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Review

Computer vision and machine learning applied in the mushroom industry: A critical review

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A R T I C L E I N F O

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A B S T R A C T

Background: Mushrooms are popular food items containing numerous vitamins, dietary fibers, and a large number of proteins. As a result, mushrooms can increase the body's immunity and prevent many types of cancer to keep the body healthy. For these reasons, the demand for high yields and safety in the production of high-quality mushrooms is increasing.
Scope and approach: This review highlights the application of computer vision and machine learning algorithms in the mushroom industry. Through a systematic review of papers published between 1991 and 2021, this article introduces key aspects related to mushrooms (e.g., species identification and quality classification based on artificial intelligence), and discusses the advantages and disadvantages of various approaches.
Key findings and conclusions: Numerous artificial intelligence and machine vision technologies have been implemented in research efforts focusing on edible fungi. However, their applications are generally limited to the identification of poisonous mushrooms according to their forms, the plucking of cultivated mushrooms covered by soil, and the mechanized grading of mushrooms. Clearly, the currently available methods cannot meet the requirements of the digitization and intelligentization in the field of edible mushrooms. Considering these reasons, it is possible to develop further application opportunities, such as digital mushroom phenotype determination, and high-throughput breeding based on big data, and mechanical picking by a harvesting robot as well. Therefore, the integration of computer vision and machine learning with the development of more efficient algorithms will undoubtedly be a hotspot for future studies in the context of the mushroom industry.

1. Introduction

Mushrooms are becoming increasingly popular with consumers for their significant amount of dietary fiber as well as low fat and low calorie. In addition, mushrooms have now even emerged as a wonderful to combat cancer and other diseases. (Tsai et al., 2007; Patel et al., 2012; Roncero et al., 2017;Ba et al., 2021). Therefore, the mushroom crop industry is under increasing pressure concerning how to enhance productivity and quality in a sustainable way. Currently, edible mushroom products typically come from cultivation or wild picking. In general, although wild mushrooms are delicious and various, the yield is too low to satisfy the market demand (Shan, 2002; Fang et al., 2015). On account of this, wild mushroom harvesting is suitable for personal consumption only. In addition, it is also worth noting that wild mushrooms may lead to poisoning due to a lack of professional knowledge. In contrast, mushroom cultivation based on the industrialized mode leads to high yields and high quality (Li, 2018), so this mode has become the major source of mushrooms on the market today. However, this strategy

Abbreviations: AdaBoost, Adaptive boosting; BP, Back propagation; CNN, Convolutional neural network; CUDA, Compute unified device architecture; DL, Deep learning; DSLR, Digital single lens reflex; GAN, Generative adversarial networks; GPU, Graphic processing units; IoT, Internet of things; LDA, Linear discriminant analysis; MPGAN, Mushroom phenotypic based on generative adversarial networks; PBR, Plant breeders' rights; PCA, Principal component analysis; PNN, Probabilistic neural network; PLC, Programmable logic controller; RGB, Red Green Blue; RIDOR, Ripple-down rule; SFM, Structure from motion; SL, Structured light; SVM, Support vector machine; TOF, Time of flight; USDA, United States Department of Agriculture.

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also faces a critical problem of labor shortages because mushroom cultivation involves labor-intensive work not only during the harvest phase but also in almost all aspects of production (Lee et al., 2019).

Recently, image processing and machine vision technology have been applied more frequently in the agricultural industry for reductions in equipment costs and increases in computational capacities (Mahajan et al., 2015). Contrary to the traditional methods, which mainly depend on manual labor, these modern strategies exhibit significant advantages and potentials in terms of monitoring the production process quickly and accurately. Researchers have used the Internet of Things (IoT) and computer vision approaches combined with machine learning, artificial intelligence algorithms and data mining methods to evaluate noninvasive phenotype data (Fernando et al., 2017). In this way, it was possible to automatically recognize plant colors, sizes, shapes, and textures and to extract point(s) of interest. However, various challenges must be addressed in future studies, e.g., how to develop an approach to characterize the plant details in the natural environment.

Strictly speaking, machine learning is not a new technology at all. In 1936, linear discriminant analysis (LDA) was proposed by Fisher et al. (1936); though there was not such a concept as machine learning at that time. Since the 1980s, machine learning has emerged as its own independent area of study, and various advanced algorithms, such as adaptive boosting (AdaBoost), support vector machines (SVMs), and convolutional neural networks (CNNs), have been established (Quinlan, 1986; Cortes et al., 1995; Lecun et al., 1989). With the development of the IoT, a vast amount of data has become available, thus creating an urgent need for the construction of efficient nonlinear information processing algorithms for complex data analysis. In response, a growing number of researchers have proposed novel machine learning algorithms to overcome these difficulties. Based on data retrieved from the University of California's (UCI) machine learning repository, Verma et al. (2018) used artificial neural networks and adaptive neuro-fuzzy inference systems to categorize mushrooms as either edible or nonedible. Moreover, Husaini (2018) investigated and compared the performance of three distinct algorithms, namely, naive Bayes, Ripple-down rule (RIDOR), and Bayes Net, with various ensemble classifiers, e.g., boosting, begging, and stacking. The results indicated that classification by a machine learning approach could be accomplished faster and more accurately than via manual sorting. These methods showcased the technical capacity and highlighted a promising application perspective of machine learning-based approaches.

Computer vision systems combined with machine learning algorithms have also demonstrated potentials in solving various problems in the agricultural industry. Currently, the effectiveness of graphic processing units (GPUs) and compute unified device architecture (CUDA), combined with deep learning (DL; a technique that exhibits outstanding performance among machine learning algorithms), provides an opportunity to realize significant achievements. According to our knowledge, by far there are no reviews discussing the planting and classification of mushrooms based on computer vision or machine learning technologies. Compared with the literatures presented above, this article focuses primarily on providing up-to-date information on studies investigating how computer vision or machine learning technology can be used to grow and distinguish between mushrooms from an overview while highlighting the strengths and weaknesses of various approaches. Then, the potential challenges and opportunities associated with these artificial intelligence techniques are also discussed in terms of how they pertain to the mushroom industry.

This paper reviews the following: (i) the relevant concepts of computer vision, (ii) the results from studies covering the detection of mushrooms in growing beds or sorting mushrooms by using computer vision and machine learning methods, and (iii) the application of novel approaches (e.g., CNN, DL, and generative adversarial networks (GANs)) in the mushroom industry. In addition, challenges related to the implementation of automated mushroom harvesting, as well as potential research directions in this area, are discussed herein.

2. Computer vision and machine learning

2.1. Computer vision

Humans acquire most information through visual systems, so images are the most important sources of visual information. In recent years, to imitate human visual perception, computer vision technology, concerning either hardware or software, developed and advanced greatly. Hardware (e.g., cameras, lights, image archiving and communication equipment) is the foundation of computer vision technology, while software (e.g., image processing algorithms) is the core of the system. In general, computer vision systems can be classified into two broad categories: two-dimensional (2D) vision and three-dimensional (3D). The typical image acquisition system is shown in Fig. 1. Depending on the requirements, the lighting equipment can be classified as point light sources, ring light sources, strip light sources, backlight light sources, structured light sources, and combined light sources, among others. According to the luminescent material, these light sources can also be further categorized as light-emitting diode (LED) light sources, halogen light sources, and high-frequency fluorescent light sources. In addition, based on the imaging method of the vision system, the camera can be characterized as either a global shutter or a rolling shutter camera.

2.1.1. 2D vision

Essentially, all of the photos acquired by commercially available RGB (red-green-blue) cameras are 2D vision images. Photos can be captured through cellphones, digital single-lens reflex (DSLR) cameras, and other digital or analog equipment. However, industrial cameras, a type of advanced and reliable equipment used in complicated circumstances, have been widely used in many fields for either high-speed surveys (Shimasaki et al., 2019) or for precision measurements (Widiasri et al., 2019) on the assembly line. The use of a 2D vision system makes it possible to compute values related to basic plant parameters, covering the leaf area, leaf inclination, stem length, stem width, color, and texture (Bai et al., 2019; Virlet et al., 2016). Moreover, bruising and other mechanical damage to fruits and vegetables that occur frequently during harvesting, stockpiling, and transportation can also be detected (Berardinelli et al., 2005). As soon as an image is acquired, noise reduction and lighting correcting are always performed. These operations generate new and higher-quality images. In some cases, geometric transformations are also carried out to obtain perfectly seamless images. In higher-level processing, various filters have been used to determine regions containing abrupt changes and facilitate the extraction of the object of interest. Overall, 2D vision systems enhance the working efficiency and reduce the labor intensity by qualitatively improving the manual data capture. However, the information acquisition from a single photo faces clear restrictions because characteristics of the objects have neither an angle nor depth. Therefore, 2D vision-based systems are generally considered ill-suited in terms of acquiring volume parameters.

2.1.2. 3D vision

To overcome the limitations of the 2D-vision-based method, scientists and engineers have proposed 3D vision-based approaches. Previous studies have demonstrated that the position of a given object can be calculated precisely by using depth data obtained from a 3D vision system. Furthermore, 3D imaging enables the acquisition of more traits (e.g., an object's volume) than 2D image capturing (Apelt et al., 2015; An et al., 2017; Paulus et al., 2014). At the moment, there are two types of 3D vision systems: passive mode and active mode. In passive mode, the vision system employs only ambient light, whereas in active mode, extra light is needed. Stereovision, acquired by using two or more cameras, is a crucial passive mode-based technology that can reconstruct an object's 3D structure. This approach has been verified experimentally and has positively impacted the 3D model construction and growth estimations of various crops (Rovira et al., 2005; Bao et al., 2019). Structure-from-motion (SFM) is another passive mode-based

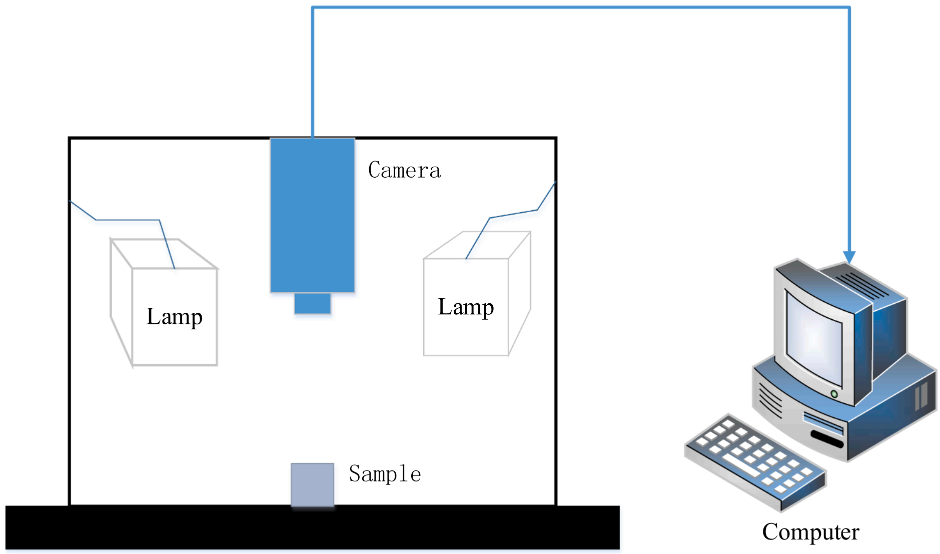


Fig. 1. Main components of the computer vision system.

method of 3D vision systems. In the typical course of events, the SFM-based equipment includes a camera and a turntable, which allow pictures to be captured from different angles (Thuy et al., 2015). In terms of three-dimensional reconstructions by using passive mode-based methods, SFM demonstrates a good balance between accuracy and cost because it only requires one common RGB camera to complete the three-dimensional reconstruction of the object. However, regardless of the method used, the shortcomings of the passive model-based approaches in the development process are clear. For example, a dark or dimly lit environment reduces the method's ability to identify objects, and these approaches require substantial computational resources. To circumvent the aforementioned problems, active model-based 3D vision systems have been designed, showing effectiveness because of additional light sources (Han et al., 2013). There are currently numerous consumer-grade active model-based vision systems, and the available technologies can be classified as structured light (SL) or time of flight (ToF) according to their working principles. The SL system calculates the depth data based on the deformation of the light pattern emitted onto the object by a light emitter. To promote higher security and performance, the emitted light should be in the invisible region of the spectrum. Kinect sensor V1 (Microsoft, Redmond, WA, USA), representing a typical SL camera designed to enhance the Xbox gaming experience for users, has been widely used in the agricultural field (Paulus et al., 2014; Andujar et al., 2016) for fruit detection, 3D crop reconstruction, and plant phenotyping (Fu et al., 2020; Li et al., 2020). Another famous consumer-grade camera is the RealSense series produced by Intel. In a case study, RealSense SR300 (Intel, Santa Clara, CA, USA), aiming to take the point cloud data between 0.2 and 2 m, has demonstrated its advantages of a lower cost and higher framerate; therefore, it has been used in agricultural applications on a small scale (Milella et al., 2019). Alternatively, ToF cameras can be utilized to measure the depth data between the sensor and the surface of the target by computing distances based on the time-of-flight of a light signal. Compared to an SL system, some of the most distinctive characteristics of a ToF camera are shown: the potential distance is longer, and the depth calculation does not depend on the color or other features of the target. The next generation of the Kinect sensor (Kinect V2, Microsoft, Redmond, WA, USA) is the most common ToF camera on the market, which has a lower depth resolution because of the limitation of the ToF principle, but the angles of the horizontal and vertical views have been increased. Overall, the quality of RGB images obtained with Kinect V2 is better than that captured by using Kinect V1. Moreover, the ToF camera (Kinect V2) is affected by sunlight to a lesser extent (although it still produces more errors under sunlight), and therefore, it achieves better accuracy in outdoor depth measurements. Thus, Kinect V2 has been used more widely in the agricultural field. Table 1 summarizes the benefits and drawbacks of various vision systems.

2.2. Machine learning concepts

As a key technology for artificial intelligence, machine learning mainly focuses on the problem of how to teach computers to obtain new knowledge and greater understanding by simulating human thoughts or behaviors. By applying machine learning algorithms, both classification and regression problems can be dealt with accurately and efficiently. In most cases, learning algorithms can be classified into three groups (i.e., supervised learning, unsupervised learning, and semi-supervised learning) based on the number of targets annotated. Supervised learning refers to the scenario involving a large existing dataset (training set) with known outputs. Hence, a model can be designed based on this dataset to predict the result of new inputs. In contrast, unsupervised learning focuses more on how to classify similar inputs into different categories because it is used in situations lacking a dataset with known outputs. However, semi-supervised learning is an intermediate approach between supervised and unsupervised learning.

Table 1
Summary of commonly used 3D vision system.

Type	Name	Advantage	Disadvantage	Typical equipment
Passive	Stereo vision	Low cost and obtaining RGB images only	Low image quality and large amounts of calculation	Zed Stereo camera (Stereolabs, San Francisco, CA, USA)
	Structure-From-Motion	Low cost and Simple to use	Needing lots of images from different angles	A Camera
Active	Time of Flight	Small size and wide measurement range	Lower depth resolution and not using in the bright light area.	Kinect V2 (Microsoft, Redmond, WA, USA)
	Structured Light	High accuracy and resolution	Being disturbed by the environment and lower outdoor accuracy	SR300 (Intel, Santa Clara, CA, USA) or Kinect V1 (Microsoft, Redmond, WA, USA)

To solve nonlinear problems that frequently emerge in the decision-making process, neural networks have been proposed by scientists based on the human brain structure and thinking patterns. The quintessential neural network comprises various interconnected nodes with associated weight coefficients designating the degree of correlation between two given nodes. In the early days, the pioneering systems of neural networks named as perceptrons and multilayer perceptrons were proposed (Rosenblatt, 1958), in which the nodes' weight coefficients were adjusted by trial and accumulative experience. This system resulted in low efficiency, high labor demand and significant errors. This process was later improved in 1986 owing to the proposition of back propagation (BP) (Rumelhart et al., 1986), and a neural network integrated with a BP algorithm can compute appropriate weight coefficients automatically.

Deep learning networks, which are slightly different from primary neural networks, contain more nodes and more layers of interconnections. Convolutional neural networks are some of the most important architectures of deep learning networks exhibiting high performance in image-based assignments, e.g., image recognition. The first convolutional network (LeNet-5) was developed by Lecun et al. (1998) and consisted of the following three types of layers: convolutional layers, subsampling layers, and fully connected layers. However, this proposal did not receive wide recognition because of the poor performance of computers at that time. Nevertheless, since AlexNet performed excellently in an ImageNet competition, DL networks have been employed to solve difficult problems that we were not even aware of in the past, and this has directly led to the design of numerous networks, including VGG Net (Simonyan et al., 2014), GoogLeNet (Szegedy et al., 2015), and ResNet (He et al., 2016), among others. Similarly, many mature CNN-based algorithms have also been developed and applied in practical engineering projects to save time and reuse codes. The YOLO (You Only Look Once) method, which was first proposed in CVPR2016 (Redmon et al., 2016), has been widely used in object detection tasks. To date, various modified models of the YOLO method can be applied in certain special situations, including the detection of fruits, leaves, pests, and diseases (Koirala et al., 2019; Angela et al.,2020; Liu et al., 2020).

3. Application of computer vision in the mushroom industry

Computer vision associated with machine learning technology represents a powerful tool to solve difficult problems that have eluded researchers thus far.

3.1. Mushroom cultivation and harvesting

Computer vision could drastically improve accuracy and increase efficiency, and it was first used in the field of mushroom agriculture by Vooren et al. (1991). Their experiments were a part of Plant Breeders' Rights (PBR) efforts and aimed to verify the identification of mushroom (*Agaricus bisporus*) varieties through the combination of DNA analysis and phenotypic data. A 2D image system was employed to quantify the following four main characteristics of each mushroom: area, eccentricity of the cap, gill shape, and shape factor of the whole fruiting body. The results indicated that it was possible to differentiate 80% of the cultivars. Thus, in their successive work (Vooren et al., 1992), the researchers attempted to increase the number of morphological characteristics estimated. A series of image-based operations, including gray-level transformation, erosion, and expansion, were applied to the raw images to acquire a smoother outline of each mushroom. Ultimately, they could evaluate 11 features (area, perimeter, shape factor, bending energy, normalized mean absolute curvature, sphericity, eccentricity, length, width, rectangle length, and rectangle width) of each mushroom, corresponding to more than a 200% increase over that of previous studies. Despite the limits of two-dimensional images, this approach provided sufficient morphological data through image analysis techniques for mushrooms. Meanwhile, an algorithm for obtaining the position and size of each mushroom in the growing bed was described by Tillett et al. (1991). The main steps of the developed algorithm were as follows: (i) estimating the center of a mushroom based on the height threshold, (ii) using the low threshold to find a starting point for the mushroom outline, and (iii) following the edge of the mushroom in the gray level image based on the center position and the expected shape of the mushroom. Although the described studies could only accurately recognize mushrooms with regular shapes and the overall accuracy was not sufficient, the study offered a good foundation for follow-up studies.

Discoloration is a crucial attribute reflecting the health of mushrooms, often resulting from senescence, damage, or bacterial infections in mushroom houses. Vizhányó et al. (2000) transformed the RGB values into independent components and eliminated the influence of highlights and shadows to identify abnormal mushrooms. The results showed that the proposed method could effectively detect discoloration caused by diseases, making it an excellent candidate for implementation in a factory setting; however, this study only focused on the algorithms, and there were still challenges to be overcome before industrial application (e.g., solving the occlusion problem in growth beds). To reduce the complexity of greenhouse control and improve the efficiency of mushroom growth management by artificial intelligence technology, Lu et al. (2019, 2020) aimed to develop equipment that could automatically measure the size and count the number of mushrooms. Such technology would be helpful for people not familiar with mushroom growth but still needing to estimate mushroom growth rates. To mitigate the color deviation caused by automatic adjustments of the camera aperture and focus during the measuring process, a CNN comprising DL combined with an innovative score-punishment algorithm was applied. This system exhibited good performance in terms of locating and measuring individuals by the circle Hough transform algorithm. However, it lost sight of the importance of color as an indication of mushroom health. In addition, for better visual effects, additional light sources were added to the experimental environment. Significantly, it is well known that the shape and color of edible fungi are intimately related to light quality, light intensity and light duration (Simon et al., 2011; Hong et al., 2021). Therefore, data inconsistent with reality may be acquired in long-term and continuous observations (e.g., taking a photo each minute) of the growth of edible fungi.

Another application of a computer vision system was described by Zhou et al. (2017). To effectively assess the formation rate of *Pleurotus eryngii* primordia, the researchers introduced a machine vision system by using statistical means to establish the model. To compensate for the drawbacks of statistics in analyzing the primordia, the following three steps were performed: image preprocessing, extraction of morphological features, and large dataset analysis. Furthermore, the new prediction approach utilized a BP neural network with primordium seeds as the input and the number of primordia as the output, ultimately achieving an accuracy of up to 94.79%. This method can also be employed to assess the primordium growth rate of other mushrooms because they are similar to a certain extent.

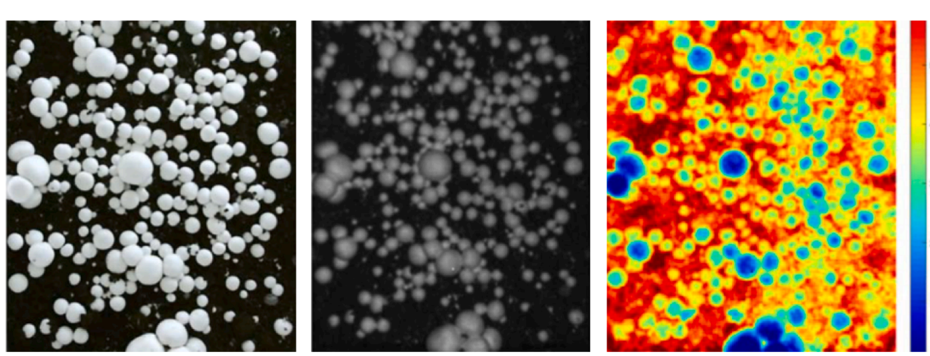
The methods described above use computer vision technology to recognize the growth status of mushrooms. However, automatic robotic harvesting remains another constant theme in agricultural research investigated in many ways. With the unstructured data, it is impossible for engineers to design a single piece of equipment to harvest all agricultural products. In particular, mushrooms often grow in the bed of a greenhouse, so it is more feasible to automatically harvest mushrooms relative to other farm products (e.g., cucumbers, tomatoes, etc.), which may be covered by leaves. To address the problem of locating objects of interest, one of the most important and difficult problems related to mushroom harvesting, Reed et al. (1994) developed an automated system by combining a vision system with a computer-controlled Cartesian robot. This system successfully positioned 84% of the mushroom targets in over 18 experiments. It was found, however, that small or overlapping mushrooms covered could not be detected perfectly. Additionally, the researchers designed a mushroom picking end effector, demonstrating a

67% success rate for mushroom picking, and its mistakes were due to poor locating by the image processing system or poor calibration of the robot. Nevertheless, the mechanical structures and algorithm were improved in their subsequent research (Reed et al., 2001), and the average success rate exceeded 80%. Similarly, Zhou et al. (1995) discussed the algorithm governing the image analysis of mushrooms and seedbeds and introduced a more accurate way to extract mushroom edges and compute perimeters, areas, and central coordinates of the closed region to locate mushrooms accurately in their natural environments. Noble et al. (1997) observed that the mushroom strain, distribution, length, growing angle, and flush number had much greater impacts on the harvesting rig. Therefore, they summarized the effects of mushroom strains, flush numbers, and diameters on the picking performance and discussed the main causes of picking failures while revealing the best cup size, strain, and other parameters that were suitable for harvesting by a robot. Since 2006, numerous methods for reducing the picking failure rate have been developed, including sequential scan and segmentation techniques (Yu et al., 2005, 2006), as well as corner density detection for overlapping mushroom images (Yang et al., 2018). All these solutions focused on using novel techniques to overcome the challenges of locating mushrooms and ultimately to achieve satisfactory results, and these studies have already led to results related to automatic harvesting. However, they have also uncovered certain limitations. For example, these studies only considered a few varieties of mushrooms, and the parameters only included diameters and cup sizes.

In all of the aforementioned studies, the authors investigated the application of 2D vision systems to address difficult and realistic problems. As mentioned previously, 2D vision-based methods cannot acquire depth data, which limits the utilization of computer vision methods to evaluate mushrooms. For example, the quality of an *Oudemansiella raphanipes* mushroom is closely related to the length of its stipe, but the top-down shooting method of ordinary cameras cannot assess the stipe length. Considering that mushrooms are generally cultivated in dark areas, active model-based vision systems, such as KinectV1/V2 and SR300, are usually employed to acquire stipe length. Fig. 2 displays pictures of growing mushrooms (*Agaricus bisporus*) captured by Kinect V2 cameras. Pictures (a), (b), and (c) are the RGB image, NIR image, and depth image, respectively. These are also the images obtained by using other depth cameras.

Aníbal et al. (2018) employed a machine vision system equipped with omnisurface software to acquire the volume data based on the method referred to previously (Lee et al., 2006). Compared with the buoyant force method, the machine vision-based approach acquired slightly higher volume data for the mushrooms and demonstrated high efficiency. However, the volume data were obtained by using a structure (with cameras and turntables) that was similar to the SFM approach in a lab environment but not in the field. Wang et al. (2018) used an SR300 RGBD camera to measure portabella mushrooms by using the depth data provided by the cameras to select the self-adaptivity threshold. After combining these results with a Hough Transform, the center and three-dimensional coordinates of the mushrooms could be accurately obtained. The maximum errors of the diameter and tilt angle were 5.57 mm and 6.3°, respectively. It took 44 ms to process a single mushroom. Therefore, this system satisfied the operational requirements of mushroom picking robots. Lee et al. (2019) used depth cameras to develop a harvest assistance system to overcome the weaknesses of traditional 2D-based methods. The 3D point cloud of each mushroom was acquired by a depth camera and used to segment an individual crop among overlapped mushrooms in clusters and to calculate the size of the mushroom caps. On the basis of the depth data acquired by the SR300 camera, Sun et al. (2021) proposed a submerged method for *Agaricus bisporus* detection and diameter measurements. Their core idea was to regard individual mushrooms as "isolated islands" and the mushroom bed substrate as a "seabed." Therefore, when the sea level rose, the protrusion on the mushroom bed was gradually submerged, while the contour of the mushrooms remained the same. With all these studies, the mushrooms' information can be accurately obtained from RGBD data, and the application of 2D and 3D machine vision technologies in the planting and picking of mushrooms is summarized in Table 2.

From the discussion presented above, it is clear that both 2D and 3D images are used in some relatively limited ways in the mushroom agricultural field. The majority of research in this field has generally focused on the picking of a few types of mushrooms (e.g., *Agaricus bisporus*). The problems solved mainly focus on the identification and location of mushrooms through image information. The methods used by most scholars are still traditional digital image processing and morphological methods. With the improvement of computer hardware performance, some studies have begun to apply deep learning technology in the mushroom industry. However, the results do not demonstrate significant progress over the traditional methods. This is likely because a large public dataset does not yet exist, so the advantages of deep learning are not entirely realized. Additionally, the inexplicability of deep learning methods slows the improvements of the models in terms of their principles. Although currently available RGBD cameras have already possessed many advantages and have been widely used for the high-throughput detection of crop phenotypes, they are, unfortunately, rarely employed in the field of edible fungi. With future technological development, computer vision- and artificial intelligence-based strategies should be integrated more tightly with mushroom planting, picking, phenotypic observations, and breeding to lay the foundation for the intelligent production of edible fungi. Therefore, computer vision technology, especially 3D-based methods, has much broader prospects in the mushroom industry.



(a) RGB image (b) NIR image (c) Depth image

Fig. 2. Images obtained by depth cameras [reproduced from Lee et al. (2019)].

Table 2
Summary of different features and methods for computer vision system used in mushroom cultivation and harvest.

Types	Hardware	Application situations	Methods	Result	Reference
2D vision	Sony XC 77 CE with 35 mm NIKON lens	Acquiring morphological characters of mushrooms, and distinguish the cultivars.	Edge detection, erosion, dilation, etc. and morphological target detection algorithms	To distinguish 80% of the cultivars used in this experiment	Van de vooren et al. (1991), Van de vooren et al. (1992)
	A video camera*	Identifying and locating for a robotic mushroom harvesting rig	Traditional image processing methods and morphological target detection algorithms	86% were found with fairly accurate outlines.	Tillett et al. (1991)
	A black and white CCD camera*			84% were located and 67% were picked successfully.	Reed et al., (1994)
	A black and white CCD camera*			70–80 mushrooms were picked per minute.	Zhou et al. (1995)
	Panasonic CD 20/B			76% of the mushroom pick were successful;	Noble et al. (1997)
	Panasonic CD 20/B with Cosmicar TU 12.5–75 mm zoom lens			81.6% of the mushroom pick were successful;	Reed et al., (2001)
	A black and white CCD camera*			Greatly effective#	Yu et al. (2005, 2006)
	A black and white CCD camera*			Location detection success rate is 86.3%	Yang et al. (2018)
	Sony DXC-151 AP color video camera with HOYA 49 mm + 1 computer TV zoom (1:1.6/12.5–75) lens	Discriminating the browning caused by diseases from the natural browning of the mushrooms.	Converting RGB values of the images into L, a, b color components, and plotting the color points to distinguish the health and diseased mushrooms.	81% of the diseased area was correctly classified	Vizhányó et al. (2000)
	Canon EOS 300D	Assessing the formation rates of *Pleurotus eryngii* primordium effectively.	Traditional image processing methods and back-propagation neural network	The accuracy of Primordium was up to 94.79%	Zhou et al. (2017)
	SVS-VISTEK (ECO445CVGE67) IP67 network camera	Measuring the diameters of clustered mushrooms to improve the efficiency of mushroom growth mana-gement.	YOLO V3 and score-punishment algorithms based on deep learning.	The average accuracy wasup to 87.03%	Lu et al. (2019,2020)
3D vision	Self-made equipment based on backlight light source, similar to SFM	Measureing the volume of selected raw produce.	A fast eight-neighborhood clockwise boundary-tracing algorithm and linear surface interpolation to measure the surface area and volume of produce.	The volume errorwas 0.6 cm^3 compared with that of Buoyant force method.	Aníbal et al. (2018); Lee et al. (2006)
	SR300	Aiming to provide working parameters for a mushroom picking robot.	Hough transform, and the eight-neighborhood, boundary-tracing algorithms to divide adhered mushrooms	The maximum error of diameter was 5.77 mm, while the maximum error of deviation-lean angle was 6.3°	Wang et al. (2018)
	Kinect	Developing the mushroom maturity evaluation system.	Faster R-CNN model used to distinguish each mushrooms; the size of mushroom caps calculated by using the point cloud, and the SVM classifier applied to determine the maturity.	The recall rate of mushroom identification was 82%, and the accuracy of distinguishing mushrooms' maturity was 70.93%.	Lee et al. (2019)
	SR300	Offering the working targets and parameter information to the picking robots	A "Submerging Method" proposed to segment mushrooms, the diameter measurement of the mushroom achieved by using Hough circle detection.	The positive detection rate of *Agaricus bisporus* was more than 89%, while the diameter measurement error was 2.15% −3.15%	Sun et al. (2021)

Note: * Product specification is not mentioned in the original # The value is not mentioned in the original.

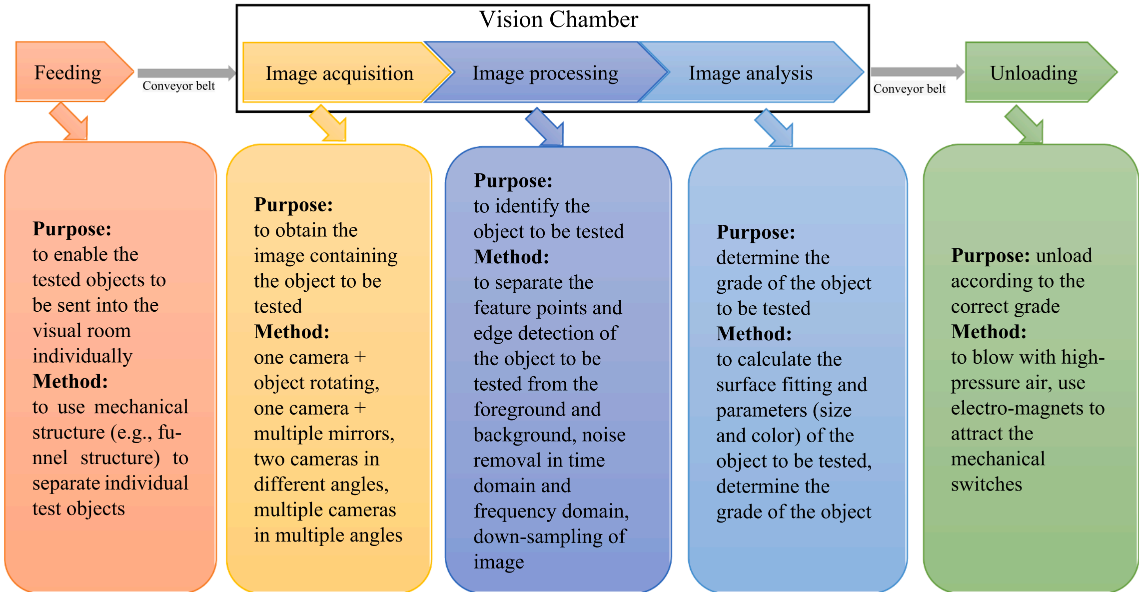


Fig. 3. The pipeline of a typical grading system.

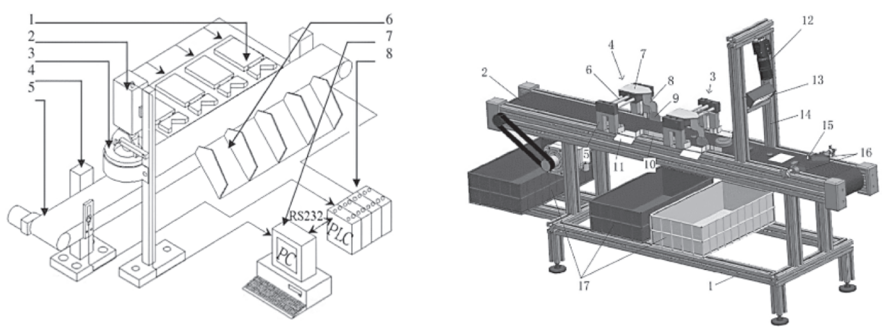


Fig. 4. Automatic sorting system for mushrooms [reproduced from Chen et al. (2004) and Wang et al., (2018)].

Table 3
Summary of different methods for the computer vision system used in the mushroom grading.

Grading parameters (measured parameters)	Main method	Mushroom applied	Results	References
Colors, shapes, stem cuts, cap veils opening	Edge detection, Threshold segmentation, morphology.	*Agaricus bisporus*	86% for shape and 66% for stem cut accuracy	Heinemann et al. (1994)
Front and back sides, roundness, edge thickness of gill surface, gray value, crack ration	Edge detection, Morphological texture extraction, neural network.	*Lentinula edodes*	88% accuracy and 0.6–0.7 s/mushroom	Hwang et al. (1994, 1996, 2005)
Shapes, colors and sizes	Edge detection, Threshold segmentation, Erosion and Dilation.	Dried *Lentinula edodes*	97.6% accuracy rate with 0.3–0.7 s/mushroom	Chen et al. (2004)
Colors	Edge detection, RGB channel background segmentation, median filtering, defect detection.	Fresh *Lentinula edodes*	96.5% total accuracy	Li et al. (2010)
Fractal dimensions, relative lengths, aspect ratios, crooked degrees of the stipe	Image segmentation, Fractal dimension, SVM.	*Pleurotus geesteranus*	Recognition rate 96.67%	Huang et al. (2010)
9 parameters such as shapes, eccentricity, density, irregularity, and so on.	Morphology, PCA, K Nearest Neighbor.	*Lentinula edodes*	A classification accuracy rate of 92.2%	Chen et al. (2014)
Diameters of the pileus	Watershed, Basic global threshold and Maximum entropy threshold method.	*Agaricus bisporus*	Grading accuracy of 97.42%, damage rate of 0.05%	Wang et al. (2017, 2018a, 2018b)

3.2. Grading of mushroom qualities

Another occasion that merits the application of vision-based technology is the classification of mushrooms according to their appearance, which may be altered during gathering and transit but still may play a role in determining the corresponding prices in the market. Sorting or inspecting mushrooms manually is a subjective and labor-intensive task, and the decisions have no objective standard. Therefore, automatic grading based on computer vision is promising because it is fast, efficient, accurate, and objective. A quintessential machine vision system for mushroom grading usually includes a mechanical platform, a vision chamber, a computer board, and a camera. Typical processing and analytical steps for grading mushrooms include feeding, image acquisition, image preprocessing, image analysis, and graded unloading, as outlined in Fig. 3.

Based on this design, Heinemann et al. (1994) first developed a mature system to obtain the shape, color, veil opening, and stem cut according to the standards of the United States Department of Agriculture (USDA). Another mushroom grading study was reported by Hwang et al. (1994), which focused on a method for recognizing the front and back sides of *Lentinus edodes* by using a neural net that achieved successful results. Based on this study, Hwang et al. (1996) developed an automatic grading and sorting system equipped with robust and efficient sorting algorithms for dried oak mushrooms. To optimize the results, three steps were carried out: capturing the image of the mushrooms, identifying the front or back side, and sorting. Chen and Ting (2004) proposed a novel method for automatically grading shiitake mushrooms based on shapes, colors, and sizes. This online grading system relied on a color charge-coupled camera combined with image processing algorithms (e.g., for geometry feature extraction) to identify the characteristics of shiitake mushrooms (e.g., color abnormality, broken caps). The researchers also introduced a computer connected to a programmable logic controller (PLC), which could run the image processing program and control the actuator in terms of grading instructions. This system was used to evaluate 250 dried shiitake mushroom samples and reached a 97.6% accuracy rate, which is better than that obtained by visual inspection. Therefore, this grading approach (Fig. 4) was ideally suited for industrialized applications. Additionally, analogous equipment was developed by Hwang (2005) that involved an automatic sorting method to choose the grading criteria interactively and control the system remotely based on the network. Similarly, Li et al. (2010) concentrated on defect identification in fresh shiitake mushrooms, which was divided into five grades based on images of their caps. The RGB components were extracted from raw pictures, while the G and B components were utilized to segment defects and backgrounds from the whole image. All stipes of the shiitake mushrooms were removed to acquire better images of the caps. Although this was not appropriate for industrial applications, the method demonstrated a satisfactory accuracy rate of 96.5%. *Pleurotus geesteranus* has emerged as the most popular edible fungus in recent years due to its deliciousness and nutritiousness. In the supermarket, the price of the best *Pleurotus geesteranus*, as determined by shapes and colors, could be twice that of the inferior specimens. To identify defects in *Pleurotus geesteranus* based on computer vision, Huang et al. (2010) extracted seven feature parameters related to their shapes: fractal dimension, relative length, roundness, shape factor, convexity of the pileus, aspect ratio, and crooked degree of the stipe. An SVM was used to build a model to discriminate *Pleurotus geesteranus* belonging to a different level. Ge et al. (2011) summarized the progress of computer vision in the grading, automatic gaining, and quality inspection of shiitake mushrooms. They revealed the deficiencies and directions for further research. Traditional methods based on the mushrooms' geometric morphologies may be abandoned because of the complexity of the algorithms and replaced by neural networks, which may lead to better results via end-to-end processes without other complex steps.

Lentinula edodes is a precious type of shiitake with higher nutritional and pharmaceutical values than the ordinary variety. The grade of *Lentinula edodes* depends on the shape, size, stipe length, and degree of damage to the cap, which may be influenced by growth, transport, and processing. Chen et al. (2014a–c) proposed a series of methods for differentiating *Lentinula edodes* according to their texture or the edges of their caps. In their study, images of each mushroom were acquired by a complex system comprising a camera, 1394 data acquisition hardware, an M0514-mp lens, and four lights. To detect the broken *Lentinula edodes*, a curve recognition algorithm was designed and applied to the images. Moreover, the textures of *Lentinula edodes* were also extracted by the following three models: a gray histogram and gray level co-occurrence matrix, a Gauss Makov random field, and a fractal dimension model. Their experimental results showed that these novel methods achieved higher accuracy and met the requirements of engineering applications.

The postharvest processing of *Agaricus bisporus* (one of the most commonly consumed mushrooms) has attracted attention all over the world because its price is affected by numerous factors, including the size and integrity of the pileus. Lu et al. (2017) and Wang et al. (2018a, b) designed an automatic sorting system based on the pileus diameters of white button mushrooms (*Agaricus bisporus*) (Fig. 4). Using the OpenCV

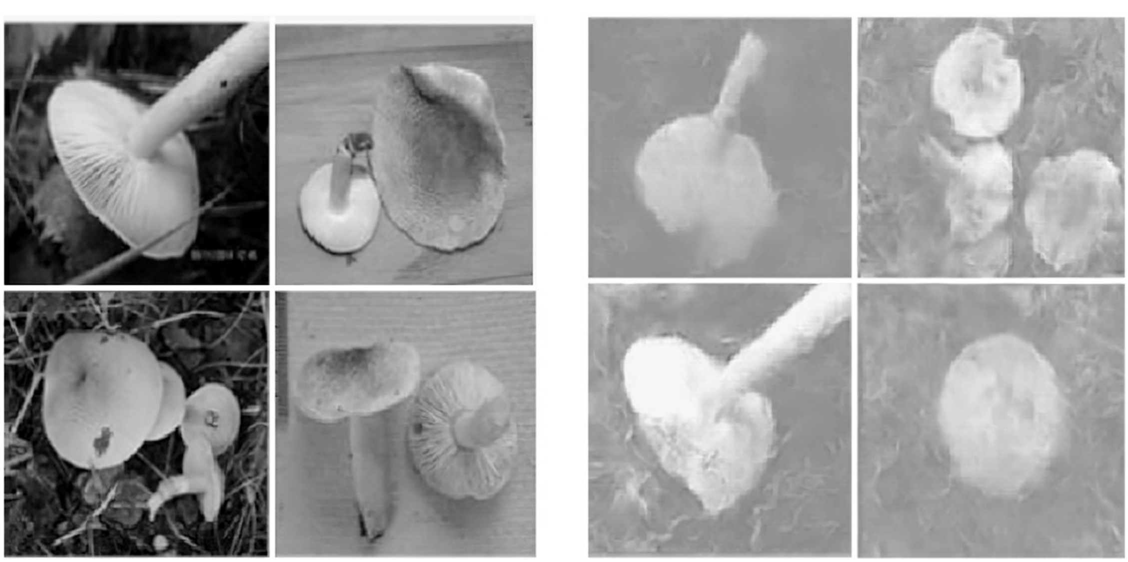


Fig. 5. Illustration of generating fungus images and original images [reproduced from Yuan et al. (2019)].

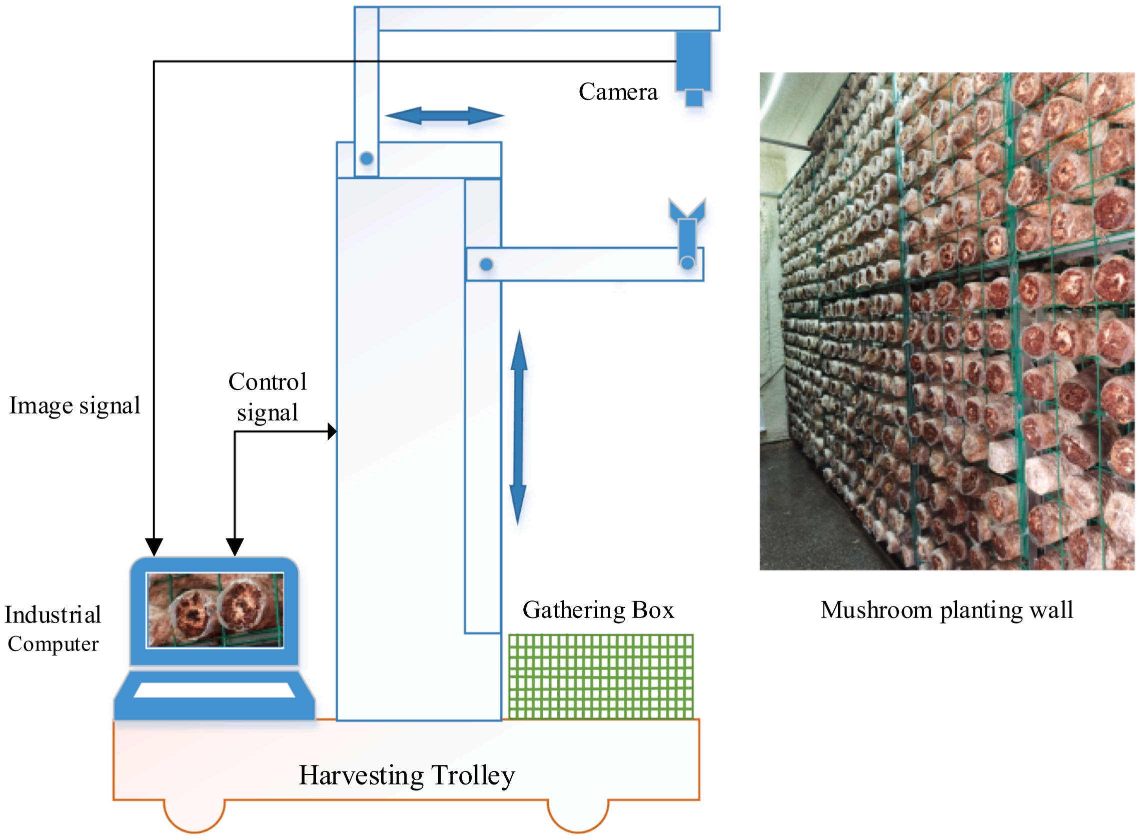


Fig. 6. Schematic diagram of a computer vision system for the new harvesting robot.

library and Visual Studio software with a Canny operator and a watershed method, they presented a novel algorithm to eliminate the influence of shadows and petioles. According to the standard NY/T 1790–2009, this system classified *Agaricus bisporus* into three grades: diameters less than 25 mm, between 25 mm and 45 mm, and greater than 45 mm. Then, the researchers recorded the efficiency, accuracy, and damaged and undetected rates of the automatic system and later compared these results with the data obtained manually. Their results indicated that whether the grading speed, accuracy, or other parameters were considered, the automated system was an effective automatic solution to *Agaricus bisporus* postharvest processing. Table 3 summarizes the methods used in mushroom grading.

3.3. Other applications

In addition to the grading, location, or monitoring of mushrooms, computer vision has demonstrated tremendous potential in many other applications. In the past few years, many people have been poisoned after eating wild mushrooms by mistake, and a few of them have even lost their lives. Considering these findings, quickly and accurately judging whether a mushroom is edible or not only by its appearance and growing environment has become a problem worthy of careful consideration.Lidasan et al. (2018) developed a mobile-based application equipped with a neural network to identify edible versus poisonous mushrooms. The GrabCut algorithm and probabilistic neural network (PNN) reached an accuracy rate of 92% with 133 mushroom images as the training data. For biology majors and fans of mushroom hunting, it was a convenient tool to identify wild mushrooms. Deep learning thus represents a novel and effective technique for fulfilling the momentous and seemingly impossible task never achieved before. Luo (2019) studied the problem of spatial redundancy in traditional CNNs and proposed a reduced gradient convolution training model to improve the performance of the mushroom recognition algorithm. The results showed that the average time and accuracy could reach 0.985 s and 91.6%, respectively, by using a mushroom dataset containing 8123 samples. In contrast, Fan et al. (2020) proposed an inedible mushroom recognition method based on a deep residual network and transfer learning. To construct appropriate models, the dataset containing 14,669 images was obtained from the internet, and the ResNet152-based model was trained. This method provided another way to recognize inedible mushrooms, with an identification rate of up to 97.35%, which was far higher than that in previous studies.

A generative adversarial network is a deep learning-based model exhibiting much more powerful feature extraction and characteristic expression. This model has been widely used in image processing and voice recognition, as well as some other fields. Yuan et al. (2019) introduced GAN into mushroom phenotype generation to obtain massive datasets for deep learning training. In addition, they also designed an elaborate mushroom phenotype generative adversarial network (MPGAN), comprising one input layer, one fully connected layer, five deconvolution layers, and an output layer. A public dataset and a private dataset were used to practice the model to obtain more realistic data used to compensate for the shortage quality mushroom images while carrying out the deep learning method. However, the defects of the model were clear. For example, the images generated by the MPGAN in Fig. 5 were actually quite similar to that of the original image, thus seemingly breaking the rule of biodiversity. Regardless of whether this algorithm has greater or fewer deficiencies, it still represents a novel means of acquiring a large number of images in a short time and should thus be improved by further developing GAN techniques in future studies.

4. Future research directions for computer vision and machine learning in the mushroom industry

4.1. Automatic mushroom spawn harvesting

As mentioned previously, a mushroom picking robot would manifest a development trend in mushroom mechanization with great prospects. Only a few studies have designed such automatic picking systems exhibiting good results, and they mainly concentrate on *Agaricus bisporus* in the growing bed. However, the soilless cultivation method based on mushroom bags has been widely used for the cultivation of edible fungi, such as oyster mushrooms and king oyster mushrooms. To improve the ventilation conditions, avoid heat and humidity during the planting process and improve the utilization of space, many edible fungus farms use "planting walls" of mushroom bags to promote three-dimensional cultivation. In this scenario, the original mechanical structure cannot perform automatic picking, so the entire picking system must be redesigned in terms of hardware, software, and mechanical structures. Fig. 6 illustrates a concept for this new picking mechanism proposed by the author team. To obtain higher yields, the mushroom-bag-based cultivation method usually requires cleaning up the residues on the mushroom bags after the picking of each mushroom stalk. In this case, it is quite challenging to design an end mechanism to be able to pick edible fungi and clean up the residues at the same time. Therefore, it is necessary to develop a strategy to locate the exact positions of picking and cleaning under poor lighting conditions.

4.2. Automatic grading

The increasing cost and decreasing supply of skilled laborers are becoming huge challenges in the mushroom industry, and they lead to the emerging trend of substituting robots for laborers because of reliability and efficiency. Currently, computer vision-based automatic grading technology for *Agaricus bisporus* and shiitake mushrooms is relatively mature in some countries, including China. However, robot sorting has only been applied for certain species of mushrooms because different mushrooms have distinct appearances, making it impossible to identify different mushrooms by using a single approach. With the development of domestic cultivation techniques, an increasing number of artificially cultivated mushrooms will be supplied to the market, and as a result, the demand for new methods and equipment for automatic grading has become urgent. It is worth noting that visible-light-based RGB cameras only acquire the appearance-based parameters of the mushrooms but cannot analyze their internal qualities. Currently, nondestructive spectroscopic methods (e.g., near-infrared, Raman, terahertz, hyperspectral, etc.) have been successful in grading fruits based on freshness or protein contents (Chen et al., 2013; Liu et al., 2015; Wang et al., 2021), and pesticide residues and heavy metal pollution on fruits have also been detected spectroscopically. As a different popular food group, the same needs exist for mushrooms. This demand makes it possible to employ spectroscopic techniques for grading mushrooms based on internal attributes via nondestructive methods, which may be a promising research direction in the future.

4.3. Acquiring 3D features of mushrooms

Currently, an important approach to feature detection is agreed upon on the basis of the acquisition of characteristic parameters from an image using a new noncontact method. Compared with those of stereoscopic images, a 2D image can only provide simple attributes, including length and width. Clearly, these parameters are not sufficient to describe mushrooms thoroughly. The shapes, sizes, stipes lengths, and degrees of damage to the caps of shitake mushrooms, for example, can all be regarded as key parameters in the sorting, but the thickness of the caps, determining the mushroom's tastes, cannot be obtained because of the limitations of the 2D vision system. This problem also arises in trying to evaluate the volume of mushrooms. To overcome these challenges, 3D systems provide additional opportunities to observe objects precisely in that they can reveal the distance between the object and the observer. In other words, these systems acquire length, width, and depth data from the sensors. In general, more accurate information can be obtained more accurately from 3D images, thereby reducing the impacts of illumination and observer angles on the images. Although the current 3D image technologies have not yet been applied to mushrooms, this development trend could be a promising direction for future research and applications, especially as the prices of 3D image sensors continue to fall.

4.4. Digital twins of mushrooms

In recent years, the concept of digital twins and crop models has become very popular in agriculture. This is a virtual-simulation-based technology focusing on the connection between physical and virtual products and has already been applied in the full-life-cycle management of industrial production. With the development of image sensors and data processing algorithms, especially 3D technology, an increasing number of small changes in the object can be captured by observation systems. This enables the construction of a growth model by continuously recording various parameters during the growth cycles of plants. As the technology continues to be improved, digital twins based on a growth model can help increase yields and decrease energy consumption by optimizing the results of various cultivation strategies before putting them into effect. To our knowledge, in contrast to other plants, the growth factors of mushrooms only include temperature, humidity, illumination intensity, and carbon dioxide concentrations, which simplifies the relationship between growth factors and mushroom status. In the future, digital twin-based mushroom cultivation may become popular, and anyone will be able to grow mushrooms perfectly simply by clicking buttons at home. Therefore, digital twin technology related to mushrooms represents another promising direction for future research efforts.

5. Conclusions and perspectives

Over the past decade, computer vision and machine learning technology have been widely used in the modern agricultural industry for locating, grading, and harvesting processes. This article provides a comprehensive review of computer vision-based and machine learning-based mushroom studies and discusses the advantages and disadvantages of various types of 2D vision systems and their applications. Additionally, 3D vision is also introduced to meet different requirements and services. Then, several future research directions using computer vision for mushrooms are also discussed, including mushroom spawn harvesting, obtaining 3D features and mushroom phenotypic data based on generative adversarial networks.

Based on these studies, it is determined that image-based methods demonstrate significant potential applicability in mushroom cultivation, specifically in automatic harvesting and sorting tasks. In particular, machine learning-based algorithms simplify the process of extracting features and thus improve the accuracy of recognition.

Nevertheless, there are several limitations affecting the application of computer vision technology in the mushroom industry. First, automated harvesting and grading are currently only available for a few varieties of mushrooms, which is not enough to satisfy the market with an increasing number of mushroom varieties being introduced in industrialized farming.

Second, high-throughput digital phenotyping is a complex and difficult task that has undergone rapid development in the plant fields, but there have been no reports on its application to mushrooms (Yuan, et al., 2021). To achieve the goal of digital twins, it is necessary to capture raw data and establish a multidimensional, multiscale digital mushroom phenotypic database by designing an advanced trait identification algorithm to extract available data from massive omics information.

Finally, since there is currently no public dataset containing information on edible mushroom industrial picking or grading, studies have relied mostly on self-built datasets. This renders the proposed methods nonuniversal, and to a certain extent, there is a negative influence on the application and promotion of machine vision based on deep learning in the field of edible fungi. In addition, the number of samples in the self-built datasets generally do not meet the massive data requirements for deep learning. This perhaps explains, on the one hand, why deep learning and ensemble learning algorithms are currently limited in applications involving the mushroom industry. However, with the advancement of current imaging technologies and the development of new algorithms, more information will be available to enhance target recognition, and more fields of mushroom cultivation and harvesting will become automatic and intelligent.

CRediT authorship contribution statement

Hua Yin: Writing – original draft. **Wen-long Yi:** Validation. **Dian-Ming Hu:** idea proposal, revision & editing.

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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