentally proven to have excellent precision in good lighting conditions. The downside of this method is that in low-light situations, there will be differences in the results. Recognition based on the spectral characteristics of the target is more stable and accurate. Liu H et al. [31] developed a multispectral computer vision system for detecting the invertebrate pests commonly found on green leaves in the natural environment. In the experiments to detect twelve common invertebrate crop pests, an acceptable level of accuracy was demonstrated. In addition to its high level of accuracy, the system can also make real-time action decisions for robots. Intelligent prediction can be achieved if based on real-time and accurate monitoring; this will play an important role in the prevention and control of agricultural diseases. Zhong Y et al. [32] designed and implemented a vision-based monitoring system that applied the you only look once (YOLO) and support vector machine (SVM) methods and showed good performance. The average system accuracy rate was 92.50%, and the average classification accuracy rate was 90.18%. In addition to providing effective and accurate identification data, the system can also form a comprehensive service platform for predicting the occurrence probability and development trend of pests, which are of great significance.

Wheat stripe rust spores are spore rust pathogens that endanger the healthy growth of wheat crops. Li Xiaolong et al. [33] developed an automatic counting system based on image processing using the MATLAB guidance platform and a local C compiler (LCC). The application of various algorithms for processes such as image scaling and clustering segmentation was realized, and the accuracy achieved by the technology was over 95%. This method has the outstanding advantage of a high level of accuracy, but further exploration of applying the system in a field environment is needed. Deep learning is the latest breakthrough in the field of computer vision, and it is expected to be used for the classification of fine-grained disease severity to quickly and accurately determine crop diseases. Wang G et al. [34] used a series of deep convolutional neural networks to diagnose the severity of a crop disease using apple black rot images from the PlantVillage dataset. The overall accuracy of the best model for the test dataset was 90.4%. This finding proves the application potential of deep learning in agricultural disease monitoring. The existing crop disease diagnostic system has a single application target, and it is difficult to diagnose a plurality of plants. Toseef M et al. [35] proposed a method for intelligent crop disease diagnosis that can be used as the main back-end decision engine. The system takes the crop symptoms as inputs and uses an inference engine to produce an output in the form of a disease diagnosis. The system caters to two major crops, cotton and wheat, and is able to diagnose major diseases with an accuracy rate of 99%. The method innovatively realizes the establishment of a small data set, can simultaneously monitor two crops, and is easy to use, with great potential.

Weeds are considered to be harmful plants in agronomy because they compete with crops to obtain the water, minerals and other nutrients in the soil. The intelligent detection and removal of weeds are critical to the development of agriculture. Sabzi S et al. [36] proposed a neural network-based computer vision expert system for identifying potato plants and three different weeds for on-site specific spraying. From each object, 126 color features and 60 texture features were extracted. The experimental results showed that the proposed expert system achieved a 98.38% accuracy and an average PC execution time of less than 0.8 s. However, when the plant density was very high; therefore, the system use is limited.

In the same year, to accurately perform pesticide spraying tasks, Zhai Z et al. [37] proposed a precision farming system (PFS) as a multiagent system (MAS). This method works well and can effectively plan tasks and allocate scarce resources. Spraying pesticides only in the exact locations of weeds greatly reduces the risk of contaminating crops, humans, animals and water resources. The previously described treatment scheme for weeds has a relatively simple function. Chang C-L et al. [38] combined computer vision and multitasking to develop a small intelligent agricultural machine capable of automatic weeding and variable irrigation on cultivated land. The machine classifies the plants and weeds in real time so that the machine can weed and water while maintaining a deep soil moisture content of 80 ± 10% and an average herbicidal rate of 90%. This method has very good prospects as it not only realizes the integration of multitasking but also the comprehensive utilization of resources.

Based on the above analysis, computer vision technology has been well applied in the prevention and control of agricultural pests and diseases, and its high efficiency, high precision and low cost are its main features. However, many of the results are still in the experimental phase and will be largely impacted when more complex factors, such as lighting variations and the plant density, are considered. Therefore, it is necessary to improve the reliability and robustness of the related systems. There is potential to establish related datasets for multitask fusion and the application of hyperspectral techniques [39] and deep learning neural networks.

2.3. *The realization of automatic crop harvesting*

In traditional agriculture, there is a reliance on mechanical operations, with manual harvesting as the mainstay, which results in high costs and low efficiency. In recent years, with the continuous application of computer vision technology, high-end intelligent agricultural harvesting machines, such as harvesting machinery and picking robots based on computer vision technology, have emerged in agricultural production, which has been a new step in the automatic harvesting of crops [40]. Researchers have performed much research on the application of computer vision technology for automatic crop harvesting, and some of the results have been applied in actual production. A long time ago, R. Noble et al. [41] designed a vision system for a mushroom strain collection robot to obtain the mushroom position and determine the optimal picking sequence. The application of computer vision technology has great potential for development [42] and will contribute to the effective and accurate development of agricultural products.

The lack of automated harvesting techniques in agricultural production management is a key issue due to the rising production costs and increased uncertainty of future labor availability. In recent years, with the development of spectroscopy technology, spectral imaging has become an important means of crop detection. Yuan Ting et al. [43] studied recognition and feature collection methods for the near-infrared images of cucumber fruit, and through the analysis and comparison of each spectral band, the spectral reflection characteristics of cucumber fruit, stems and leaves were marked and captured. According to the algorithm verification procedure, the extraction success rate of the grab area was 83.3%. This method used spectroscopy innovatively, but there is still a need to improve the accuracy of recognition. In order to realize the automatic identification of cherries in the natural environment, Zhang Qirong [44] designed a robot vision system method for identification. The method uses median filter preprocessing, Otsu algorithm threshold segmentation, area threshold noise elimination and an implementation of the Hough transform. The cherry identification success rate was over 96%. This method greatly reduces the difficulty and cost of picking and improves efficiency. Sweet pepper crops grown in a field present some challenges to a robotic system, such as height occlusion issues and the similarity between the crop and background colors. To overcome these problems, Christopher McCool et al. [45] proposed a new vision-based sweet pepper (chili) detection system and a new method of crop segmentation using the local binary pattern (LBP) method. The average detection accuracy of a human viewing the same color image was 66.8%, and 65.2% of the field-planted sweet peppers were detected at three locations using the LBP approach. This result is very exciting, and the system uses new features and has high precision. However, there is still much room for improvement in terms of accuracy.

The most time-consuming and labor-intensive task in fresh fruit production is harvesting, but the production of high-value specialty crops such as apples still relies on manual labor. In the past decade, the harvesting efficiency of the apple harvesting system studied was approximately 80%, and the picking time ranged from 8 to 15 s per fruit [46]. In recent years, researchers have explored apple harvesting and have improved the related performance in terms of speed and robustness. Joseph R. Davidson et al. [47] introduced a preliminary design for a robotic apple harvester. The robotic machine vision system combines a circular Hough transform and speckle analysis to detect clustered and occluded fruits. The experimental results show that the system collected 95 out of 100 fruits, with average positioning and picking times of 1.2 and 6.8 s, respectively. The robot demonstrates the advantages of low cost and high efficiency. In order to improve the efficiency of robots in picking mature apples in terms of time and the ability to continuously identify and operate at night, Ji Wei et al. [48] proposed a retinex algorithm based on a guided filter to enhance nighttime images. The experiments showed that compared with a retinex algorithm based on a bilateral filter, the algorithm displayed better real-time performance and higher efficiency. It is very beneficial to improve the accuracy and efficiency of night-time apple picking robots.

The main focus of harvesting operations is to ensure product quality during harvesting to maximize the market value [49]. Noise is extremely challenging for automated harvesting due to the harsh weather conditions, changes in brightness and the presence of dust, insects and other unavoidable sources of noise. The existing technology overcomes many difficulties and innovatively applies spectroscopy, deep learning and other methods that demonstrate high accuracy and low cost. It is worth noting that there is still much room for improvement in efficiency and accuracy in more complex situations. At the same time, agricultural harvest automation must be economically viable, which means that the technology must be capable of rapid perception, calculation and response to environmental changes [40]. The development of such technology requires multidisciplinary cooperation in many fields, such as horticultural engineering, computer science, mechatronics, deep learning, intelligent design and system design. There are great challenges associated with the requirements of technology and the talent needed. In addition, in many studies, it has also been found that the development of automated harvesting requires more suitable and powerful 3D imaging system image processing algorithms to play an increasingly important role in enhanced 3D imaging systems [50].

2.4. The classification and quality inspection of agricultural products

A quality inspection of agricultural products helps to judge and determine the quality of the products and promote their commercialization [51]. With the development of computer vision technology, the automatic grading and quality inspection of agricultural products has been achieved, and computer vision systems have been widely used in different fields of the agricultural and food production market segments, avoiding the high cost and low efficiency of traditional operations [52]. At present, the technology is mainly applied for the evaluation and grading of vegetables and fruits to better improve the economic benefits of agricultural products [53].

The quality of agricultural products is one of the important factors affecting market prices and customer satisfaction [54]. In the past few decades, manual inspections have had many problems in maintaining consistency and ensuring a satisfactory detection efficiency. Computer vision provides a way to perform external quality checks and achieve high degrees of flexibility and repeatability at a relatively low cost and with high precision [55]. Researchers have conducted extensive research on the classification of fruits and vegetables based on computer vision. Carrot grading is a labor-intensive, time-consuming process; in order to improve the classification efficiency and achieve automatic detection, Deng et al. [56] developed an automatic carrot sorting system using computer vision technology. The experimental results showed that the detection accuracy, fiber root detection accuracy and crack detection accuracy were 95.5%, 98% and 88.3%, respectively. The proposed method and the constructed sorting system met the requirements of carrot quality detection and classification. The method can achieve satisfactory detection accuracy and high efficiency. However, the detection accuracy of the crack portion needs to be improved. Rouhallah Abedi Firouzjaei et al. [57] proposed a fast, nondestructive method to detect sweet lemon mechanical damage using image processing techniques and UV radiation for better classification. To this end, 135 sweet lemons were tested based on a completely random factor design. The accuracy of distinguishing between healthy and damaged sweet lemons was 100%. The quality detection and classification of sweet lemons achieved very high precision.

Potato is one of the world's major food crops. Kim et al. [58] proposed a nondestructive testing system based on computer vision technology to distinguish between the normal and black hearts of potatoes according to different transmittances. The results showed that the established nondestructive system combined with the processing method detect potato black hearts with high precision. The advantages of this detection technology are that it is non-destructive and can be used to achieve the accurate detection of potato black hearts. Tomato is one of the most popular and best-selling fruits in the world, and the quality of a tomato depends on its visual characteristics. Therefore, it is important to classify tomatoes according to certain quality levels. Mohammad Saber Iraji et al. [59] used a multi-input feature based on a tomato image dataset, neural network, regression and extreme learning machine (ELM) to build the multilayer system of the SUB Adaptive Neuro-Fuzzy Inference System (MLA-ANFIS) method. A deep sparse automatic encoder (DSSAE) method was proposed for the direct use of image data in tomato quality grading. The sensitivity of this method was 83.2%, with an accuracy of 95.5%. Therefore, this method can improve the inspection and quality treatment of tomatoes. The advantage of the DSSAE approach is that the system builds the relevant datasets that are used to classify the data directly from the tomatoes without the need to apply image processing techniques to extract features.

Recent studies have shown that spectroscopy is an effective nondestructive fruit quality testing technique. Tao Wang et al. [60] applied a spectroscopy technique to develop a low-cost, cloud-based portable near-infrared (NIR) system called "SeeFruits", which was designed for fruit quality inspection. In the experiment, 240 sweet cherries were selected as fruit samples to evaluate the performance of the 'SeeFruits' system. The 'SeeFruits' system scored 0.89 in qualitative tasks and 0.83 in quantitative tasks. In general, even though it was ultra-portable, it achieved a satisfactory level of accuracy. The 'SeeFruits' system provides fast, flexible and friendly sweet cherry quality testing capability for nonprofessionals. However, there are still some gaps in the system, and further exploration and research are needed to expand the type and range of fruit detection and reduce the detection error. In order to check the internal mechanical damage in blueberries, Zhaodi Wang et al. [61] used hyperspectral transmittance data to detect damage using the residual network (ResNet) model, the improved ResNeXt model and two deep convolutional neural networks (CNNs). The experiments showed that the two deep learning models displayed better classification performance than traditional machine learning methods. For the ResNet and ResNeXt models, the classification of each test sample required only 5.2 ms and 6.5 ms, respectively. The results of this study demonstrate the potential of the deep learning framework for analyzing fruit mechanical damage. The method innovatively combines a CNN structure with hyperspectral transmittance data and has strong development potential.

Computer vision is widely used in the quality inspection of agricultural products by analyzing the obtained optical image information and has the advantage of being nondestructive [14] while offering a simple operation that is of low cost and high precision [62]. At the same time, research shows that technologies such as deep learning and spectroscopy have become powerful tools and have great potential in analyzing fruit quality and sorting fruit types. The current technology still has a narrow application range and can only detect and classify relatively simple varieties. The detection accuracy needs to be improved, and other problems require solving. These issues also points the way for future development. In the future, relevant data sets will be established to expand the application range of the systems and enhance their versatility and portability.

2.5. *Automated management of modern farms*

After two and a half years of research, the Iron Ox company in the United States developed a complete cloud-based intelligent unmanned indoor hydroponic farm. The productivity of the farm is 30 times that of an ordinary outdoor farm. In 2018, the first crop of the farm was sold. With the further strengthening of technology, the "unmanned farm" has the advantages of precise operation and high efficiency, and it offers intelligent decision making, environmental protection and visual management in a simple and controllable operation [63]. The integration and implementation of automated crop production management, plant irrigation and yield assessment, and the application of computer vision technology are key [40]. The automated management of modern farms provides a wealth of knowledge and insights in terms of decision support and the practices of farmers [5]. This approach will save manpower and material costs; realize the simple, scientific and effective management of farms; and eliminate much of the hard work of farmers [64]. This section focuses on soil management, crop maturity testing and agricultural production estimates for unmanned farms.

Soil management [65] is a technology that maintains and enhances soil productivity through cultivation, fertilization, irrigation, etc. and has a notable impact on modern agricultural production. Bharath Sudarsan et al. [66] studied the cost-effective in situ design and development of new computer vision-based sensor system for estimating the soil texture and SOM. An image acquisition system was developed using a small, inexpensive handheld microscope. Images with variable texture and SOM were obtained in the laboratory and processed using a computer vision algorithm based on geospatial data analysis. The low cost and portability of the acquisition system and computer vision algorithms developed in this study demonstrate their suitability for laboratory and field conditions and show promise as a near-end soil sensor. However, the system requires further testing of robustness for soils with different humidity conditions. The use of low-cost cameras has expanded to all areas of technology, especially in agricultural applications. By obtaining useful information about the growth of horticultural crops through images, the soil water balance can be accurately estimated to achieve accurate irrigation planning [67]. J.M. González-Esquiva [68] proposed a novel computer vision system using a low-cost camera and a client-server architecture to provide users with valuable information about the irrigation management water balance. The proposed method achieved high precision in the estimation of PGC, with an average error of less than 5% and a processing time of less than 2 s per image in the server. The advantages of this approach are its scalability, integration and adaptability to different use cases.

Crop maturity estimates are still very challenging to obtain in unstructured environments such as farms [69]. New advances in computer vision offer opportunities for new applications in agriculture. Michael Halstead et al. [70] proposed a robot vision system that uses the Parallel-RFCNN structure to accurately estimate the maturity of sweet pepper (*Capsicum annuum* L.) crops. The model can accurately estimate the maturity, with an average accuracy of 82.1%. This tracking method is a visual-only solution, so it is cheap to implement because it only requires one camera. This method exhibits considerable ability under various conditions related to the image quality, variable illumination, presence of leaves and young fruit. WAN P et al. [71] proposed a method for detecting the maturity of fresh-market tomatoes by combining feature color values with back-propagation neural network (BPNN) classification techniques. The maturity detection device based on computer vision technology is specifically used to obtain tomato images in the laboratory. The tomato images are processed to obtain the color feature values. The maturity level of the sample is described based on the color feature value. Thereafter, the color feature value is imported as an input value into the BPNN to detect the maturity of the tomato sample. The results showed that the average accuracy of the tomato sample maturity was 99.31%, which was a very satisfactory result.

Crop yield estimation is an important task in the context of precision agriculture and an important factor in the planning of production processes. Production estimates play a decisive role in product marketing strategies and training practices and make it easier for farmers to plan and use resources in advance. Based on the known correlation between the number of visible fruits in a digital image and the total number of orange trees, Walter Maldonado Jr et al. [72] developed a green fruit feature extraction method to estimate the yield of citrus crops. This method combines the Laplace and Sobel color model transformation operators, threshold processing, histogram equalization, spatial filtering and Gaussian blur. The method has a false positive rate of 3% for images obtained under good conditions and takes approximately 8 min without any human interaction. Hyperspectral imaging (HSI) has been extensively studied and used in many food and agricultural applications because of its enormous potential and ability to characterize various target traits. Guti Rrez S et al. [73] made full use of hyperspectral technology and introduced a new method for estimating the mango yield using line scan hyperspectral images obtained from large orchard unmanned ground vehicles. The hyperspectral images were collected in commercial mango park blocks and preprocessed for illumination compensation. After tree delimitation and mango pixel recognition, an optimization process was performed to obtain the best fruit count model using the mango count obtained by manually counting the fruits on the tree. This model then used the most advanced RGB technique for the yield estimation. The model has been validated and tested on hundreds of trees and is comparable to the most advanced RGB technology.

Through the application of computer vision technology, the functions of soil management, maturity detection and yield estimation for farms have been realized. Moreover, the existing technology can be well applied to methods such as spectral analysis and deep learning. Most of these methods have the advantages of high precision, low cost, good portability, good integration and scalability and can provide reliable support for manager decision making. However, the existing technologies still have much room for improvement, such as improving robust performance, building related data sets, and expanding the scope of applications for smarter and more comprehensive management. In the future, the automated management of modern farms will be supported by digital agriculture. It is possible to move from cumbersome business processes to continuous automated processes [40]. Robots, small robots and drones that cooperate in the field for reconnaissance and harvesting, as well as the automated management of small and medium-sized multipurpose vehicles on the farm, will be the focus of future research [74]. Deep learning [75], as a modern image processing technology with great potential, will be very promising by extending its application to achieve farm management and large-scale ecosystem observation deployment to strengthen management and decision making [63].

2.6. *Monitoring of farmland information with UAV*

Real-time farmland information and an accurate understanding of that information play a basic role in precision agriculture [76]. Over recent years, UAV, as a rapidly advancing technology, has allowed the acquisition of agricultural information that has a high resolution, low cost, and fast solutions [77]. UAV platforms equipped with image sensors have provided detailed information on agricultural economics and crop conditions [78,79]. UAV remote sensing has contributed to an increase in agricultural production and a decrease in agricultural costs [80,81].

Rapid, accurate and economic estimation of agricultural biomass plays a prominent role in achieving accurate agricultural management. Traditional biomass acquisition methods mainly involve destructive sampling, which is time-wasting and challenging, problems that can be relatively easily mitigated by using UAV remote sensing, which, with the help of computer vision technology, can contribute to biomass estimation [82,83]. Guilherme Martineli Sanches et al. [84] evaluated and predicted the yield of sugarcane fields by UAV that obtained RGB images and contributed to evaluations that included the LAI (Leaf Area Index) and GRVI (Green-Red Vegetation Index), which were obtained by field sensors and UAV, respectively. Experiments have shown that estimates of the agricultural yield of sugarcane can be obtained by UAV. However, the use of such images to improve the yield model and extract plant height remains to be explored. Nondestructive digital modeling of forage biomass can prominently and effectively contribute to decision-making. Victor P. Rueda-Ayala et al. proposed the application of UAV technology and RGB-D reconstruction methods to monitor vegetation height and biomass, two approaches that are largely consistent. UAV systems are cheaper and simpler, covering a larger surface than RGB-D-based approaches [85]. Liang Han et al. conducted an in-depth study on the biomass estimation of maize, a very important crop [86], in which UAV remote sensing was used in combination with machine learning to provide spectral information to estimate the biomass of maize. Furthermore, they proposed an improved method for extracting plant height from UAV images and to indicate volume in experiments, which showed that the method can contribute to improvements in precision. Therefore, the combination of machine learning with UAV remote sensing serves as a promising alternative. In addition, Yaxiao Niu et al. obtained altitude directly from the UAV-RGB point cloud and estimated maize biomass. In short, the results show that this method is favorable for building a high-performance estimation model by machine learning [87].

Continuous crop monitoring plays a prominent role in precision agriculture [88,89]. Application of UAV can contribute to more sustainable agricultural automatic crop monitoring and provide a prominent support for agricultural decision-making [90,91]. In addition, the use of UAV is advantageous when constructing a scientific framework for agricultural resource management [77,92]. Thus, the next paragraph focuses on crop monitoring and irrigation management.

To realize UAV-based chestnut tree automatic monitoring, Pedro Marques et al. proposed a canopy height model based on calculating the vegetation index (VI) that combined bands of visible light (RGB) and near-infrared (NIR) domains, which contributed to the rapid management and sustainable development of a chestnut plantation. Subsequently, UAV-based image processing was determined to be fast and stable [93]. Juan Enciso et al. studied the potential of UAV for use in measuring tomato height and canopy coverage, with the UAV measurements showing high consistency with manual measurements. However, some systematic errors can still be found, making intensive data and sample size collection in the future necessary to avoid systematic errors [94]. Carlos Henrique Wachholz de Souza et al. proposed an object-based UAV image analysis (OBIA) method that uses object analysis of UAV images to map sugarcane hoppers. The OBIA method showed a high degree of automation and adaptability, providing useful information for decision-making and agricultural monitoring [95]. Significant differences exist in the irrigation demand among different fields, making real-time irrigation management extremely important. Xiang Shi et al. developed a variable speed irrigation decision support system (VSI-DSS) based on UAV multispectral remote sensing. The system can process multispectral images acquired by UAV to obtain the vegetation index (VI) and then provide guidance for users. The results show that the method is reasonable and consistent with the expected results, but the reliability of the method needs to be improved [96]. In practical application, the integration of various technologies will contribute to a better application of the UAV platform. Luxon Nhamo et al. integrated UAV technology, auxiliary data, and knowledge-based rules into land cover classification processing. The accuracy of irrigated areas was improved from 71% to 95% based on the application of UAV in postclassification correction. In short, research has demonstrated that UAV remote sensing plays a prominent role in irrigation area monitoring and water resource management decisions [97].

Currently, UAV platforms, because of the easy access to image data, are used in almost all agricultural applications [78,98]. UAVs are generally acknowledged to be advantageous when applied to crop monitoring, protection, management and other farm operations [80,99]. With the characteristics of flexibility, timeliness and stability, this approach makes assessment more scientific and promotes the planning as well as the management of agricultural resources [90,92]. Comprehensive analysis shows that UAV-based reference data acquisition approaches are alternatives to traditional methods. However, challenges remain in developing appropriate technologies and promoting the adoption of this technology by farmers [80], among which, problems such as limitation and accuracy are still worthy of deep discussion [91]. Therefore, UAV-based hyperspectral technology, combined with deep learning, machine learning and other technologies, will show more promising performance in the future [100].

3. The serious challenges faced by computer vision technology in the field of agricultural automation

3.1. *The continuous expansion of application fields*

With the rapid development of artificial intelligence, computer vision technology will be widely used in the field of agricultural automation. However, due to the complexity of agricultural production and the diversity of organisms, computer vision technology is currently used in the production management of individual crops for monitoring, plant protection and harvesting [40]. The technology still cannot overcome every obstacle in agricultural production, nor can it be popularized in all aspects of agricultural production. The application of computer vision technology in agriculture is still in the initial stages of development.

There is currently no large-scale public database [65,101] in the agricultural sector, and the existing research results often rely on data collected by the researchers themselves during the research and development process, which are not universal and comparable. Therefore, it is necessary to establish a complete agricultural database. To prevent and control crop pests and diseases, the existing computer vision techniques are limited to detecting a single species of pest. For the quality inspection of agricultural products, computer vision technology can only detect single varieties of agricultural products. For the automated management of unmanned farms, computer vision technology is still not applicable to all aspects of unmanned farm management, and there are many areas and functions that need to be explored. The large collections of data that are not shared are the key to the problem. In addition to the application areas and databases that need to be extended, researchers have found many problems, such as slow image information acquisition and slow response to different environmental systems.

3.2. *The growth in the demand for professional talent*

Due to the development of GPUs that have increased computing power in recent years, deep neural networks [63] have become a viable solution for image classification and are one of the most effective techniques for pattern recognition applications with a large number of images. Computer vision-based statistical machine learning algorithms will be widely used in agricultural applications [14], mainly using the high-density data parallel computing functionality highlighted in the GPUs. Emerging technologies and effective tools are inseparable from technology professionals and require professionals to continue to promote innovation and development.

Computer vision technology involves many disciplines, such as computer science, pattern recognition, artificial intelligence, and many others [14]. The existing technical achievements have problems such as low generality and a high demand for professional skills. If computer vision technology is widely used in the field of agricultural automation, there will be higher requirements for professionals and practitioners [102]. This advancement requires high-quality, all-round talent; the continuous development of new technologies; the exploration of new results; and the integration of results from various disciplines into complex agricultural production environments [103]. In addition, computer vision technology needs to overcome many of the difficulties and complementary gaps in the field of agricultural automation. Whether applied to scientific research in this field, education and training, or application promotion, this approach has a high demand for a number of skills.

3.3. *Robust performance in a variety of complex situations*

Agriculture is a comprehensive discipline full of diversity and uncertainty. Notably, the crop varieties and methods of agricultural production management are not only numerous but also very complicated. The same crops grow in different environments, and the end result is different. There are a variety of elements that are heterogeneous in production and harvesting. In such a complicated situation, computer vision technology, with strong comprehensiveness and high complexity, is applied to the field of modern agricultural informationization, and the robustness and performance have been rigorously tested.

In the application of computer vision technology, in terms of image acquisition, processing and classification, the individual characteristics of the problem must be considered to choose the appropriate algorithm [104]. There is no default workflow or common method for implementing computer vision technology. In these cases, the state of the target changes, the influence of the environment changes, etc., and all of these changes increase the number of factors that need to be analyzed in the image processing stage. At the same time, most of the existing technologies and methods are implemented in a laboratory environment or on an experimental platform [105]. When the experimental results are applied to an actual natural environment, the actual data and experimental data will be very different due to natural factors. The application of visual technology in the field of agricultural automation involves the integration of multiple disciplines, and the various irregularities will have a huge impact on practical applications. The real-time, accurate and robust performance of related technologies are challenging to ensure.

4. Analysis of application prospects for computer vision technology in agricultural automation

Agriculture is the foundation of modern human society [106] and plays a decisive role in human survival [107]. As an emerging technology, computer vision technology combined with artificial intelligence algorithm for a computer vision solution will become a necessary condition for improving agricultural efficiency and has broad prospects in future agricultural applications and research [3].

Computer vision technology will be better used in agriculture for automation and robotic farming [108]. Computer vision intelligence technology [109] is widely used in crop automation, growth monitoring, disease prevention, fruit harvesting and other aspects of agricultural automation production management. Future agricultural automation equipment will rely on large-scale agricultural datasets to maintain a mechanism coordinated by multiple participants [110] and a more innovative agricultural industrialization business model [111]. By using computer vision, expanding the use of GPUs [112] and applying advanced artificial intelligence technology to automate field tasks, the economic performance, general performance, coordination performance and robust performance of agricultural automation systems will be much improved.

In addition, computer vision technology will be more widely used to address current open agricultural issues, thereby ensuring agricultural production, quality and food security [113]. As a new technology in agricultural production management and a universal tool for providing reliable predictions of complex and uncertain phenomena, deep learning technology [114] will be better integrated with traditional imaging methods, hyperspectral imaging and other imaging modes to promote computer vision technology applications and developments. This approach will promote the development of agricultural automation equipment and systems in a more intelligent direction. In the future, the use of computer vision technology in the field of agricultural automation will play a role in improving agricultural productivity, quality and economic growth [52] and promote the development of agriculture towards improved the yield, efficiency, quality, ecology, safety and intelligence.

5. Conclusion

Overall, the application of computer vision technology in the field of agricultural automation is reviewed and analyzed in detail in this paper based on the summary of studies on it over the past three years. More specifically, the paper focuses on six areas, namely, crop growth monitoring, disease control, automatic harvesting, quality testing, automated management of modern farms and the monitoring of farmland information with UAV. We can conclude that the prior work contributes to the development of agricultural automation in the individual fields, with the advantages of low cost, high efficiency and high precision. In addition, based on the status quo, we analyzed the challenges that computer vision technology will face in future agricultural automation applications. First, as the technology continues to expand in the future, in order to achieve the versatility and coordination of technology, it is necessary to establish a large-scale dataset. At the same time, the technologies and challenges that need to be addressed in the future will continue to increase. Second, with the rapid development of agricultural automation, this field will involve the integration of more disciplines, and the requirements for professionals in terms of quality and quantity will continue to increase. Finally, due to the complex environmental background of agricultural production management, ensuring the accuracy and robustness of related technologies in various complex situations will also be challenging.

Based on the above analysis and discussion, we conclude that computer vision technology, as an emerging technology, will be better applied to agriculture. In the future, computer vision intelligence technology based on large-scale datasets will be widely used in every aspect of agricultural production management and will be more widely used to solve the current agricultural problems. Computer vision technology combined with artificial intelligence algorithms will improve the economic performance, general performance, coordination performance and robust performance of agricultural automation systems. Through the application of cutting-edge technologies such as deep learning technology and spectral analysis technology, agricultural automation equipment and systems will be developed in a more intelligent direction. In the future, with the application and development of computer vision technology, the efficiency and quality of agricultural production will be improved and will provide valuable suggestions and insights to farmers for decision support and actions [14,67], as well as aid the rapid and comprehensive development of agricultural automation.

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.

Acknowledgments

The authors thank the English speaking experts from American Journal Experts for editing our paper. The work in this paper was supported by the National Natural Science Foundation for Young Scientists of China (31801804), the Guangxi Innovation-Driven Development Special Fund Project (GuikeAA18242011), the Key Research and Development Program of Nanning (20192065), and the Fund Project of the Key Laboratory of Integrated Pest Management on Crops in South China, Ministry of Agriculture and Rural Area, P.R. China (SCIPM2018-05).

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