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Review Article

Sensors, systems and algorithms of 3D reconstruction for smart agriculture and precision farming: A review

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ABSTRACT

Perceiving the shape and structure of the real three-dimensional world through sensors and cameras is indispensable across various domains. The 3D reconstruction technology is dedicated to realizing this ideal process. 3D reconstruction technology serves as a transformative tool, enriching our ability to perceive the genuine shape and stereo structure of objects and scenes in the real world. Through combining advanced sensors, image processing algorithms and 3D reconstruction methods, it captures the shape and structural information of targets from multiple perspectives and dimensions, and creates highly realistic 3D models in the virtual environment. With the rapid modernization of agriculture and ongoing technological progress, the demand for more efficient and precise management and monitoring methods in agricultural production is increasing. Traditional observation and measurement methods face challenges such as low efficiency and incomplete data. 3D reconstruction technology provides more accurate and intelligent management tools for smart agriculture. This paper provides a detailed introduction to the research progress based on 3D reconstruction technology in smart agriculture. It delves into the characteristics and development of various sensors and sensing systems, discussing various methods to implement 3D reconstruction technology. Different from applications in industrial environments, agricultural environments and crops are usually complex and variable, and consideration of diverse factors is required for the selection of suitable sensors and reconstruction methods. Therefore, several aspects of applications are summarized, such as agricultural robotics, crop phenotyping, livestock, and the food industry. Finally, the challenges and potential future trends of 3D reconstruction in agriculture are given.

1. Introduction

With the adoption of advanced technologies, 3D reconstruction has become a focal point in both robotics and computer vision research, playing a pivotal role in shaping the landscape of modern agriculture (Zahid et al., 2021; Paturkar et al., 2017). 3D reconstruction in agriculture aims to comprehensively sense the agricultural environment using various sensors. Subsequently, the gathered information is leveraged to execute necessary and precise operations (dos Santos Rosa et al., 2017). Combined with 3D reconstruction, robotics not only have the capability to diminish production and labor costs but, furthermore, contribute to heightening environmental control and have a significant impact on enhancing the overall standard of agricultural products (Vazquez-Arellano et al., 2016). The advancement of smart agriculture is intricately linked to the progress of 3D reconstruction technology. This technology employs diverse sensors to sense and understand the agricultural scenes, enabling precise operations and informed decision-making for tasks like crop monitoring, yield estimation, and environmental control in modern agricultural practices (Sampaio et al., 2021; Sachithra & Subhashini, 2023).

However, achieving 3D reconstruction in agriculture poses a challenge due to factors such as variable light conditions, unstructured environments, plant occlusion and overlap, etc. (Paturkar et al., 2017; Zollhöfer et al., 2018; Khazem et al., 2023). In the past few years, the exploration of 3D reconstruction techniques has witnessed substantial advancements and become hot point of research, this process involves not only technical aspects but also extends to hardware considerations (Aharchi and Ait Kbir, 2020).

Sensors play a crucial role in 3D reconstruction technology by providing essential data to create virtual models (Kang et al., 2020), they have the ability to acquire depth information or capture high-resolution images for 3D reconstruction (Silva et al., 2013). In most

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cases, optical sensors are employed for 3D reconstruction, including monocular cameras, stereo cameras, RGB-D cameras, Light Detection And Ranging (LiDAR), and laser scanners, etc. (Wang et al., 2020; Massot-Campos & Oliver-Codina, 2015). The monocular cameras capture a series of images for camera calibration, and then accomplish 3D reconstruction by projecting these images to 3D space (Pradeep et al., 2013). The binocular cameras capture images of the same object from different positions, resulting in the creation of binocular disparity, then the distance can be calculated according to the disparity (Wang et al., 2020). Applying disparity distance measurement will able to calculate depth details information (Rahman et al., 2017). The RGB-D cameras are capable of acquiring both colour and depth information about the target simultaneously (Liu et al., 2022), it has the advantages of being easy to develop, having high real-time performance, and possessing robust anti-interference properties (Zhou et al., 2020; Chen et al., 2020). In recent years, due to the affordability and excellent capabilities of RGB-D cameras, many experts and scholars have focused on these cameras to realize 3D reconstruction (Zhou & Koltun, 2014; Izadi et al., 2011; Nguyen et al., 2018), such as Microsoft Kinect (Zhang, 2012) and Intel RealSense (Keselman et al., 2017). Furthermore, the advancement in laser technology has enhanced the efficient acquisition of highly precise 3D data for objects (Chen et al., 2019). As high-precision laser-based devices, both LiDAR and laser scanners excel in the implementation of 3D reconstruction. However, the widespread use of these devices is hindered by their prohibitive cost (Raj et al., 2020). Additionally, the depth information provided by a single sensor may not be detailed enough, so multiple sensors need to be integrated to obtain more reliable and accurate results (Aharchi and Ait Kbir, 2020). The multi-sensor fusion method involves integrating two or more types of sensors to enhance the acquisition of detailed depth information. A system uses RGB camera, LiDAR, GPS, and IMU (Chen et al., 2019) to fuse images and 3D point clouds to realize the fusion of color point clouds in the outdoor driving environment of smart cars for 3D reconstruction. In some real-time 3D reconstructions of expansive scenarios, researchers selected a depth camera with an inertial measurement unit (IMU) to facilitate the reconstruction process (Li et al., 2020). The integration of 3D structured photo scanners and a stereo camera reconstructs free-form artworks (Barone et al., 2012). Non-optical sensors such as acoustic (ultrasonic, Sonar), and electromagnetic (infrared, ultraviolet, microwave radar, etc.) offer alternative sensing schemes (Sansoni et al., 2009).

The success of 3D reconstruction not only depends on the selection of sensors but also hinges on the choice of reconstruction methods built upon the chosen sensors (Kang et al., 2020; Ryo, 2022). 3D reconstruction methods have recently been divided into two categories: traditional reconstruction methods and deep-learning based reconstruction methods (Xu et al., 2022). The traditional reconstruction methods include both passive reconstruction methods and active reconstruction methods. The passive reconstruction methods usually use a RGB camera to acquire images and then get the depth information to reconstruct the 3D model (Yang & Cho, 2021), such as Shape From Shading (SFS), Multi-View Stereo (MVS), Structure From Motion (SFM). The active reconstruction methods usually use the sensors to illuminate, project or cast a signal to measure and enhance the depth data (Massot-Campos & Oliver-Codina, 2015), common methods include time of flight (ToF), structured Light and triangulation. Active reconstruction methods generally yield much higher point cloud density and accuracy, particularly in low-contrast scenarios (Roman et al., 2010). In recent years, researchers have focused on using deep neural networks to complete 3D reconstruction, and made numerous research achievements combining traditional methods with deep learning models (Fu et al., 2021; Chen et al., 2019). The reconstruction methods based on deep learning are used to process large amount of data, comparing with the traditional methods (Fu et al., 2020). In the field of multi-view 3D reconstruction, researchers used the VGG network to encode different views. The 3D convolutional decoding was utilized to obtain the corresponding coarse models, followed by feature fusion to achieve the final voxel model (Xie et al., 2020). NeRF (Neural Radiance Field) is now considered as a pioneering approach in 3D reconstruction. This method employs several simple MLPs to model the radiance field of a scene, enabling high-fidelity reconstruction. By training the neural network to learn radiance values for each point in the scene, and finally achieves detailed capture of both geometry and lighting (Mildenhall et al., 2021).

Recently 3D reconstruction algorithm and methods have been widely investigated and applied for smart agriculture and precision farming (Sampaio et al., 2021; Vázquez-Arellano et al., 2018). The integration of progressive sensing technologies and machine learning approaches have paved the way for transformative advancements in agriculture (Ma et al., 2022). These techniques, ranging from LiDAR and RGB-D cameras to deep learning models, play an important role in capturing and analyzing spatial information, facilitating precise monitoring, and enabling data-driven decision-making in agricultural practices (Xie et al., 2022).

To improve the accuracy of 3D reconstruction, as well as meet various challenges to achieve efficient reconstruction, many excellent solutions have been put forward. A full description of the challenges and solutions of 3D reconstruction for smart agriculture and precision farming is not available. As a result, the main purpose of this review paper is to summarize the sensors, systems and algorithms of the 3D reconstruction and provide a comprehensive review of agricultural 3D reconstruction, serving as a valuable resource for researchers to carry out studies in 3D reconstruction, particularly within the agricultural domain. The advantages and disadvantages of the methods of 3D reconstruction are compared and discussed. Additionally, the remaining challenges and potential future trends are also coverd.

2. Sensors and systems of 3D reconstruction

Sensors serve as the bridge connecting real-world objects, scenes and their three-dimensional models of structures. 3D reconstruction in smart agriculture utilizes various sensors and systems: LiDAR, vision sensors and laser scanners, etc. LiDAR uses laser technology to measure distance. The vision camera acquires the morphological characteristics of objects in the agricultural environment. The laser scanner generates a high-density point cloud (Mousavi et al., 2018). Additionally, the multi-sensor fusion system improves reconstruction accuracy by overcoming limitations of a single sensor (Kim et al., 2009). Multi-view stereo vision, structured light scanning and motion estimation methods can achieve accurate 3D modeling of agricultural environment by fusing these sensor data (Vazquez-Arellano et al., 2016). Common sensors and systems include LiDAR sensors, Laser Scanners, Monocular sensors, Stereo sensors, RGB-D sensors, Multi-sensor Fusion and Non-optical sensors. A summary of sensors and sensing systems involved in 3D reconstruction techniques is shown in Fig. 1.

2.1. LiDAR

LiDAR (Light Detection And Ranging) is capable of emitting light pulses and correlating the light reflected from a surface with the origin signal (Kang et al., 2018). This kind of sensor can quickly and efficiently gather the surface feature information from the test object, presenting it as point cloud data. This data format facilitates the reconstruction of a 3D digital model of the object (Pan et al., 2019). LiDAR systems offered dependable and accurate perception capabilities around the clock, thanks to their broader field of view, extended detection range and depth perception capabilities (Yeong et al., 2021). Additionally, LiDAR sensors have accrued an increasing presence in the agricultural sector due to their non-destructive mode of capturing data and high precision (Moreno et al., 2020), these sensors are broadly used to measure structural characteristics of agricultural landscape topography and trees, they are also used for observing crop biomass, phenotypic characterization, and crop growth. LiDAR-based systems and LiDAR data can

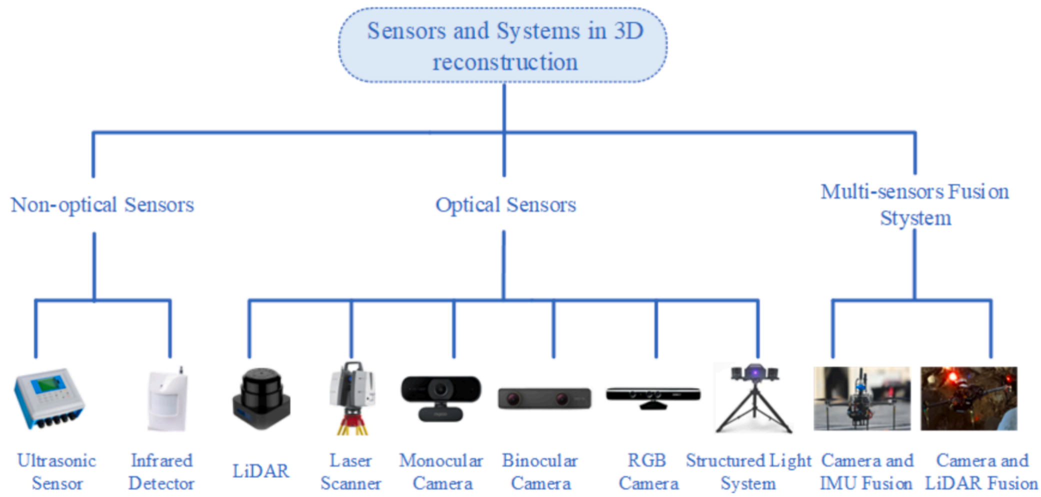

Fig. 1. Summary of sensors and sensing systems involved in 3D reconstruction technology.

also serve to quantify spray drift and identify soil characteristics (Debnath et al., 2023; Rivera et al., 2023). However, 3D systems equipped with LiDAR technology are expensive, and may encounter challenges due to the interference of intricate scenes with dense vegetation, as well as the complexity involved in processing data. (Wu et al., 2018).

2.2. Laser scanner

Laser scanner is a laser device and the principle of its work is similar with LiDAR. LiDAR is designed to measure the time of flight of laser and calculate distance by phase difference, and laser scanner uses a laser beam and measures its reflection time to obtain distance information from the target surface (Pfeifer & Briese, 2007). The 3D laser scanning technology is also called the real scene reproduction technology, it offers support for 3D design across various tested objects, leveraging favorable data (Peng et al., 2021). Laser scanner sensors are generally divided into two types: terrestrial laser scanners and aerial laser scanners (Pfeifer & Briese, 2007). Terrestrial laser scanners offer user-friendly operation and swiftly generate detailed 3D point clouds of object surfaces within minutes. With high spatial resolution, these scanners can capture several thousand points per square meter, contingent upon the distance to the measured object. While image-based remote sensing techniques have been widely applied in agriculture and precision crop management, aerial laser scanners are generally deemed unsuitable due to their high costs and limited accuracy (Lumme et al., 2008). 3D laser scanning technology can rapidly and accurately capture dense point data (Arayici, 2007), but the performance of the laser scanner may be affected by ambient light in some specific environments, reducing the accuracy of the data (Revilla-León et al., 2020). Additionally, laser scanners may have difficulty with transparent objects because it is challenging for laser beam to reflect accurately from these objects (Ebrahim, 2015).

2.3. Monocular cameras

Monocular camera sensors extract information using a single light path (Ding et al. 2022). The data captured by a monocular camera comprises a sequence of 2D images illustrating the projection of objects or object parts. These images represent the three-dimensional world in two dimensions, resulting in the loss of depth data in the process (Shu et al., 2021). In the data preprocessing stage, it does not require matching the image, making it a favorable choice (Gao et al., 2023). Currently, there are two commonly used monocular vision ranging methods: deep learning-based and geometric model-based (Height-Variable) ranging methods (Zaffar et al., 2018). Monocular camera sensors are widely used in agriculture for image acquisition and analysis in crop monitoring and precision farming applications (Krul et al., 2021). They capture visual data that is essential for disease detection, quality assessment, and growth monitoring in crops. Monocular cameras offer the benefits of a straightforward design and affordability. Their low cost and compact design have contributed to their widespread adoption in the agricultural industry. However, monocular camera sensors have limitations in directly perceiving 3D depth, which necessitates supplementary techniques for depth sensing (Bai et al., 2023). Additionally, their sensitivity is underscored by susceptibility to variations in lighting conditions and environmental factors. Although they provide real-time visual insights for timely decision-making, they exhibit constraints in comprehensive spatial perception and depth awareness within agricultural landscapes (Wu & Pradalier, 2019).

2.4. Binocular cameras

Binocular sensors based on the principle of stereoscopic vision, mimicking the human visual system (Banks et al., 2012). These sensors with two cameras capture images from different perspectives. The resulting binocular disparity, or the variance in the apparent position of an object in the two images, enables the system to calculate depth information through triangulation (Patel et al., 2013). This depth perception is invaluable for applications such as object recognition, spatial mapping, and precise measurements. With two strategically positioned cameras, these sensors calculate depth information through binocular disparity. Their ability to perceive 3D space, provide stereo vision effects, and capture rich spatial details contributes to the accurate and realistic reconstruction of scenes (Ding et al., 2022). In agriculture, binocular sensors enable precise plant modeling, growth monitoring, and field management (Peng et al., 2021). Although vision system based binocular sensors is broadly used in 3D reconstruction due to wider space perception, it also has limitations. On the one hand, achieving precise calibration between the paired cameras is critical for accurate depth perception, and any misalignment can introduce errors in the reconstruction. (Bradley & Heidrich, 2010). On the other hand, binocular vision’s inaccuracy in precisely determining depth over long distances can impact its suitability for large-scale reconstruction tasks (Wang et al., 2022).

2.5. RGB-D cameras

RGB-D cameras have emerged as instrumental tools in the realm of agricultural 3D reconstruction, providing a comprehensive solution for capturing both color and depth information (Zollhöfer et al., 2018). RGB-D cameras, also referred to as depth cameras, are a combination of monocular camera, Infrared Radiation (IR) transmitters and IR receivers, and they are also commonly-used sensor systems capable of capturing RGB images alongside per-pixel depth data (Lao et al., 2023; Zaffar et al., 2018). The cameras acquire the depth information of objects using either 3D structured light or ToF (Time of Flight) (Zanuttigh et al., 2016). Utilizing infrared light projection as its foundation, the RGB-D sensor mitigates the reliance on image texture in binocular matching, enhancing matching robustness (Li et al., 2022). This innovative approach ensures more reliable depth perception, particularly in scenarios with limited or homogeneous textures. At present, common RGB-D cameras include Microsoft Kinect, Intel RealSense, ASUS Xtion, and Orbbec Astra. These devices integrate RGB and depth sensors, enabling simultaneous capture of color and spatial information for various applications (Fu et al., 2020). However, achieving high-quality 3D reconstruction with most RGB-D cameras remains challenging due to constraints such as limited measurement range and elevated levels of noise. The depth images generated by consumer-grade RGB-D cameras usually exhibit noise and incompleteness, especially in scenarios involving shiny, bright, transparent, or distant surfaces (Li et al., 2022).

2.6. Structured light systems

As a vision system, structured light involves projecting a sequence of light patterns, including stripes or arbitrary fringes, onto the object. The projected light sequence undergoes deformation on the object (Bell et al., 1999). In contrast to traditional stereo systems, which passively extract features from stereo images, structured light systems use projectors to actively project optical patterns containing encoded information onto object surfaces, subsequently, cameras capture the scene's structured illumination. Through computation of alterations in the light signal prompted by the object, its position and depth are inferred. As a result, analyzing the correspondence between the projected frames and captured frames yields the 3D information of the scene (Huang et al., 2021; Wang et al., 2019). Structured light sensors can be divided into point, line, and area structures based on the form of light projection (Yang et al., 2008). The working principle and classification of structured light are shown in Fig. 2. As a non-contact sensor, structured light sensors provide benefits including high measurement accuracy, rapid operation, straightforward computation, and resistance to interference (Wang et al., 2020a). Additionally, these sensors use infrared light projection for depth data acquisition, rendering them effective for objects lacking distinct texture characteristics (Kuan et al., 2019). However, structured light systems are susceptible to interference from various devices and ambient lighting conditions. In practical scenarios such as agricultural environments, structured light sources may contend with strong background illumination. In bright agricultural scenes, limited dynamic range in structured light sensors can result in very low signal in captured images, leading to suboptimal 3D reconstruction results (Wang et al., 2019; Gupta et al., 2013).

2.7. Non-optical sensors

Non-optical sensors operate beyond the electromagnetic spectrum of visible light (Ferreira et al., 2017). Various types, including acoustic, electromagnetic, and other non-optical sensors, function based on distinct physical phenomena (Yaacob et al., 2014). For instance, ultrasonic sensors emit sound waves and measure their reflection to determine distances, while electromagnetic sensors detect signals such as infrared, ultraviolet, or microwaves to identify objects or capture specific characteristics (Daoud et al., 2015). Non-optical sensors play a crucial role in diverse applications due to their ability to sense beyond the limitations of optical sensors. Acoustic sensors, like ultrasonic devices, are employed for distance measurement, object detection, and reconstruction, particularly underwater where light penetration is limited. Electromagnetic sensors, such as infrared detectors, find applications in heat sensing, motion detection, and night vision. Microwave radar sensors are utilized for object detection, navigation, and weather monitoring (Scalise et al., 2012). The non-optical nature of these sensors makes them valuable in environments with adverse lighting conditions, providing flexibility in sensing modalities for various agriculture, scientific, and technological applications. In essence, non-optical sensors bring a valuable dimension to agricultural

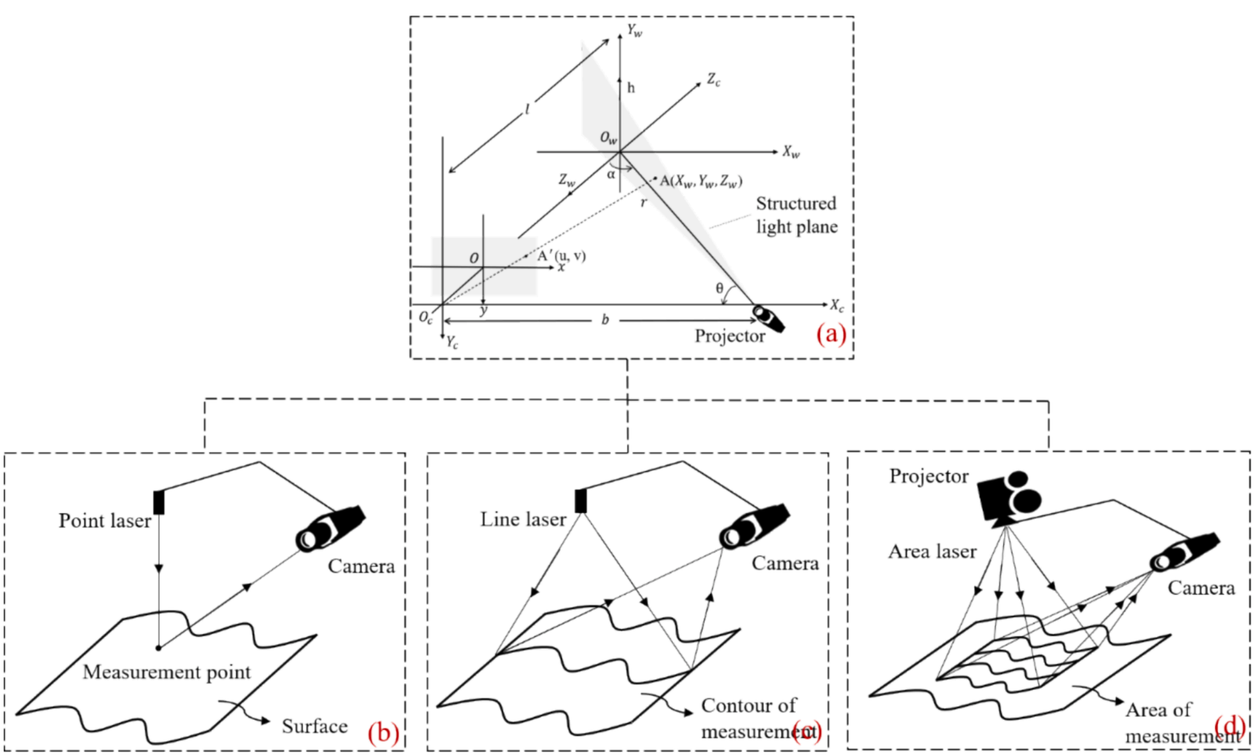

Fig. 2. Schematic diagram of the principle of structured light triangulation (a) (Zheng et al., 2020) and the classification of structured light (b–d).

3D reconstruction by providing detailed and accurate spatial information that complements the data obtained from optical sensors (Hwang et al., 2019). However, electromagnetic interference, background noise, or interference from other sources can impact the accuracy and reliability of measurements in certain non-optical sensors (Lei & Manfait, 2007).

2.8. Multi-sensor fusion systems

Multi-sensor fusion involves combining information from multiple sensors to enhance the overall perception and understanding of a system or environment. This approach leverages the complementary strengths of different sensors, such as cameras, LiDAR, GPS, and IMUs, to overcome individual sensor limitations (Peng et al., 2020). By integrating data from various sources, multi-sensor fusion aims to improve accuracy, reliability, and robustness in tasks such as object recognition, navigation, and 3D reconstruction (Gravina et al., 2017). Three main methodologies are employed to integrate sensor data from different sensing modalities within multi-sensor fusion frameworks: High-Level Fusion (HLF), Low-Level Fusion (LLF), and Mid-Level Fusion (MLF) (Banerjee et al., 2018). In general, LiDAR and cameras are commonly fused in 3D reconstruction, LiDAR provides high-resolution depth point cloud data, while cameras provide RGB information, making them the most intuitive source of data for 3D reconstruction. Achieving spatial alignment requires joint calibration of these two different sensors. After joint calibration, it is possible to establish a correspondence between certain 3D points in the point clouds and the pixel points on the image. This correspondence allows for the fusion of colorful point clouds that contain both initial 3D environment information and RGB information, resulting in more realistic 3D environment reconstruction (Wang, 2013). Integrating diverse sensors into a system presents a significant challenge due to increased complexity. Sophisticated algorithms and hardware are required to ensure accurate data fusion, as synchronization issues may arise from differences in sensor sampling rates and temporal delays (Munnaf et al., 2020).

3. Methods of 3D reconstruction

After collecting data from various sensors, reconstructing the 3D structure of agricultural scenes or objects requires specific methods. 3D reconstruction methods are divided into traditional methods and deep learning-based methods (Samavati & Soryani, 2023). Summary and classification of 3D reconstruction methods are shown in Fig. 3. Traditional methods can be divided into active and passive reconstruction methods (Moons et al., 2010). Traditional reconstruction methods rely on geometry and image processing techniques, require manual design of feature extraction, matching, and 3D reconstruction processes, and depend on precise camera calibration and geometric information (Zheng et al., 2020). Deep learning-based 3D reconstruction methods utilize neural networks to learn the mapping from images to 3D scenes, without the need for manual feature design or geometric models. These methods can learn representations end-to-end, automatically extract and learn features from the data, and demonstrate stronger adaptability to complex scenes and diverse data.

3.1. Traditional-active methods

Accuracy, adaptability, real-time are required in some agricultural environment 3D reconstruction. Traditional active 3D reconstruction shows better characteristics and advantages in these three aspects (Moons et al., 2010). Active 3D reconstruction is a technology that actively measures the depth of the environment to reconstruct the 3D model of the object. This technology uses sensors to emit signal sources to the surface of the object, and then calculates the relative position of the signal source and the target object surface, and obtains the 3D information of the object by analyzing the returned signal (Aharchi & Ait Kbir, 2020). Commonly used traditional-active methods include Time of Flight (ToF), Triangulation, Structured light, etc.

3.1.1. Time of flight (ToF)

Time of Flight (ToF) as an accurate distance-measuring technique, the emitter unit emits a laser pulse towards the target surface (Sansoni et al., 2009), after which a receiver detects the reflected pulse. Subsequently, appropriate electronics measure the roundtrip time of the returning signal and its intensity (Bianco et al., 2013). By determining the speed of the signal in the medium it traverses, the distance can be inferred (Kowdle et al., 2011). Based this principle, the ToF method can be categorized into pulsed-wave (PW-iToF) or continuous-wave (CW-iToF) modulation (Süss et al., 2013). Generally, Sensors such as LiDARs, TOF cameras and Flash LiDARs, use this method. ToF sensors can penetrate the plants and obtain accurate elevation information of the ground, which is suitable for the reconstruction of agricultural scenes with high plant coverage, and the ToF sensor can achieve high-precision distance measurement. Fujimura et al. (2020) proposed a method to simultaneously estimate the target area and depth by using a CW TOF camera, which used a robust estimator and an iterative weighted least squares optimization scheme to simultaneously estimate the scattering component and area. He et al. (2020) proposed an error point correction method to solve the problem of incorrect registration of TOF camera depth data, and automatically generated an image model in 3D space for error correction. This method greatly improved the matching accuracy. However, Time-of-flight sensors encounter obstacles when dealing with glossy surfaces, which reflect minimal scattered light energy except in the case perpendicular to the line of sight. (Sansoni et al., 2009).

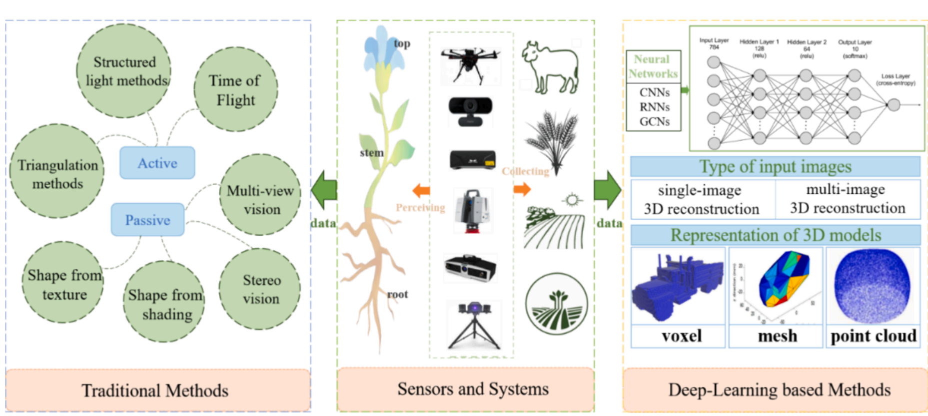

Fig. 3. Methods of 3D reconstruction technology.

3.1.2. Triangulation methods

Triangulation method involves geometric calculations where one point of a triangle represents the target, while the other two points are predetermined components of the measurement system. By measuring the angles or baseline of the triangle, it is possible to ascertain the distance to the target (Biskup et al., 2007). Delaunay triangulation is the most representative triangulation , there are mainly three kinds about Delaunay triangulation: point-by-point insertion method, divide and conquer method and triangulation growth algorithm. Although the point-wise insertion method is easy to implement, its real-time performance is not very good when dealing with large-scale scatter set data. In order to improve the efficiency of the point-wise insertion method, Liu et al. (2013) proposed a deterministic insertion sequence based on breadth-first search, which used k-d tree to construct Delaunay triangulation. However, the construction of k-d is complex and takes a lot of time. Based on the multigrid insertion method, Su et al. (2016) proposed to use Hilbert curve to traverse the insertion points, which reduced the number of long and narrow triangles in the triangulation process, thereby reducing the local optimization time. The limitation of triangulation sensors lies in the requirement for an overlapping region between the emitter's field of view and that of the receiver (Jaffe, 1990). Moreover, nearby objects exhibit greater parallax than distant ones, resulting in triangulation-based devices having higher z resolution for closer distances compared to farther ones (Massot-Campos & Oliver-Codina, 2015).

3.1.3. Structured light methods

The system of structured light involves projecting specific patterned light onto the target object with a projector, capturing the two-dimensional image of the target object with a camera, and then determining the 3D information of the target object through image processing and visual modeling. The fundamental principle relies on the triangulation method, calculating the positional relationship and distorted stripes between the projector and the camera to obtain the object's 3D information (Nguyen et al., 2015). This method is susceptible to lighting conditions, suitable for indoor environments, and the reconstruction accuracy may decrease with the increase in detection distance (Pintore et al., 2020). Based on the technical principles, structured light can be categorized into structured light reconstruction based on the triangulation method and grating reconstruction based on the phase method, these two methods exhibit a gradual improvement in reconstruction efficiency (Cheng et al., 2008). In the triangulation-based structured light reconstruction, the projection modes of the light signal emitter can be categorized into point, line, and area structured light. In phase-based grating reconstruction, commonly used methods include Fourier transform profilometry (FTP) technique (Takeda & Mutoh, 1983) and phase measurement profilometry (PMP) technique. Feng et al. (2021) analyzed the impact of real environments and physical models on 3D reconstruction. To address the issues of reconstruction loss and low accuracy caused by brightness saturation, they proposed a method combining phase fusion and multi-frequency heterodyne algorithms. Shichao et al. (2021) examined the reasons for phase jump errors generated by traditional three-frequency heterodyne, introduced error range constraints, and utilized formula backtracking and multi-frequency heterodyne algorithms to unfold phase information. This approach resulted in a smoother surface and clearer details in the 3D reconstruction results.

3.2. Traditional-passive methods

Passive 3D reconstruction involves capturing images of the target object through one or multiple cameras, utilizing image analysis to obtain 3D data of the object's surface, and subsequently achieving the reconstruction of the object in three dimensions (Siudak & Rokita, 2014). Compared to active 3D reconstruction, passive 3D reconstruction has the advantage of not requiring the emission of signals, resulting in no additional interference with the environment (Bianco et al., 2013). Additionally, it is generally capable of reconstructing 3D representations of various surface types, including transparent, reflective, and surfaces with less apparent texture (Saaidi & Satori, 2014).

3.2.1. Multi-view vision technology

Multi-view vision technology involves capturing images of objects from various angles using calibrated cameras (Furukawa & Hernández, 2015). Feature points obtained from overlapping images are utilized to determine the shooting position (Koutsoudis et al., 2014). There are two primary multi-view vision approaches: utilizing multiple cameras to acquire 3D data and rotating cameras or objects to obtain 3D data (Qi et al., 2021). Although multi-view vision yields more accurate images, its calibration and synchronization, especially concerning camera positioning, are more complex (Zhang et al., 2017). Its primary applications include structure-from-motion (SFM) and multi-view stereo (MVS) technologies (Koutsoudis et al., 2020).

The SFM and MVS process follows a sequential order: SFM is utilized to estimate camera poses, calibrate intrinsic parameters, and initiate feature matching, followed by MVS for reconstructing detailed 3D scenes (Lou et al., 2014). SFM estimates a 3D structure by capturing a series of 2D images at various locations in a scene . The 3D positions of features are then matched using algorithms such as the scale-invariant feature transform (SIFT), SURF, or ORB (Hossein-Nejad et al., 2021). After determining camera poses and extracting point clouds with Bundler, MVS technology is employed to construct a comprehensive 3D object model. This is achieved by processing a set of images captured from pre-calibrated camera positions (Jin et al., 2005). Generally, SFM produces sparse point clouds, and MVS photogrammetry algorithms are employed to significantly increase point density. Consequently, the integrated workflow is more accurately described as 'SFM-MVS' (Smith et al., 2016). The steps of point cloud formation based on SFM-MVS typically include feature detection, key point correspondence, identifying geometrically consistent matches, structure from motion, scale and georeferencing, refinement of parameter values, and multi-view stereo image matching algorithms (Javadnejad et al., 2021).

3.2.2. Stereo vision

Stereo vision, a conventional technique in traditional 3D reconstruction, employs multiple cameras to capture images of a scene from slightly varying viewpoints. The key principle is triangulation, the disparities between corresponding points in the images are used to calculate depth information. By comparing the parallax or differences in pixel positions, the system can deduce the distance to various objects in the scene (Li et al., 2008). At present, the most frequently utilized stereo vision method is binocular stereo vision method. The process of real-time 3D reconstruction method based on binocular stereo vision mainly includes four steps: calibrating cameras, detecting features, performing stereo matching, and conducting 3D reconstruction (Yang et al., 2017). The binocular stereo vision method has the advantages of low cost, good robustness, and can collect images in an instant, so it is more suitable for 3D reconstruction of moving scenes. However, challenges include sensitivity to changes in lighting conditions and the need for detailed feature matching, making it less suitable for dynamic or textureless environments (Bruno et al., 2011). Current research on binocular stereo vision methods focuses on improving the speed of 3D reconstruction by improving the efficiency of feature detection and stereo matching (Fan et al., 2018). Banz et al. (2010) implemented a stereo matching method based on semi-global matching on the FPGA platform, which was able to perform 3D reconstruction at 30FPS for images with a resolution of 640x480. Chang et al. (2011) studied the adaptive weight algorithm on a GPU model GTX 285, which was able to perform 3D reconstruction at 20FPS when processing images with a resolution of 320x240.

3.2.3. Shape from shading

In 1970, Minsky proposed the shape from shading (SFS) method, also known as the shading method (Horn, 1970). The method needs to know the direction of the light source, and assumes that the surface of the object is Lambertian reflection model and the imaging geometry is orthogonal projection. According to the corresponding brightness value of each point in a single image, it is put into the pre-designed chromaticity model. SFS method only needs one image for 3D reconstruction, and the running time is short (Matsushita, 2020). However, the information obtained from a single image is less, the reconstruction effect is not ideal, and the illumination has a great influence on it, so it is not suitable for outdoor 3D reconstruction (Sansoni et al., 2009). Shape from shading methods have been developed for many years, including minimization methods, evolution methods, local analysis methods, linearization methods, etc. (Liu et al., 2022).

3.2.4. Shape from texture

The Shape from Texture (SFT) method is used to obtain 3D information of an object based on its texture information in an image, and then reconstruct a 3D model of the object. This method can reconstruct a 3D model from a single image with relatively high accuracy and speed, and is not sensitive to light or noise (Aloimonos, 1988; Johnston & Passmore, 1994). Massot and Hérault, (2008) proposed a method for shape recovery from texture using image local frequency estimation. The method decomposed the image into small patches to estimate the local frequency change of the image, eliminating the need to select the optimal local scale. Loh and Hartley, (2005) proposed a method to extract shape from texture by assuming a smooth surface, estimating the frontal texture, a correct estimation leading to the most consistent surface, and recovering the surface by consistency constraints. Lobay and Forsyth, (2006) developed a maximum posteriori estimate of surface coefficients based on the deformation of a single texture element. They described a shape from the texture approach by assuming that texture elements have a finite number of fixed shape types. However, the shape from texture method is limited to physics with texture features and may not be practical for other applications.

3.3. Deep learning based methods

Ciresan et al. (2012) published the research results of convolutional neural networks (CNN) in the field of computer vision, and deep learning became popular in the field of computer vision. The deep learning-based method for 3D image reconstruction leverage used a large amount of data to establish prior knowledge, framing the task as an encoding and decoding challenge to reconstruct objects. As the volume of 3D datasets grows and computer processing power continues to improve, deep learning-based approaches enable the reconstruction of 3D models from single or multiple 2D images without the need for complex camera calibration. Compared with the traditional 3D reconstruction methods, the 3D reconstruction method based on deep learning avoids the process of feature extraction and data reconstruction, resolving the weakness that depend on handcrafted features highly.

The taxonomy of 3D reconstruction works include several crucial variations, including input modality and shape representation, etc. (Jin et al., 2020) According to the type of input images, 3D reconstruction can be classified into single-image 3D reconstruction and multi-image 3D reconstruction. In single-image 3D reconstruction methods, early approaches employed end-to-end networks to obtain a 3D model represented in the form of voxel or point cloud. Alternatively, some methods initially acquire a depth map, point cloud, or implicit function as an intermediate representation of the 3D model. Subsequently, this intermediate representation is transformed into a mesh model. The completeness of 3D models reconstructed from single images is relatively low. Therefore, some methods extend to multi-image 3D reconstruction, so the information from multiple images is combined to enhance the performance of 3D reconstruction networks (Van den Heuvel, 1998). Moreover, based on the representation of 3D models, 3D reconstruction can be categorized into voxel-based reconstruction, point cloud-based reconstruction, and mesh-based reconstruction. Voxels are like the pixels in 2D images, possessing real 3D data. This method involves 3D reconstruction through an encoder-decoder approach. Point clouds are collections of points within a defined coordinate system, each point representing 3D spatial coordinates and supplementary attributes like color. Point cloud data is characterized by its unordered and irregular nature, requiring regularization processing. Mesh refers to a polygon mesh containing information such as points, edges, and faces of a 3D model. Compared to the first two methods, mesh-based representation methods have the advantage of rich shape details and connections between adjacent points (Fu et al., 2021).

Common neural networks suitable for 3D image reconstruction include convolutional neural networks, recurrent neural networks and graph convolutional networks (Lin et al., 2020). CNNs (Convolutional Neural Networks) are widely applied in reconstruction tasks for its appropriateness of dealing with 2D information. RNNs (Recurrent Neural Networks) are specifically employed for capturing sequential features in the input. GCNs (Graph Convolutional Networks) are more suitable for dealing with non-Euclidean structure data (Jin et al., 2020). Additionally, for training the networks, a large amount of datasets are used (Mazurowski et al., 2008), such as ShapeNet (Chang et al., 2015), Pascal 3D+ (Xiang et al., 2014), ObjectNet3D (Xiang et al., 2016), KITTI (Geiger et al, 2012).

4. Applications of 3D reconstruction for precision agriculture

In the field of smart agriculture, 3D reconstruction technology can be flexibly served to obtain better results according to the requirements of different agricultural tasks. The application of 3D reconstruction in smart agriculture mainly involves agricultural robotics, crop phenotyping, livestock, food industry and other related aspects.

4.1. 3D reconstruction for agricultural robotics

The rise of agricultural robotics marks a technological revolution in farming, providing innovative solutions for precision agriculture, efficiency growth, and sustainable development (Karunathilake et al., 2023; Dhanya et al., 2022). Autonomous agricultural robots, equipped with advanced sensing and control capabilities, play a crucial role in modern agriculture. Some researches of 3D reconstruction on agricultural robotics are shown in Fig. 4. Integrating 3D reconstruction technology enhances their ability to perceive and navigate the agricultural environment effectively. Utilizing sensors like LiDAR, stereo vision, and structured light systems, these robots capture detailed information about terrain, crops, and obstacles (Chen et al., 2020). Key applications of 3D reconstruction in agricultural robots include robotics navigation, agricultural mapping, and automated agricultural operations. More applications of 3D reconstruction for agricultural robotics are shown in Table 1.

Agricultural robot navigation relies on vision sensors, LiDAR, or other depth sensor technologies to create detailed 3D maps of the agricultural landscape, obtaining structural information about the surroundings. This spatial perception capacity facilitates the processing of environmental data through computer algorithms, extracting valuable navigation details regarding crops, trees, obstacles, and more. This extracted information directs the autonomous positioning, movement, and path planning of agricultural robots and vehicles (Bechar and Vigneault, 2016). The ability to recognize paths between crop rows is a crucial aspect of automated navigation. Kise et al. (2005) proposed a practical row-detection algorithm for an agricultural machinery guidance system based on stereo vision. The method involved reconstructing a 3D elevation map of crops from stereo vision images of rows and subsequently identifying optimal navigation points on the map. Similarly, Choi et al. (2014) designed an autonomous navigation system

Fig. 4. Applications of 3D reconstruction for agricultural robotics. (a) Using binocular vision system and homography matrix for 3D reconstruction to obtain the road self-dominant route (Li et al., 2019). (b) Outdoor robot navigation system based on monocular vision. 3D reconstruction computed from the reference video sequence (top view) (Royer et al., 2005). (c) Commercial orchard environment mapping based on RGB-F camera and UGV (Tagarakis et al., 2022). (d) Reconstruction of vineyard crops based on LiDAR technology (Moreno et al., 2020). (e) An automatic grapevine pruning robot system, which builds a 3D model of a vine based on a trinary stereo camera (Botterill et al., 2017). (f) 2D lidar scans droplets in air to obtain 3D droplet distribution visualization (Wang et al., 2023).

employing a laser scanner. A crop row localization method was utilized to determine the relative position and direction of crop rows, and a steering controller was developed to guide the crop divider appropriately. Moreover, detecting and avoiding obstacles represent another significant aspect in the movement process of agricultural robotics (Ball et al., 2016). Nissimov et al. (2015) introduced an obstacle detection method in a greenhouse scene utilizing the Kinect 3D sensor, particularly for spray vehicles. The approach involved creating an obstacle map through 3D reconstruction using color and depth information. This method proved effective for small fields, allowing for the reconstruction of 3D maps of the entire environment, enhancing navigation. In a study by Weiss and Biber (2011), a mobile robot equipped with the FX6 LiDAR by Nippon Signal demonstrated comprehensive 3D reconstruction, detection, and segmentation of plants and ground for localization, mapping, and navigation in a small maize field.

Agricultural mapping is a critical component of modern farming practices, utilizing advanced technologies to create detailed spatial representations of agricultural landscapes. This process involves the systematic collection, analysis, and interpretation of geospatial data to generate accurate maps that provide valuable insights into various aspects of the farming environment (Huo et al., 2024). 3D reconstruction plays a crucial role in advancing agricultural mapping by providing detailed spatial information and enhancing the precision of data collection and analysis. 3D reconstruction techniques, such as LiDAR (Light Detection and Ranging) and structure-from-motion (SFM), contribute to creating accurate terrain models. Shu et al., (2021) presented a system that integrated indirect, sparse, monocular visual SLAM with offline and real-time MVS reconstruction algorithms, and provided the first evaluation of monocular SLAM in agricultural settings, exploring unsupervised depth estimation through simulated RGB-D SLAM. Tagarakis et al. (2022) autonomously mapped orchards using RGB-D cameras and unmanned ground vehicles (UGV). Comparison with 3D orthomosaics from a UAV revealed similar height measurements, but the RGB-D camera calculated tree volume more accurately due to its detailed 3D point cloud.

Automated agricultural operations based on agricultural robots represent an agricultural model that utilizes advanced technology and automated systems for intelligent management and operations throughout the agricultural production process. (Gonzalez-de-Santos et al., 2020) Agricultural robots equipped with 3D reconstruction capabilities exhibit a significantly higher level of automation compared to traditional counterparts, enabling more efficient execution of intelligent agricultural tasks such as harvesting, pruning, and spraying. Yandun et al. (2020) done the visual 3D reconstruction and dynamic simulation of tree fruits, and the robot can intelligently interact with the tree crown, including automated harvesting or pruning with a complete geometric and dynamic model of a fruit tree. Botterill et al. (2017) described a robot system for the automatic pruning of grape vines. Trinocular stereo cameras were used to image vines and then reconstructed a 3D model of the vines using a computer vision system, so that to decide which canes to prune and a robot arm makes the required cuts. Danton et al. (2020) introduced a control approach that involves LiDAR-based plant detection for both regulating robot motion and facilitating automated spraying.

4.2. 3D reconstruction for crop phenotyping

Crop phenotyping aims to measure complex traits related to growth, yield, and stress adaptation across various organizational levels, from individual organs to entire canopies (Fiorani et al., 2013; Ullah & Bais, 2022). Phenotypic characteristics encompass a range of complex traits, including root morphology, biomass, leaf characteristics, fruit attributes, yield-related traits, photosynthetic efficiency, and abiotic stress response (Li et al., 2014). 3D reconstruction enables high-throughput, non-destructive, fast, and automated phenotyping of crops in a temporal sequence (Yang et al., 2020). Crop 3D reconstruction holds significant importance for acquiring high-throughput crop phenotypes, evaluating plant type features, and analyzing the correlation between plant structure and phenotype (Zhu et al., 2020; Sunil et al., 2022). In recent years, numerous researches have focused on precise crop

Table 1
A detailed summary of applications of 3D reconstruction technology for agricultural robotics.

Type of Robotics	Crop species/ Scenarios	Sensors/System	Technology/Algorithms	Application	Reference
Navigation	Rose	Stereo camera	Convolutional Segmentation Network FCSN and BM algorithm	Rose pruning	Cuevas-Velasquez et al. (2020)
	Field	Kinect v2 camera and VR device	Bundle fusion and voxel hashing algorithms	Obstacle detection and Navigation	Chen et al. (2020)
	Fruit trees	Stereo cameras	Space colonization and the Laplace based contraction algorithms	Motion prediction	Yandun et al. (2020)
	Field Roads	Binocular camera	Epipolar constraint and homography matrix	Navigation line extraction	Li et al. (2019)
	Grape vines	Intel ZR300 visual-inertial (VI) system	Triangulating feature matches	Spraying and navigation	Botterill et al. (2017)
	Soya beans	STH-MD1 camera	Stereo vision	Navigation and crop reconstruction	Kise et al. (2005)
	Green house	Kinect camera	Obstacle detection algorithms	Navigation	Nissimov et al. (2015)
	Outdoor environment	Monocular camera	SFM	Navigation	Royer et al. (2005)
	VineyArd	Kinect and 3D LiDAR	Gmapping algorithm	Autonomous navigation	Roure et al. (2018)
	Farm field	VIS-NIR sensor and IMU	Semi-Global Matching algorithm Stereo reconstruction algorithm	Soil mapping navigation	Milella et al. (2018)
	Field	Laser scanner	Crop row localization method	Autonomous navigation	Choi et al. (2014)
	Corn	Stereo vision	Algorithms	Harvesting and Navigation	Rovira-Más et al. (2007)
Mapping	Orchard	Multi-spectral cameras	Extended Kalman Filter (EKF) Multi-sensors fusion	Rapid mapping of largefarms	Das et al. (2015)
	Maize field	FX6 LIDAR	TOF	Crop localization	Weiss & Biber. (2011)
	Filed	RGB-D camera	TOF	Target recognition and tracking	Yin et al. (2013)
	Crop Field	UAV camera	SIFT matching	Monitoring growth parameters	Chebrolu et al. (2018)
	Banana orchard	Binocular camera system	Stereo matching and MVS	Positioning of fruit- Clusters	Chen et al. (2020)
	Agricultural scenes	Monocular vision	MVS	Mapping	Shu et al. (2021)
	Orchard scene	RGB-D cameras and UAV	SFM	Mapping	Tagarakis et al. (2022)
	Citrus orchards	Intel RealSense camera, NIKON camera	SLAM VINS-RGBD framework, semantic segmentation algorithm	Real-time localization, semantic reconstruction	Xiong et al. (2023)
	Orchard scene	Smart phone	NeRF model	Immersive visual interactive features	Zhang et al. (2024)
	Unstructured orchard	–	SLAM system and eye-in-hand stereo vision system	Support fruit-picking robot	Chen et al. (2021)
Pruning	Apple tree	Kinect v2	Semicircle fitting. Incremental Global approaches	Pruning	Chattopadhyay et al. (2016)
	Jujube trees	Kinect V2 camera	Deep learning method (SPGNet) DBSCAN clustering algorithm	Detecting branches pruning	Ma et al. (2022)
Grasping	Orange and cucumber	Kinect and Laser scanner	Kinect Fusion algorithm SAC-IA ICP algorithm	Fruit grasp planning	Guo et al. (2020)
Spraying	Potting	Binocular Camera system	Stereo vision	Spraying and 3D leaf position measurement	Xia et al. (2009)
	vineyard	Velodyne LiDAR	Edge detection approach	Spraying	Danton et al. (2020)
	Apple orchard	SICK LMS111 and SICK TiM310 LiDAR	SLAM and point cloud assembly	Spraying	Lepej et al. (2017)
	Field and weeds	UAV and UGV	Multi-spectral perception algorithms	Spraying	Pretto et al. (2021)
Havesting	Apple tree	ZED (STEREO LABS)	Triangulation and Convolution Neural Network (CNN)	Fruit harvesting	Onishi et al. (2019)
	Guava fruits	Kinect V2 camera	Tiny Mask R-CNN, Principal component analysis	Plan obstacle avoidancepath for harvesting	Lin et al. (2021)
	Sweet-pepper green house	USB CMOS colour Autofocus Camera (DFK 72AUC02-F)	Large Scale Direct SLAM, Point cloud registration	Fruit detection and harvesting	Barth et al. (2016)
	Strawberry	CCD cameras and laser diodes	Stereo vision and structured light	Fruit harvesting	Tarrío et al. (2006)
	High bush blueberry	Digital cameras (X-A10)	Mask R-CNN and Triangulation	Extract fruit harvest ability traits	Ni et al. (2021)
	Apple	Xtion PRO Live camera	Euclidean clustering algorithm Random Sample Consensus algorithm	Fruit detection and harvesting	Nguyen et al. (2014)
	Sweet-pepper	Monocular vision	Module software framework	Harvesting	Barth et al. (2016)
	Orchard Apple	RGB-D cameras	RANSAC algorithm and Euclidean clustering algorithm	Harvesting	Thanh Nguyen et al. (2014)
	Apple	Monocular vision	SVM	Fruit Picking	Tao & Zhou, (2017)
	Cucumber	Monocular vision	MVS	Harvesting	Van Henten et al. (2002)

phenotyping using various sensors. Some research findings on crop phenotyping are illustrated in Fig. 5. The application of crop 3D reconstruction is categorized into three main parts: single crop reconstruction, field population reconstruction, and root reconstruction based on different research objectives. Table 2 shows a detailed summary of applications of 3D reconstruction technology on crop phenotyping.

The 3D reconstruction of single-plant crops serves as a crucial information technology tool for non-destructive research into the morphological structure and growth patterns of individual plants. The acquisition of phenotypic data based on 3D models not only supports

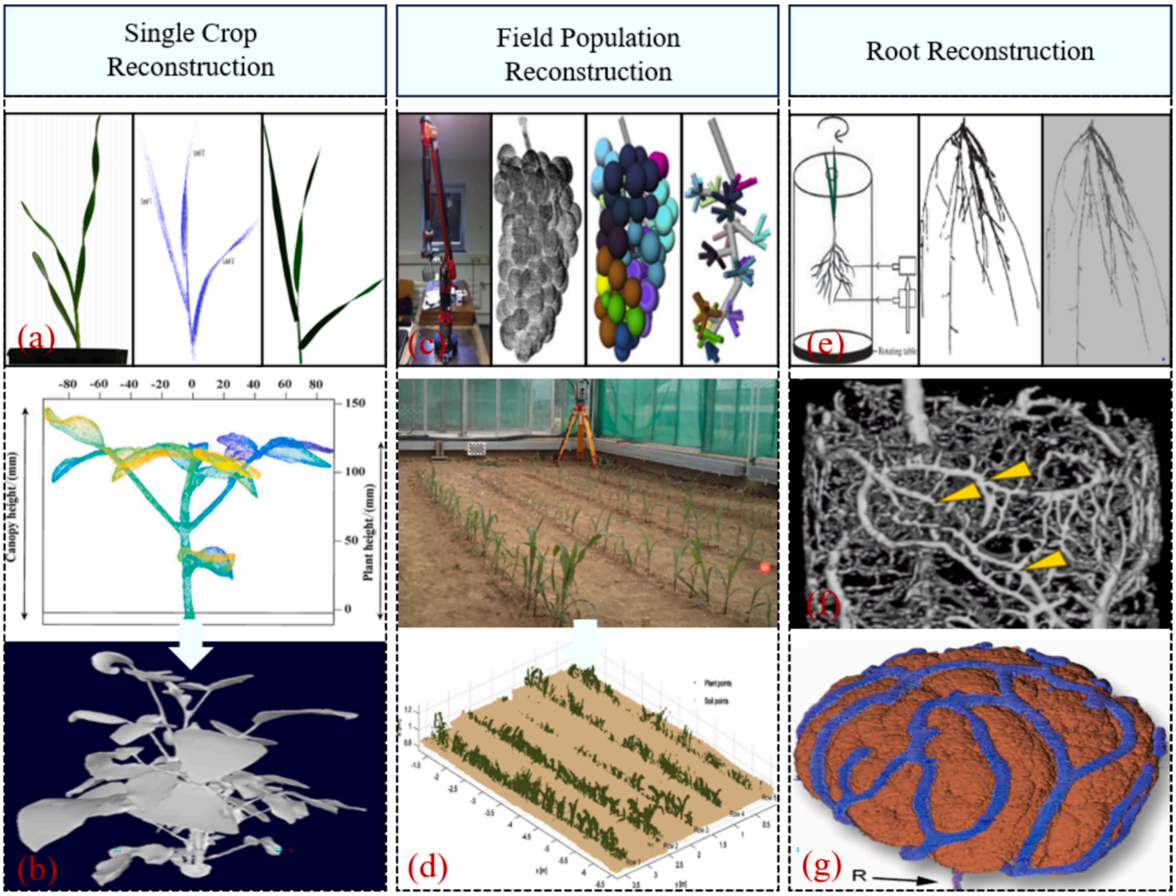

Fig. 5. Applications of 3D reconstruction for crop phenotyping. (a) 3D reconstruction of wheat leaf surface (Kempthorne et al., 2014). (b) A primary perspective of a 3D reconstructed soybean plant featuring calibrated canopy and plant height. (Zhu et al., 2020). (c) Fully automatic 3D reconstruction of grape cluster structure (Schöler et al., 2015). (d) 3D reconstruction of field maize crop rows (Vázquez-Arellano et al., 2018). (e) Capturing the soybean images, extracting the root skeleton and reconstructing the soybean root architecture (Fang et al., 2009). (f) Using MRI and CT to reconstruct the root system in the soil medium (Metzner et al., 2015). (g) 3D reconstruction of the root nodules of soybean using a microscope and optical imaging system (Livingston et al., 2019).

correlation analyses between molecular and phenotypic factors but also establishes the premise and foundation for various applications (Paulus, 2019). Generating 3D digital models of plants is crucial for researchers to obtain detailed insights into dynamic crop growth parameters. Zhu et al. (2018) presented a comprehensive pipeline for reconstructing surfaces from point clouds of rice plants and maize, generated through either active or passive approaches. Their two-step clustering method effectively partitioned points of individual plant components based on maize and rice properties, producing realistic 3D visualizations for high-throughput plant phenotyping. The Kinect v2, as a cost-effective and robust 3D sensor, has significant potential in agriculture applications. Hu et al. (2018) proposed an automatic system utilizing Kinect for non-invasive growth measurement of leafy vegetables, employed suitable algorithms to achieve fine 3D reconstructions and measure important growth parameters. For delicate cereal plant leaves prone to movement during reconstruction, Kumar et al. (2014) addressed this challenge by developing a high-throughput 3D reconstruction setup. The setup involved a stationary plant and a moving camera on a circular path, capturing multi-view digital images to achieve phenotypic quality 3D volumetric reconstructions in less than a minute per potted plant. 3D reconstruction technology based on multi-view images offers a low-cost and powerful alternative for non-destructive plant phenotyping. Lou et al. (2014) employed an efficient Structure-From-Motion method followed by stereo matching and depth-map merging processes. This approach yielded abundant phenotypic parameters, including plant height, plant topology, stem width and length, number of leaves, leaf area, and leaf angle.

The establishment of a 3D model for field crop populations is a key method to achieve automated, high-throughput acquisition of field plant population phenotypes. It represents an important technical approach for studying the growth and development patterns of crops and the characteristics of crop population structure (Hui et al., 2018). The reconstruction of a 3D model for crop rows serves as a foundation for retrieving plant structural parameters. Jay et al. (2015) introduced a method for characterizing crop row structures adapted to phenotyping-related challenges. They employed the Structure from Motion method with RGB images captured by a monocular camera along the crop row. This approach discriminated between plants and the background to estimate plant height and leaf area. Complete 3D reconstruction of crops proves valuable for monitoring and yield estimation in fields and orchards. Schöler and Steinhage (2015) proposed a fully automated, sensor-based 3D reconstruction approach for grape cluster architecture. They utilized optical sensors and fusion of different sensor modes, including LIDAR technology, demonstrating promising results for defoliated vineyard reconstruction. Moreno et al. (2020) constructed a system that comprised of a mobile platform equipped with a laser scanner, an RTK-GPS receiver, and an on-board computer. The derived volume values indicated that 3D models could accurately estimate vine weight swiftly and efficiently. In the field environment, few studies based on multi-view photography have explored the accurate reconstruction of 3D plants, particularly linking plant architecture with a radiation model to quantify dynamic canopy light interception. Accurate reconstruction of 3D plants using multi-view images opens possibilities for high-throughput 3D phenotyping, provides a better understanding of

Table 2
A detailed summary of applications of 3D reconstruction technology for crop phenotyping.

Type of phenotyping	Crop species	Sensors/System	Technology/Algorithms	Application	Reference
Single crop phenotyping	Maize and rice	Line laser scanner LemnaTec system	SFM, Surface fitting, Edge fitting	Parameter space exploration	Zhu et al. (2018)
	Lettuce	Kinect v2 camera	Triangulation	Key growth parameter measurement	Hu et al. (2018)
	Cereal	Canon EOS 5D Mark III Camera	Visual hull algorithm	3D volumetric reconstruction	Kumar et al. (2014)
	Arabidopsis	Canon 600D camera Nikon digital cameras	Multi-view vision	Plant height, stem width, leaf area, branch angle measurement	Lou et al. (2014)
	Rosebush, apple tree	Kinect V1	–	3D parameter measurements	Chéné et al. (2012)
	–	Canon EOS1300D	Multi-view vision	leaf area measurement	Shi et al. (2020)
	Arabidopiss, barley	3D laser scanner	Multi-view vision	Quantitative results of the rhythmic growth patterns	Chaudhury et al. (2018)
	Maize, sorghum	LMS 511 LiDAR	TOF	Leaf area, leaf inclination angle	Thapa et al. (2018)
	Maize Shoots	stereo vision system	MVS	Plant height, leaf width, leaf area measurement	Wu et al. (2020)
	Wheat	Canon PowerShot ELPH 110 HS camera	MVS-SFM	Phenotypic parameters calculation	Duan et al. (2016)
	Wheat	AVT Stingray F-504B/F-504C camera	Multi-view vision	Phenotypic parameters extraction	Fang et al. (2016)
	Wheat	3D Artec S scanner	Structured light finite element method	Realistic virtual of leaf surfaces	Kempthorne et al. (2014)
	Basil, Ixora	Digital cameras	SFM MVS	Computation of useful information	Santos & Oliveira (2012)
	Tomato	Canon EOS 450D	Pix4D Mapper, SFM-MVS	Phenotyping at the organ level	Rose et al. (2015)
	Strawberry fruit	Canon EOS 1200D	Agisoft Photoscan, MVS	Height, length, width, volume, calyx size, colour and achene number measurement	He et al. (2017)
	Potato tuber	Basler camera acA2040-25gc	Agisoft Photoscan, SFM-MVS	Trait measurement	Liu et al. (2021)
	Tomato	Canon EOS Rebel T3, NIKKOR-P	Stereo vision, Structured light	Plant height, total leaf area, and total leaf shading area measurement	Nguyen et al. (2015)
	Corn	PMD Camboard nano	Multi-view vision, TOF	Phenotypical data obtained	Li & Tang (2017)
	Banana, maize	AVT MANTA G-504	–	Trait derivation	Scharr et al. (2017)
	Cucumber	Digital camera	SIFT, Delaunay triangulation	Realistic reconstruction of plant leaves	Yang et al. (2009)
	Maize	FSFE-3200D-10GE	Multi-view vision	Extract the phenotypic parameters	Li et al. (2022)
	Corn, cotton, sunflower, tomato, nightshade plants	RGB-D camera	Stereo vision	Obtaining growth characteristics	Lati et al. (2013)
	Strawberry	PMD Camcube3.0	TOF	Effective blades, average single leaf length and blade distance difference Measurement	Zhang et al. (2017)
	Wheat	Canon 77D	MVS	Plant height, leaf length, and leaf width measurement	Wu et al. (2022)
	Apple	MV-CA00-11UC	Binocular stereo vision	Estimation phenotypic parameters	Ma et al. (2021)
	Maize	3D scan arm	Triangular meshing, 3D semantic point selection	Extracting semantic feature points from plant leaves	Wen et al. (2024)
	Tomato	Kinect V2	Intrinsic Shape Signatures Iterative closest point algorithms	Acquisition of tomato canopies phenotypic traits	Zhu et al. (2023)
Group crops phenotyping	Maize	Kinect v2	TOF, Random Sample Consensus algorithm	Qualitative analysis parameters	Vázquez-Arellano et al. (2018)
	Grape bunches	Kinect depth camera	TOF	Volume and mass quantification	Marinello et al. (2016)
	Grape cluster	Scan Works V5	Expert knowledge, Training data generative model	Derive phenotypic traits	Schöler & Steinhage (2015)
	Sprouts, Cabbages, sunflowers	Canon 500D	SFM	Leaf area estimation	Jay et al. (2015)
	Grape cluster	LiDAR	–	Vineyard characterization	Moreno et al. (2020)
	Groundnut, millet	SLR cameras	Stereo vison, Mathematica	Quantification of the light, environment and photosynthetic	Burgess et al. (2017)
	Maize, soybean	Canon 500D	SFM-MVS, Visual SFM, MVS	Leaf length, leaf width, plant height and leaf area	Zhu et al. (2020)
	Sorghum	12 Point Grey GRAS20S4C-C2-Megapixel color cameras	Stereo view	Field plant phenotyping system	Bao et al. (2019)
	Basil	RGBD sensors	Deep network estimation	Height, weight and leaf area measurement	Franchetti et al. (2019)

(continued on next page)

Table 2 (*continued*)

Type of phenotyping	Crop species	Sensors/System	Technology/Algorithms	Application	Reference
	Sorghum	Phoenix 3.2MP	Triangulation, stereo matching	Stem diameter measurement	Xiang et al. (2020)
	Guava fruits	Kinect V2	Consensus-based sphere fitting method, Principal component analysis-based cylindrical segment fitting method	Detect guava fruits and branches	Lin et al. (2021)
	Cotton bolls	UAV	SfM-MVS	High-throughput capture of organ-scale traits of field cotton bolls	Xiao et al. (2024)
Root phenotyping	Rice	3D laser scanner	–	Phenotyping content of rice and soybean	Fang et al. (2009)
	Sugar beet taproots sugar beets leaves, wheat ears	David laser scanning system Kinect	ReconstructMe V 0.6.0–405	Parameters evaluated	Paulus et al. (2014)
	Rice, soybean	MRI, Camera	–	Illustrates influences of Si on root morphology and root architecture	Tripathi et al. (2021)
	Rice,wheat	Root configuration digitizer	–	Root phenotyping	Chen et al. (2017)
	Maize	SLR camera	WinRhizo GiARoot SmartRoot	Reveal growth and architecture	Le Marié et al. (2014)
	–	Digital camera EX-F25	SFM-MVS, VisualSfM MeshLab	Clarification of root architecture	Okamoto et al. (2020)
	Barley, wheat canola	CT	Datoslx software	Growth and development of root analysis	Pfeifer et al. (2015)
	Rice	Digital imaging system	RootReader3D	Measure root traits	Clark et al. (2011)
	Soybean	CT, MRI	Volume image algorithm (MAVI)	Root Structure Analysis	Metzner et al. (2015)
	Corn, barley	MRI	NMRooting	Root system architecture traits Precise measurements	van Dusschoten et al. (2016)
	Tomato	CT	RooTrak	Visual 3D structure of roots growing	Mairhofer et al. (2013)
	Rice	3D imaging sensors	GiA Roots (General Image Analysis of Roots)	Characterizing root system architecture	Galkovskyi et al. (2012)
	Ash tree	Tree radar	BP neural network	Root system architecture reconstruction	Fan et al. (2022)
	Wheat	Infrared-spectrometer Industrial camera	Omni-directional microscopic image 3D reconstruction	Evaluate single kernel 3D morphologies	Wu et al. (2023)

the relationship between canopy architecture and the light environment (Zhu et al., 2020).

The non-destructive and precise observation of crop root growth has been a longstanding pursuit among botanists, with 3D reconstruction technology emerging as a promising avenue to fulfill this goal (Biskup et al., (2007)). The structure of roots is crucial for plants to acquire water and nutrients. However, accurately representing the root system with realism, depicting roots in the soil, is a challenge due to the absence of appropriate tools for non-invasive and precise measurements of root system architecture in its natural environment. Metzner et al. (2015) addressed this challenge by employing nuclear magnetic resonance (NMR) and CT scanning to individually reconstruct the root system in the soil medium. This work was of significance for the non-destructive and dynamic observation of the root system in the soil, enabling researchers to study and observe crop root systems without disrupting the unique medium. In a related context, Fang et al. (2009) described a root growth system that dynamically simulated changes under various nutrient conditions with a high degree of precision. Utilizing a 3D laser scanner combined with a transparent gel-based growth system, this integrated approach successfully captured 3D images of roots. The system was effectively employed to reconstruct rice and soybean root architectures, facilitated the determination of their changes under various phosphorus supply conditions.

4.3. 3D reconstruction for livestock

Livestock farming involves the breeding, care, and management of animals such as cattle, sheep and pigs to meet human needs. The principles of livestock management encompass various aspects, including nutrition, health, reproduction, and overall well-being, to ensure optimal productivity and sustainable practices in animal agriculture (Neethirajan & Kemp, 2021; Dubourvieux et al., 2023). 3D reconstruction technology has been employed in livestock management. This technology offers some non-destructive and accurate approaches to measure morphological traits, evaluate body condition, and determinate the body weight of animals (Rahman et al., 2017; Guo et al., 2023). A exhaustive summary of applications of 3D reconstruction technology for livestock is presented in Table 3. The main application of 3D reconstruction technology in livestock management can be divided into three categories: precision breeding, health monitoring, and behavior analysis. The research on the application of 3D reconstruction technology in livestock breeding, health monitoring and behavior analysis is shown in Fig. 6.

Livestock breeding aims to improve agricultural output and economic efficiency through genetic improvement, so that the offspring of livestock and poultry show more ideal traits (Kiplagat et al., 2012; Hossain et al., 2022). Body measurement and body shape scoring are crucial parts of current breeding evaluation work, but traditional measurement methods require a lot of human resources and time. 3D reconstruction technology enables precise and detailed assessments of morphological traits, contributing to a more informed and targeted approach to selective breeding. Shuai et al. (2020) developed a 3D surface reconstruction and body size measurement system using multi-view RGB-D cameras, specifically Kinect depth cameras. The system captured point clouds from three different views and utilized a rectangular cuboid for registration, and then reconstructed local point clouds. The distribution of point cloud projections in various directions was leveraged to locate measuring positions, enabling precise measurements of key parameters, including body height, body length, body width, and abdominal girth. Pezzuolo et al. (2018) presented a novel Structure of Motion (SfM) photogrammetry approach for reconstructing animals in a barn. Advanced software tools enabled the automatic estimation of

Table 3
A detailed summary of applications of 3D reconstruction technology for livestock.

Reconstruction animal	Sensors/System	Technology/Software/Algorithms	Application	Reference
Cattle	Kinect v2	Multiple Iterative Closest Point (ICP)	Estimation of body dimensions	Ruchay et al. (2019)
	Kinect DK	ToF, Multi-view vision	Automatic extraction body parameter	Li et al. (2021)
	Kinect DK	Random Sample Consensus (RANSAC)	Collecting parameter	Li et al. (2022)
	DJI Phantom 4 (UAV)	SFM, YOLO v2	Detection and counting	Shao et al. (2020)
	Kinect v2	Pattern recognition using 3-D feature extraction techniques	Body condition scoring	Ruchay et al. (2020)
	O3D303 3D LiDAR camera	Iterative Closest Point (ICP) matching Greedy Projection Triangulation (GPT)	Non-Contact Body Measurement	Huang et al. (2018)
	Kinect v2	–	A novel approach to the lifetime evaluation	Ruchay et al. (2022)
	Depth cameras	Real-time point cloud collection system	Monitoring cattle growth	Li et al. (2022)
	Morpho3D system	Triangulation	Monitoring the growth and body condition	Le Cozler et al. (2019)
	Kinect v1	SPIP software	Monitoring of bodygrowth	Marinello et al. (2015)
	Kinect v1	Structured Light, SPIP software	Checking on body growth	Pezzuolo et al. (2018)
	Huawei P20	SfM, Random Sample Consensus (RANSAC)	Body measurement	Yang et al. (2022)
	Kinect v2	TOF, Multi-view vision	Estimating BCS (body condition scores)	Maki et al. (2017)
	Xtion pro live sensors	Photogrammetry stereo Live Stock Shape Analysis	Monitoring growth status	Guo et al. (2017)
	Kinect DK	3D point cloud reconstruction	Measure the body size parameters of beef cattle in different postures	Li et al. (2023)
Pig	Nikon D5100 camera	SFM	Growth indication measurement	Pezzuolo et al. (2018)
	JAI CV-S3200 camera Sony VPL-CS6 projector	Structured Light	Internal structures of abdomen observation	Albitar et al. (2007)
	Kinect v2	Multi-view vision	Body measurement	Shuai et al. (2020)
	MRI	–	Rectum model reconstruction	Plakhotnyi et al. (2020)
	Gig-EthernetMultiple slits laser with random dots	–	Weight estimation	Yoshida & Kawasue, (2018)
	Nikon D5100 camera Kinect v1RPLidar A3	SFM, Triangulation, SPIP software	Body measurement and non-invasive extraction of parameters	Pezzuolo et al. (2019)
	Azure Kinect	Mesh reconstruction and deep learning	Body type and weight measurement of livestock	Kwon et al. (2023)
	Azure Kinect, Microsoft	Mesh-model reconstruction based on a point cloud	Determine the breeding status of livestock	Kwon et al. (2022)
	–	PointNet++ point cloud segmentationmodel	Point cloud segmentationand body size measurements	Hao et al. (2023)
Chicken	Mars 2000-50gc	Binocular vision matching	Health condition monitoring	Xiao et al. (2019)
	Hikvision DS-2TD2636-10	Patch Match Stereo (PMS) DBSCAN algorithm	Body parameters and surface temperature measurement	Zhang et al. (2021)
	Kinect	–	Assess the lameness	Aydin et al. (2017)
	Kinect v2	KinectFusion	Weight estimation	Muni et al. (2018)
Sheep	WebCam Logitech C920 hdpro	Stereo vision, Triangulation	Size and weight estimation	Menesatti et al. (2014)
	3D scanner	Algorithm of k-nearest neighbor, Delaunay triangulation	Obtain the sheep growth parameters	Zhou et al. (2019)
Fish	Camera	Stereo matching, Convolutional neural networks (CNNs)	Tracking	Ubiña et al. (2021)
	Kinect v1	Structured light	Tracking	Saberioon & Cisar (2016)
	IMU, single camera	SFM, visual-inertial odometry	High-precision reconstruction and analysis of fish move-ment	Butail & Paley. (2010)
	Monocular camera, Structured light sensor	Structured light projection	High precision reconstruction of 3D shape of fish body	Veinelians et al. (2023)
Horse	Velodyne Lida	TOF	Non-contact measurements	Pérez-Ruiz et al. (2020)
	–	hSMAL model	Behavioral analysis of horse motion	Li et al. (2021)

camera parameters during reconstruction, eliminating the need for a preliminary calibration phase.

Regular monitoring of livestock body condition in a quantitative manner is essential for early detection of health abnormalities, and to reduce the risk of problems related to infertility, lameness, or other diseases (Roche et al., 2009; Pan et al., 2023). While live body weight or measurements have traditionally been used to assess individual animal development, manual measurements are time-consuming, expensive, and can induce stress, especially in younger livestock (Guo et al., 2017). Zhang et al. (2023) proposed a method to quantitatively analyze local 3D morphology of domestic animals to evaluate their physical condition. Using point-to-point correspondence in 3D shapes, the differences between shapes were finely calculated, and then the difference values were mapped to the range of body condition scores. They tested and analyzed the body conditions of cows, beef cattle and pigs separately, and the results were more accurate and general than previous methods. Marinello et al. (2015) validated a new automatic measurement system based on Microsoft Kinect™ rgb depth camera, this system utilized infrared laser transmitters, infrared cameras, and RGB cameras to provide rapid reconstruction of 3D objects, quickly extracted and monitored

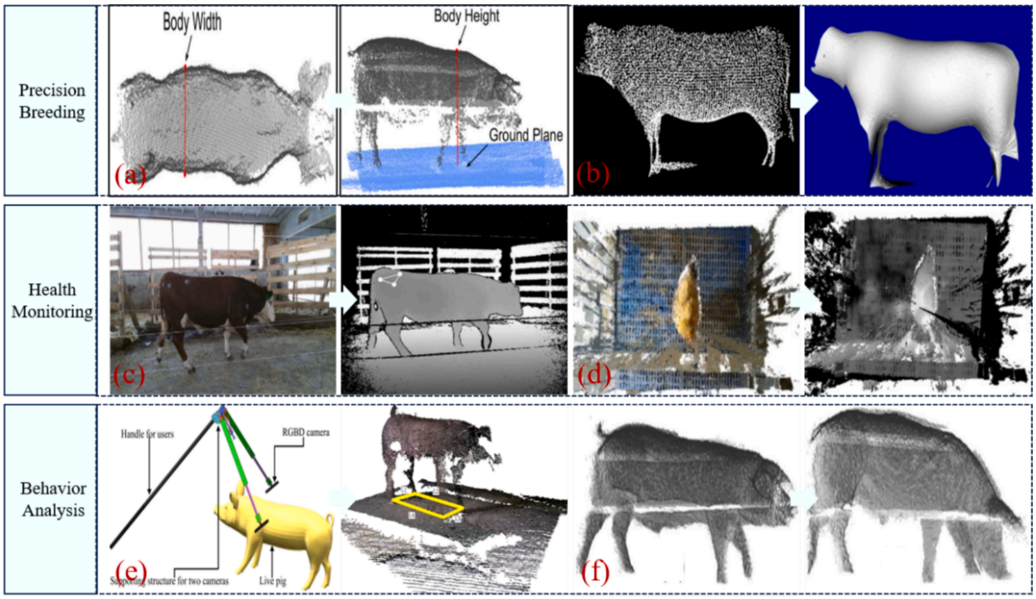

Fig. 6. Applications of 3D reconstruction for livestock. (a) 3D surface reconstruction and body size measurement of pigs (Shuai et al., 2020). (b) Non-contact measurement of body size of Qinchuan cattle (Huang et al., 2018). (c) Quantitative analysis of local 3D morphology of cattle to evaluate their body condition (Zhang et al., 2023). (d) A 3D reconstruction method of Chicken by fusing color and thermal information (Zhang et al., 2021). (e) Implementing a prototype system for live individual pig body surface 3d scanning based on two consumer depth cameras. (Guo et al., 2017). (f) Two types of pig posture from left view: Walking with head forward and walking with head downward (Shuai et al., 2020).

different body parameters, and was suitable for continuous 3D reconstruction of calf and cow bodies for monitoring.

In the context of livestock behavior analysis, 3D reconstruction contributes to understanding and optimizing animal welfare (Tscharke & Banhazi, 2016). By tracking and reconstructing the movements of livestock in three dimensions, researchers can gain insights into behavioral patterns, social interactions, and stress indicators. This information aids in designing better living environments for animals, promoting their well-being. Guo et al., (2017) implemented a portable 3D scanning system to capture a continuous stream of point clouds from the live surface of single pig body, they introduced a novel detection technique to identify frames containing the correct posture of pigs based on the geometric features of the pig's shape. This method was subsequently integrated into a livestock body measurement framework as a

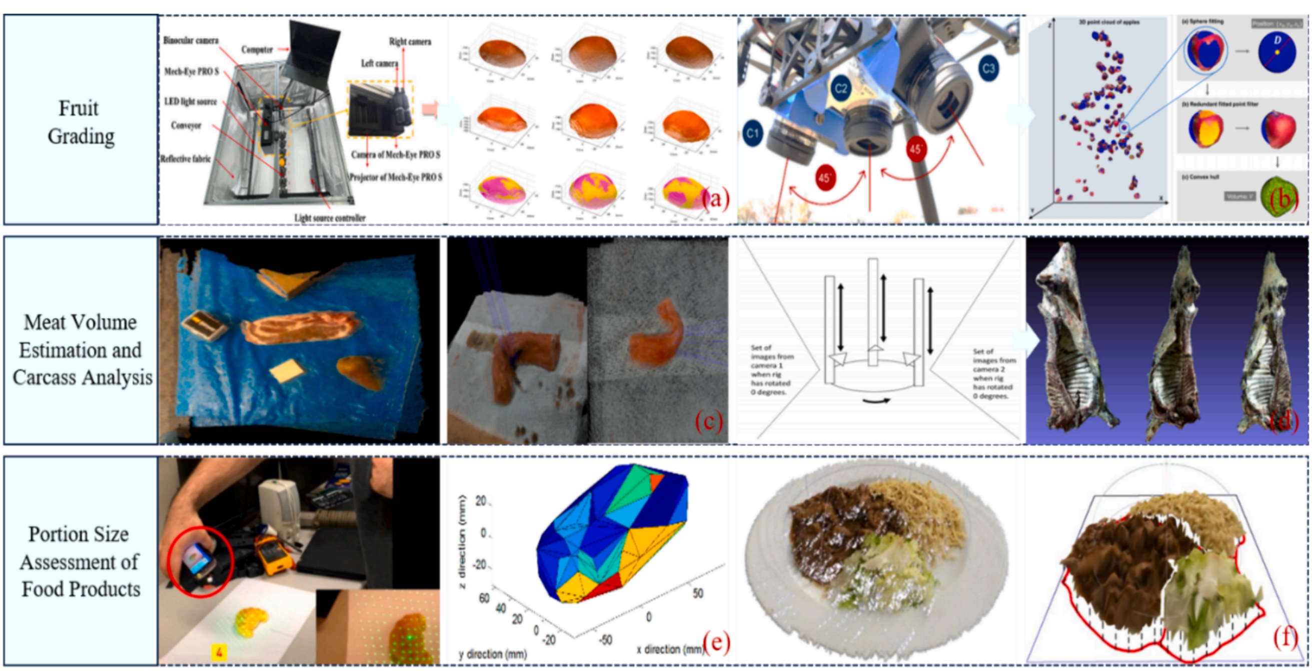

Fig. 7. Applications of 3D reconstruction for food industry. (a) The system of achieving 3D reconstruction of navel orange surface (Gao et al., 2024). (b) 3D point cloud reconstruction of apple from multi-view images collected via unmanned-aerial vehicle (Dong et al., 2023). (c) Accumulated point clouds of the pork loin, salmon fillet (Isachsen et al., 2021). (d) 3D carcass side reconstruction to estimate LMY (Lean Meat Yield) (Alempijevic et al., 2021). (e) DDRS scanner for 3D reconstruction of mango to measure portion size assessment (Makhsous et al., 2019). (f) Dense reconstruction with stereo matching and volume estimation (Dehais et al., 2017). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

preprocessing step.

4.4. 3D reconstruction for food industry

The food industry involves processes such as food quality control and production process monitoring (Jadhav et al., 2018; Rizzo et al., 2023). Traditional manual processes face challenges such as expensive labor costs, time consumption, and inconsistent product evaluations. 3D reconstruction technology can reconstruct food of arbitrary shapes, enable the detection and assessment of visual characteristics like size, shape, and texture. This technology overcomes the drawbacks of manual processes, providing dynamic and non-destructive capabilities to the food production process (Patel et al., 2012; Houetohossou et al., 2023). Numerous studies focus on the potential development of 3D reconstruction technology in three main areas: fruit grading (Zhang et al., 2015; Rejeb et al., 2022), meat volume estimation and carcass analysis and portion size assessment of food products. A summary of this work is shown in Fig. 7.

In the realm of 3D reconstruction-based fruit grading systems, a significant obstacle lies in accurately identifying various features including shape, size, skin flaws, and even 3D structure. Addressing this challenge, Mon & ZarAung, (2020) introduced a straightforward and effective image processing algorithm for estimating volume and 3D shape of mango fruit. The width and length of the mango fruit were derived from a 2D color image. Subsequently, the fruit's thickness was estimated using the light intensity distribution in the top view of the mango fruit, along with the maximum width-thickness correlation. Finally, the algorithm reconstructed the 3D shape of the mango fruit. Some types of agricultural products require examination from multiple angles to assess the overall appearance, but using multiple images may result in redundant data. Yimyam & Clark, (2016) presented techniques to estimate the quality of fruit using 3D reconstruction from multiple images. Employing features extracted from multiple view images without object area duplication achieved higher accuracy than employing the original multiple view images for apple grading. Jadhav et al. (2019) presented a non-destructive and precise fruit grading system leveraging volume and maturity characteristics through 3D reconstruction. The system utilized a volumetric 3D reconstruction method in a multi-camera setup to estimate the fruit's volume, achieving high accuracy in computing the percentage of matured regions within the fruit.

Lean Meat Yield of carcass is an important industry trait, 3D reconstruction technologies can be used to meat volume estimation and carcass analysis (Delgado-Pando et al., 2021). Traditional methods to assess lean meat volume involves manual methods and 2D image-based techniques. However, the manual quality assessment of half-carcass through cutting and dissection is laborious, costly, and demands the expertise of skilled butchers (Font-i-Furnols et al., 2021). To overcome this, a novel approach for assessing the quality of pork carcasses through 3D reconstruction analysis is introduced by Masoumi et al. (2021). They focused on obtaining a high-quality 3D model of half-carcasses without compromising the speed of 3D reconstruction. The proposed method not only outperformed existing approaches but also proved to be rapid, user-friendly, and highly applicable in commercial slaughterhouses. Hence, it holds promise as a viable alternative to traditional methods in the pork industry. Researchers have attempted to use a variety of 3D reconstruction techniques to estimate volume and ketone content. Vaskoska et al. (2020) examined the novel application of 3D laser scanning technology to estimate the volume of pork cuboids before and after heating. Wakholi et al. (2018) developed a 3D reconstruction system using multi-view structured light scanning, MVSLS and multiple view geometry for accurate beef carcass yield estimation. Frisullo et al. (2010) employed the X-ray microtomography (lCT) technique to generate 3D model of beef, facilitating the quantification of intramuscular fat content and the examination of fat distribution across various breeds and commercial meat cuts.

Food portion size assessment is of great significance to nutrition research. As diet-related chronic diseases become more prevalent and traditional dietary management methods prove less effective, there is a growing demand for new tools capable of accurately and automatically assessing diets (Who & Consultation, 2003). Dehais et al. (2017) proposed a 3D reconstruction system to calculate portion sizes using two images of a dish acquired by mobile devices. A dense 3D model was built from the two images, and served to extract the volume of the different items. Makhsous et al. (2019) presented an innovative instrumentation system designed to accurately measure dietary intake for diabetic patients. This system utilized a mobile Structured Light System (SLS) to measure the volume and portion size of food consumed by patients in their daily lives. After calculating the volume of a food item, its nutritional content could be estimated using established nutritional databases. Estimating the volume of food presents the most challenging aspect of determining its nutritional composition. Konstantakopoulos et al. (2021) presented a system for estimating food volume based on structure-from-motion smartphone cameras, employing a two-view 3D reconstruction approach. Their methodology utilized stereo vision techniques, which involved capturing two food images alongside a reference card placed next to the plate. This enabled the reconstruction of the food's 3D structure and estimation of its volume.

4.5. 3D reconstruction for other applications

With the rapid advancement of 3D sensors and high-precision reconstruction algorithms, 3D reconstruction finds applications across diverse agricultural scenarios (Chao et al., 2020). In recent years, numerous researches have explored alternative applications leveraging a variety of sensors. Some research results are shown in Fig. 8. Beyond the mentioned applications, researchers have explored additional uses of 3D reconstruction techniques in agriculture, including crop monitoring, crop yield estimation, and seed research.

Automated crop monitoring plays a crucial role in maximizing crop yield while minimizing costs and environmental impact (Adeyemi et al., 2017). 3D reconstruction holds significant potential in automated crop monitoring, thanks to its enhanced measurement accuracy and detailed spatial morphology representation of crops. Non-destructive plant growth measurement forms the cornerstone of crop growth monitoring. Hu et al. (2018) proposed an automated system utilizing Kinect technology for non-invasive growth assessment of leafy vegetables. Employing a Kinect v2 camera, they captured multi-view point clouds of the crops, subsequently applying a set of appropriate algorithms to achieve detailed 3D reconstruction of the plants. While SFM and MVS algorithms could finely reconstruct the 3D structure of a field with low-cost image sensors, these algorithms failed to capture the dynamic nature of continuously growing crops. To recover above problem, Dong et al. (2017) proposed a 4D reconstruction approach to crop monitoring by employing a spatiotemporal model of dynamic scenes. Additionally, they provided a robust data association algorithm to address the problem of large appearance changes due to scenes being viewed from different angles at different points in time.

Yield estimation is critical for agriculture managing to optimize growth and eventual crop quality (Nuske et al., 2014). 3D reconstruction technology could realize non-invasive and low-cost crops yield estimation. Precise vineyard yield estimation allows more efficient grapevines to be obtained and the production of higher-quality wines (Dunn & Martin, 2003). Herrero-Huerta et al. (2015) proposed an automatic method to reconstruct the grape clusters from a close range using SFM. The proposed method could decide in advance the actions to be taken in the vineyards, predict the outcome and plan the vintage optimally. For purposes of pineapple crop mapping and yield estimation, Moonrinta et al. (2010) presented an image processing framework for in-field fruit detection, tracking, and 3D reconstruction. The primary aim was to generate a detailed farm map containing essential information for farmers, such as 3D representations of pineapple volumes and their

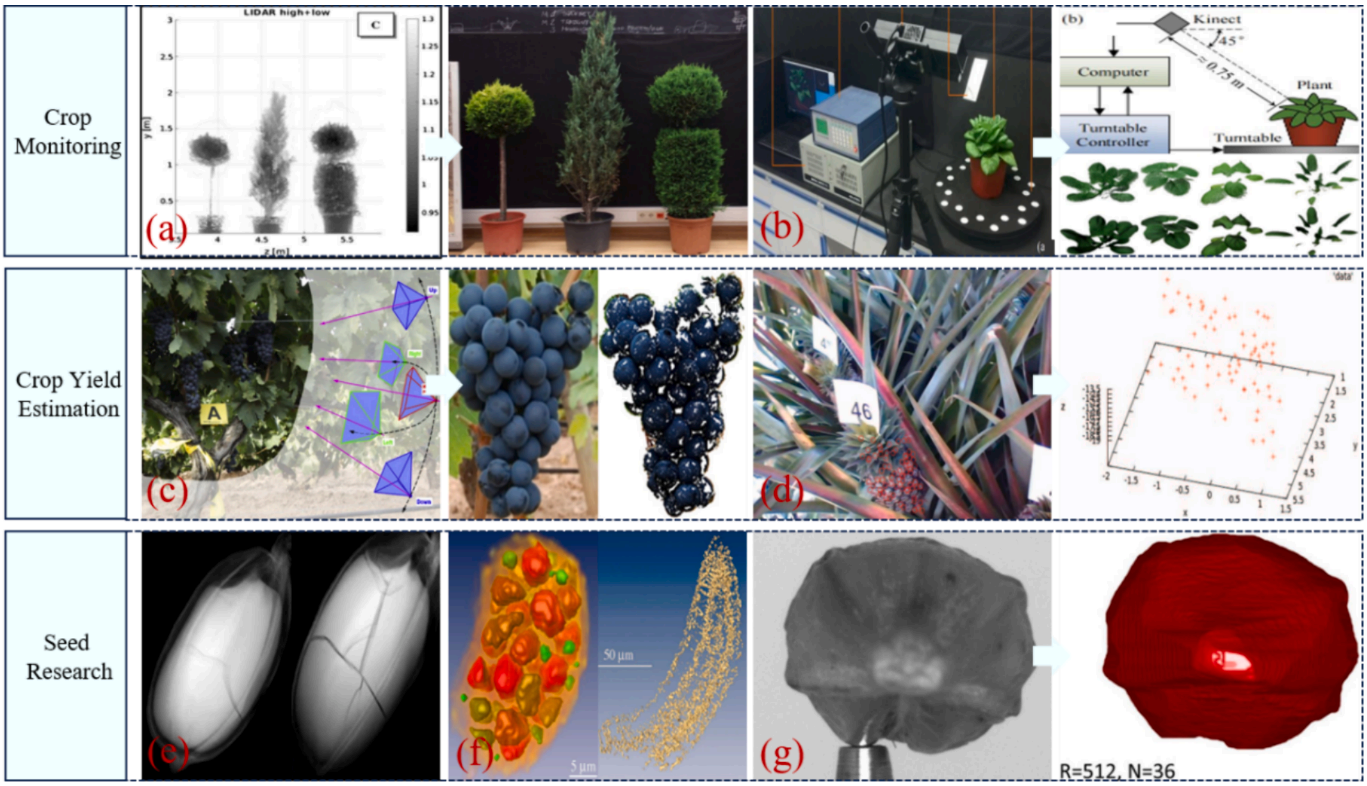

Fig. 8. Other applications of 3D reconstruction in smart agriculture. (a) 3D reconstruction of three plants on the basis of the points coming from both the scans (Bietresato et al., 2016). (b) 3D reconstruction for different species of leafy vegetables to measure plat growth (Hu et al., 2018). (c) Algorithms and 3D techniques were combined to estimate the most relevant parameters in the productivity of a vineyard: volume, mass and number of berries per bunch (Herrero-Huerta et al., 2015). (d) SURF feature points in tracking region for one fruit and 3D point cloud reconstructed from the tracking region (Moonrinta et al., 2010). (e) 3D reconstruction of grain internal damage under different extrusion loads (Chen et al., 2017). (f) 3D reconstruction of a mesophyll cell and intercellular air space in a cotyledon (Cloetens et al., 2006). (g) 3D reconstruction of barley seed surface (Roussel et al., 2016).

geographical distribution.

Crop seed analysis is the key to breeding and ensuring high seed germination rate. 3D reconstruction could be applied in seed research due to its capacity to visualize and characterize external and internal micro structure of small objects in 3D level (Gargiulo et al., 2020). Volume carving is a well-known shape-from-silhouette technique. Based on volume carving, Roussel et al. (2016) described a method for Three-Dimension (3D) reconstruction of plant seed surfaces. The presented method obtained highly accurate seed reconstruction when researchers were interested in seed volume. The most of the inner detection in seeds was still in 2D levels, and some of the details might have been lost. In the research of Yin et al. (2018), the configuration of lipid droplets (LDs) in seeds was obtained by confocal imaging and 3D reconstruction technology in Brassica napus. Their presented work provided a new way to enhance the seed oil content at the single cell level within seeds.

5. Challenges and future trends

3D reconstruction technology has demonstrated brilliant advantages and promising prospects in the field of agriculture. In recent years, many researchers have carried out a lot of scientific research on 3D reconstruction and made significant breakthroughs in key technologies. However, the practical application of 3D reconstruction technology in agriculture is still challenging. Therefore, considering the current research status of 3D reconstruction in the field of agriculture, there are still several challenges to be solved to effectively combine 3D reconstruction technology with smart agriculture.

The main challenges in the application of 3D reconstruction technology in agricultural environment are the complexity and variability of agricultural scenes. Agricultural scenes often contain diverse natural elements such as irregular terrain, diverse crop types, and changing lighting conditions. These factors increase the difficulty of accurately inferring 3D structures from 2D images. Dynamic changes in agricultural scenarios, such as crop growth, seasonal turnover, and weather changes, require 3D reconstruction techniques to be able to update and adapt to these changes in real time, and current techniques may not be mature enough for real-time data processing and updating. In addition, achieving accurate and high-fidelity reconstruction is currently a hot issue for many researchers, but occlusion of the crop canopy structure may lead to issues such as gaps, texture-less regions, and blurred images in the resulting 3D model of certain plants (Bai et al., 2023).

Another challenge for 3D reconstruction in agriculture is the limitation of computing power and storage space when dealing with large-scale data. Agricultural environments are generally large-scale, unbounded, and plants, crops and animals are mostly clustered, involving multiple varieties and numbers. In the 3D reconstruction of agricultural environment or whole animals and plants, due to the large amount of data to be analyzed, the process of 3D reconstruction is time-consuming and inefficient, especially when dealing with multi-view images. The quality of the reconstruction depends on the number of images used, while a larger number of images generally yields better results, it also requires more computational resources, resulting in even longer reconstruction times (Rahman et al., 2017).

The emergence of new artificial intelligence technologies such as NeRF (Neural Radiance Fields) (Mildenhall et al., 2021) and 3DGS (3D Gaussian Splatting) (Kerbl et al., 2023) have introduced new methods to solve the above challenges and problems, and brought vitality and creativity to the application of 3D reconstruction technology in agriculture. NeRF uses implicit representations and differentiable volume rendering techniques to handle complex details and changing lighting conditions, making it suitable for highly variable agricultural environments. The NeRF method is able to generate high-quality 3D models from fewer images and still be able to handle details and illumination changes from learning common features of the scene, which can reduce the time and computational resources required for 3D reconstruction in agriculture. 3DGS is another innovative approach that represents a 3D scene as a collection of Gaussian functions, enabling efficient rendering and manipulation of 3D models. This method enables the effective management of large-scale agricultural environments through incremental construction of models, providing high-resolution and accurate reconstructions without requiring significant computing power. And 3DGS can update the attributes of Gaussian points in real time, which helps to capture the changes of dynamic scenes for accurate reconstruction. Furthermore, these two high-precision, high-fidelity reconstructions also support the synthesis of new perspectives and will reduce the impact of occluded objects and facilitate more accurate and complete reconstruction effects, this will help make more informed decisions in agricultural management and enhance crop monitoring, disease detection, and yield prediction capabilities.

The rapid development of large-scale AI models and AIGC technology like the described above have further amplified the potential of 3D reconstruction in agriculture. In terms of data acquisition and processing, unmanned aerial vehicle (UAV), autonomous agricultural machine and sensor network are used to realize large-scale real-time automatic data acquisition, simplify the 3D modeling process and reduce the need for manual intervention. In terms of model systems, AI technology can realize automatic generation and real-time update of models, and the accuracy and detail of 3D model will be greatly improved as AI algorithms are good at recognizing and classifying various elements in agricultural scenes. In terms of application, the progress of AI technology will further promote the development of AR and VR technology in the field of agriculture, and realize the further development of human–computer intelligent interaction and digital agriculture. Future development of 3D reconstruction in the field of agriculture will enhance the overall effectiveness and applicability by focusing on precision, high-fidelity reconstruction and efficient data processing. This will ultimately support more informed decision-making, thereby advancing the field of smart agriculture.

6. Conclusion

This paper had reviewed the application progress of 3D reconstruction technology in smart agriculture and precision farming. The successful application of 3D reconstruction techniques requires consideration of the agricultural environment and scene, as well as appropriate choice of sensors and sensor systems. In order to acquire environmental information, the characteristics and development of sensors and sensing systems are described in detail. In terms of environmental data processing and 3D reconstruction methods, the traditional active methods, passive methods and deep-learning based methods are summarized. Then, the applications of 3D reconstruction technology in agricultural robotics, crop phenotyping, livestock, and food industry are introduced. Agricultural robots mainly include navigation planning, agricultural mapping and intelligent agricultural operation. In terms of crop phenotypes, three parts are introduced, namely, single plant crop reconstruction, field population reconstruction and root reconstruction. In terms of animal breeding, this paper summarizes the research development of 3D reconstruction technology application in precision breeding, health detection and behavior analysis. In the food industry section, applications of 3D reconstruction techniques to fruit grading, meat volume estimation and carcass analysis, and portion size assessment of food products are presented. After reviewing the above sensors and technologies, this paper concludes finally analyzes some challenges that persist in the practical implementation of 3D reconstruction technology in the field of smart agriculture, such as natural environment changes, plant canopy occlusion, and the efficiency of data processing.

Future prospect of the application of 3D reconstruction in agriculture will focus on the integration of hardware and software optimization. Considering the complexity of agricultural environments and the challenges in practical applications, a prospective outlook has been provided for the development of 3D reconstruction technology in the field of smart agriculture. Despite the existing challenges, the future appears promising, with numerous researchers dedicated to advancing this work.

CRediT authorship contribution statement

Shuwan Yu: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Xiaoang Liu:** Visualization, Investigation, Conceptualization. **Qianqiu Tan:** Supervision, Resources. **Zitong Wang:** Methodology, Investigation. **Baohua Zhang:** Supervision, Project administration, Funding acquisition.

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.

Data availability

No data was used for the research described in the article.

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