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Recent Advancements in Agriculture Robots: Benefits and Challenges

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Abstract: In the development of digital agriculture, agricultural robots play a unique role and confer numerous advantages in farming production. From the invention of the first industrial robots in the 1950s, robots have begun to capture the attention of both research and industry. Thanks to the recent advancements in computer science, sensing, and control approaches, agricultural robots have experienced a rapid evolution, relying on various cutting-edge technologies for different application scenarios. Indeed, significant refinements have been achieved by integrating perception, decision-making, control, and execution techniques. However, most agricultural robots continue to require intelligence solutions, limiting them to small-scale applications without quantity production because of their lack of integration with artificial intelligence. Therefore, to help researchers and engineers grasp the prevalent research status of agricultural robots, in this review we refer to more than 100 pieces of literature according to the category of agricultural robots under discussion. In this context, we bring together diverse agricultural robot research statuses and applications and discuss the benefits and challenges involved in further applications. Finally, directional indications are put forward with respect to the research trends relating to agricultural robots.

Keywords: agriculture robot; complex environments; robot navigation; robot manipulation

1. Introduction

The number of hungry people has been mounting due to the COVID-19 pandemic, and surpassed 80 million in 2021, as reported by World Health Organization (WHO) [1]. Moreover, to handle the challenges of the aggravation of population ageing and acceleration of the pace of life, traditional labour-intensive and risky farm work should be empowered by more automated control work for promising outcomes. In the aspect of academic study, many researchers have dedicated significant efforts to studying agricultural robots, especially during the COVID-19 pandemic, as shown in Figure 1. Therefore, it is reasonable to explore agriculture further using advanced technology in order to keep promoting the current status. It should be mentioned that agriculture robots and intelligent automatic systems are usually equipped with versatile sensing and fast-learning units [2], which provide encouraging capabilities. In addition, much effort has been put towards achieving complete automation and improving the operating efficiency of agriculture robots.

Agriculture robots generally refer to machines designed for farming production use [3]. As an integral member of the robot family, they usually possess advanced perception abilities, autonomous decision-making abilities, control, and precise execution abilities. Furthermore, they can achieve accurate and efficient production goals even under complex, harsh, and dangerous environments. In Ref. [4], the authors proposed a mechanism for considering the coupling effect of temperature and pressure, and investigated the accuracy of the flow characteristics, which is helpful in the development of agriculture robots.
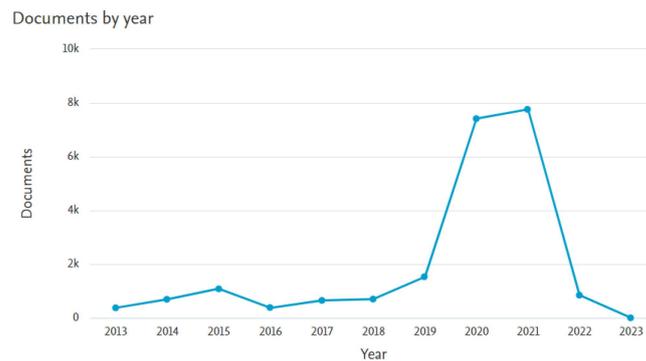
Figure 1. Trend of indexed publications related to agriculture robots based on search keywords "agriculture robot" and "agricultural robot" (data collected from Scopus and processed by authors).

Rovira et al. [5] developed navigation algorithms based on perception, which is the critical technology used for navigation. A UAV designed by Alsalam et al. [6] for agriculture implemented a configuration approach to fulfil decision-making. In terms of control, Zhang et al. [7] developed high-precision control to enable field robots to achieve efficient phenotyping. Due to their soft properties, tomatoes must be picked carefully. Therefore, Wang et al. [8] designed a flexible end effector to pick tomatoes, with a successful rate of 86%. These advancements in agriculture robots have inspired progress in other types of robots, such as industrial robots. Inspired by these applications, in [9] the authors proposed a new method for quantifying the energy consumption of pneumatic systems that combines air pressure, volume, and temperature.

Due to the practical requirements for labor-saving and efficient agricultural production, the categories of agriculture robots have been continuously expanding, and their application scenarios have become more diversified. In light of their different objects, agricultural robots are usually divided into field robots [10], fruit and vegetable robots [11], and animal husbandry robots [12]. Furthermore, based on an analysis of the relevant literature, the research on agricultural robots mainly involves field robots and fruit and vegetable robots, especially in the harvesting domain. Although different agriculture robots are characterized by their respective application scenarios, they bear a number of similarities in core technologies. For example, a stable mobile platform, multi-sensor collaboration, advanced visual image processing technology, sophisticated algorithms, and flexible locomotion control are usually indispensable in constitute an agricultural robot. Moreover, other related techniques are presented together in Figure 2.
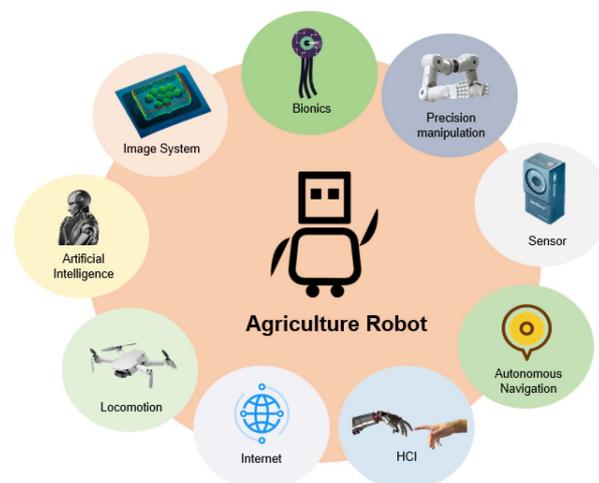

Figure 2. Core technologies involved in agricultural robotic applications.

The rest of this manuscript is structured as follows. An overall introduction to the implementation of agricultural robots is provided in Section 2. In Sections 3–5, field robots, fruit and vegetable robots, and animal husbandry robots are introduced in terms of their features, functions, categories, and applications. Section 6 provides a comparative review of agriculture robots based on several criteria. Section 7 discusses the legislative aspects of agricultural robots. In Section 8, a detailed discussion is offered to clarify the existing challenges and recent noteworthy advancements in agricultural robots. Finally, Section 9 draws a concise conclusion and offers an outlook for the future of agricultural robots.

2. Implementation of Agricultural Robots

With the rapid evolution of robotics, innovating in the field of agricultural robots continues, and they are widely used in diverse agricultural production areas. In general, agriculture robots can be catalogued into three types based on their application scenarios, ranging from fields and orchards to farms. Moreover, agricultural production is a long-term cycle. Seeding, planting, nurturing, harvesting, and processing are crucial steps towards agricultural industrialization. Therefore, agricultural robots can be classified using the industrial chain as well (Figure 3).
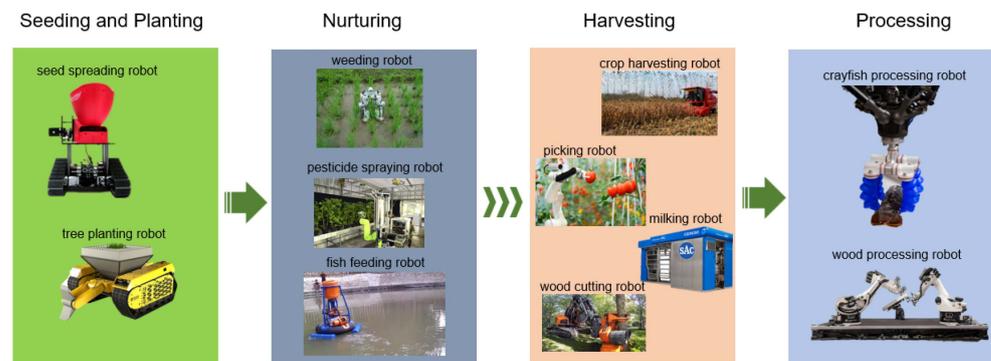
Figure 3. Agricultural robots along the industrial chain [13–17].

The conditions for agricultural production are versatile and complex, which requires agriculture robots to be equipped with outstanding adaptability, precise navigation, and obstacle avoidance ability. Therefore, they are mainly manufactured with four parts to conduct their assignments: a vision system, a control system, mechanical actuators, and a mobile platform, as shown in Figure 4.

Figure 4. Components of agricultural robots [18,19].

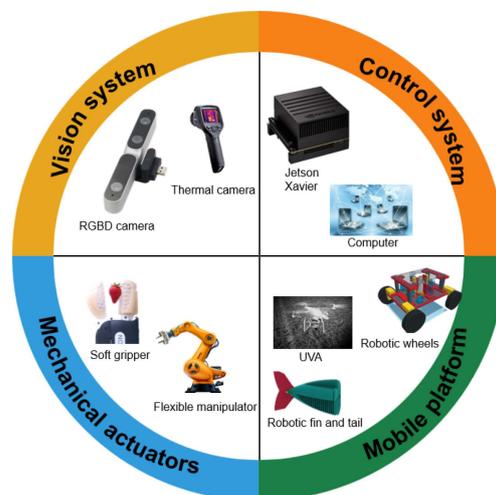Accordingly, these four parts exert their own influence on agricultural production. First, the vision system can transform captured data into images using various cameras, such as thermal, RGBD, TOF, and multi-spectral cameras. Thermal images are conducive to detecting hidden vegetables, as proven by Hespeler et al. [20]. Second, the control system is the brain of the robot, playing an instrumental role decision-making and motion planning. Third, advanced mechanical actuators are a prerequisite for precise operation, especially for tender fruits and vegetables. Lastly, mobile platforms enable robots to navigate, avoid obstacles, perform detection, and carry out tasks [21–25] (Figure 5).
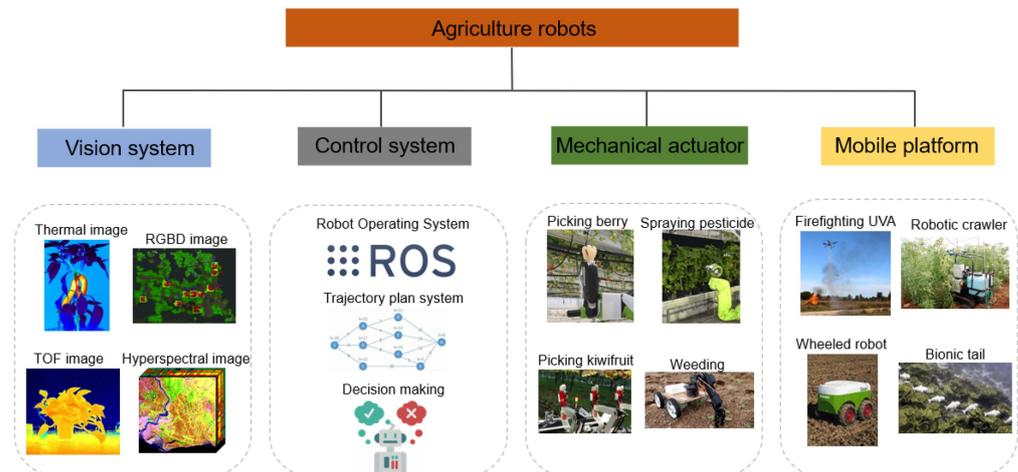

Figure 5. Implications of robotic components [14,19,20,26–30].

3. Field Robots

Field robots usually refer to autonomous, decision-making, mechatronic, and mobile operation devices that can accomplish various crop production tasks semi-automatically or automatically. In this section, 35 pieces of literature are reviewed, including 25 robots and their respective modes of locomotion. Most field robots are designed to locomote using wheels; the use of caterpillars and drones is rare. Interestingly, the implementation of drones is centered on crop protection via spraying of pesticides. Typical assignments include tilling, seeding, crop protection, information collection, and harvesting [31].

3.1. Tillage Robots

Tillage robots refer to intelligent machines that are utilised to cultivate the land. As we all know, tillage is a monotonous and labour-intensive task. Tillage robots can free farmers from heavy labour while enhancing the efficiency and quality of cultivation, and play an instrumental role in digital agriculture.

The machinery of tillage robots is relatively developed owing to arduous exploration. As a result, recent advancements in tillage robot technology mainly lie in updating robot systems. Owing to severe population ageing, the Japanese are quite concerned about the automation of agriculture production. Early in 2013, Tamaki et al. [32] developed a robotic system with three robots for large-scale paddy farming. In the automated system, the first element is a tillage robot navigated by RTK-GNSS and inertia measurement unit (IMU) or GPS compass that can locomote between the paddy fields. In a way, this invention previewed Japan's promising future of agriculture robots. In 2021, Panarin [33] developed existing software for tilling robots, partly aiming to ensure adaptation between software systems and manufactured robots. Furthermore, customer requirements have been fully satisfied by using ROS (Robot Operating System) [33] and adapting digital robots to their surroundings. In addition to typical tillage robots, robotic tractors contribute to tilling operations to a great extent [34,35]. Recently, John Deere rolled out an electric robot tractor called Sesam 2, which can produce 300 kW (400 hp) of power and play a key role in both tilling and harvesting. Moreover, it is able to achieve synergy with several other robots [36].

3.2. Seeding Robots

Sowing is the primary process in field production. Therefore, seed-sowing robots are conducive to sowing seeds in exact positions, saving both time and cost for farmers.

To date, many functional seeding robots have been invented and put into extensive practice. The precision seeding robot for wheat shown in Figure 6 [37] was designed with four wheels, servo motors, and stepper motors. According to the trial results, its seeding rate surpassed 93% in typical sowing speed. In [18], the authors proposed a seeding robot that can dig soil, plant seeds, and cover them with soil. The function of adding fertiliser and watering is available as well. In 2019, Raj et al. [38] designed and tested an automatic robot for seeding and microdose fertilising. It was expected that the robot could plant different seeds, and the trial outcome displayed outstanding prototype performance. Kumar et al. [28] developed an intelligent seed-sowing robot controlled by an IoT system which was able to achieve complete seeding automation. Stepper motors and DC motors were utilised to power the robot.

Figure 6. Wheat precision seeding robot [37].

3.3. Crop Protection Robots

Generally speaking, traditional crop protection involves spraying poisonous pesticides manually, which adversely affects farmers' health. In order to diminish exposure to pesticides, an intelligent robotic system [39] was developed to automatically spray pesticides based on a control algorithm for navigation and a high-efficiency trajectory calculating algorithm. Deshmukh et al. [40] studied and analyzed a multi-purpose pesticide spraying robotic system using a fuzzy control system; it was able to locate infected plants and then spray the appropriate pesticide.

However, ordinary crop protection tends to incur overuse of pesticides, which raises production expenses and does harm to the environment [41]. More precise crop protection methods are expected to cope with this issue. One well-known piece of equipment is the Yamaha R-MAX, developed by the Japanese, which is a leading platform in aerial pesticide spraying [42]. Ghafar et al. [43] developed a cost-saving spraying robot to satisfy the need for spraying pesticides and fertilizers, shown in Figure 7. As shown in Figure 8, Iost et al. [44] introduced novel technologies for small drones, including sensing and actuation drones. By collaborating with each other, the intelligent system provides sustainable pest control. A new modular system for precision farming was put forward in [45] based on the technology of individual nozzles and computer vision. The application of these machines can both protect the environment and save farming expenses.

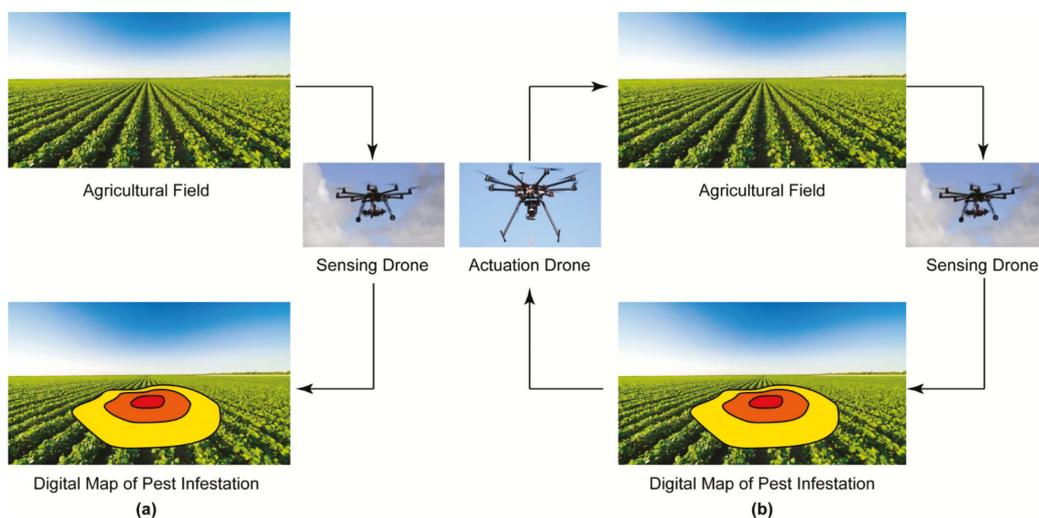**Figure 7.** Agricultural robot prototype moving along a crop path [43].

Figure 8. (**a**) State-of-the-art open-loop remote sensing paradigm and (**b**) closed-loop IPM paradigm envisioned in [44]. Sensing drones can be used to detect pest hotspots, while actuation drones can be used for precision distribution of solutions.

Apart from pest control, overall environmental management pertains to crop protection as well. Martini et al. [46] proposed an automated gardening robot that can automatically plant and monitor soil and water. Similarly, based on DTMF, Srivastava et al. [47] developed a multi-function field robot that can measure soil moisture, irrigate and spray pesticides, etc. Furthermore, it can be controlled remotely. Sori et al. [13] developed a robot for weeding in paddy fields. This robot, equipped with two wheels, touch sensors, and a turning azimuth sensor, can pull weeds by stirring up the soil and blocking sunlight, potentially improving crop yield in view of experimental results.

Several advanced technologies have been applied to crop protection robots, such as the ant colony algorithm, trajectory method, and optimized robot systems. An et al. [48] proposed a more precise and efficient ant colony algorithm for plant protection robots, aiming to improve the reliability and accuracy of path planning. For the agricultural development of crop planting in western China, a region characterized by fragmentary cropland, Ma et al. [49] determined a novel trajectory method by analyzing the arrangement of crops using the ant colony algorithm. In Figure 9, Nascimento et al. [50] optimized an autonomous pesticide spraying robot system, enabling the sprayer to detect rows and activate nozzles.

Figure 9. Tractor-mounted boom sprayer [50].

3.4. Field Information-Collecting Robots

Although collecting information in the field can be laborious and gruelling, the data gathered as a result assists farmers in making invisible decisions. In light of this, field information-collecting robots have been developed to accomplish this assignment. At the University of Saskatchewan, Bayati et al. [51] developed, implemented, and verified a field-based high-throughput plant phenotyping mobile robotic platform to monitor Canola plants. Wide-range images of plant canopies can be gathered and analyzed by the platform automatically. This innovation has been demonstrated to improve the productivity of farms while decreasing costs in the long run. As shown in Figure 10, Cubero [52] developed a field robot called Robhortic for detecting pests and diseases in horticultural crops. After three trials in carrot fields, its performance was outstanding, with a detection rate of 66.4% and 59.8% in the laboratory and field, respectively. An ROS-driven mobile robot [53] was specially designed to navigate the area and collect phenotyping data, with an error rate of only 6.6% and 4% for plot volume and canopy height, respectively. Ultimately, this work has aided in expediting the evolution of agricultural robots, especially in phenotype monitoring.

Figure 10. A remotely-driven RobHortic operating in a carrot field, showing the external appearance of the robot [52].

The technological development of information-collecting robots has included breakthroughs in neural network algorithms and visual navigation. Gu et al. [54] enhanced a field information-collecting robot's convolutional neural network algorithm by manipulating the path tracking to ensure stable movement, minor deviation, and human–machine separation.

3.5. Crop Harvesting Robots

As is well known, rice cutter machines have been available for many years. Based on the existing mechanical framework [55–57], many algorithms have been developed to automate such harvesters. In 2022, Geng et al. [16] developed an automatic corn harvester system able to fulfil trial requirements with a deviation rate of 95.4% at normal harvester speeds. Notably, these advancement represent a benchmark for improving the automatic row alignment process. Li et al. [58] developed and applied a deep-learning algorithm based on ICNet to assist a robotic harvester with accurate obstacle detection in real-time, as shown in Figure 11. This automatic harvester, equipped with a pruned model, was able to realize collision avoidance with a success rate of 96.6% at an average proceeding speed. Considering the deficiencies of the current navigation algorithms used in harvester robots, Li et al. [59] developed an enhanced detection algorithm that reached a success rate of 94.6%, higher than the least squares method. However, precise corner detection was hard to attain. Having improved the PSO algorithm, Pooranam [60] invented a robotic swarm harvester to help farmers with large-scale reaping, threshing, and cleaning. Using a simple mathematical operation, they were able to optimize course of harvesting. Considering the large overshoot and long convergence time caused by large initial heading errors, Wang et al. [61] explored a novel trajectory planning algorithm for harvesting robots that could enhance stability, thereby improving operational performance.

Figure 11. Robotic combine harvester and installed devices [58].

4. Fruit and Vegetable Robots

Manpower cannot fully meet the rapid requirements of the agricultural products market. Alternatively, smart robotics can be an efficient solution to increase the planting areas for the markets in combination with changes in cultivation, preservation, and processing technology. In this section, five major types of fruit and vegetable robots are be introduced, including transplanting robots, patrolling robots, pesticide spraying robots, gardening robots, and picking robots.

4.1. Transplanting Robots

With regard to transplanting performance, accuracy and stability are two critical indicators. Therefore, Jin et al. [62] proposed an advanced control approach using manipulators for hydraulic transplanting robots. As a result, the control accuracy and stability of transplanting was improved. Yang et al. [63] developed a transplanting robot with three degrees of freedom. A subsequent trial was conducted, and the result showed that the transplanting robot could achieve a success rate of 95.3% even as the acceleration reached 30 m/s^2. Han et al. [64] constructed and evaluated a multi-task transplanting robot that could reach a success ratio of 90% even at a speed of 960 plants/min per gripper. Future research that integrates agronomic and mechanical requirements is expected. Furthermore, the design of more inexpensive products for smallholder farmers is anticipated. In Figure 12, Liu et al. [65] designed an advanced transplanting robot for sweet potatoes which was distinguished by two-degree-of-freedom path control. Notably, this machine

can automatically implement diverse transplanting strategies in light of different terrain types. The minimum qualified rate of seedling erection angle and planting depth was 94.7% and 94.8%, respectively, satisfying the practical requirements of mechanical transplanting of sweet potatoes.
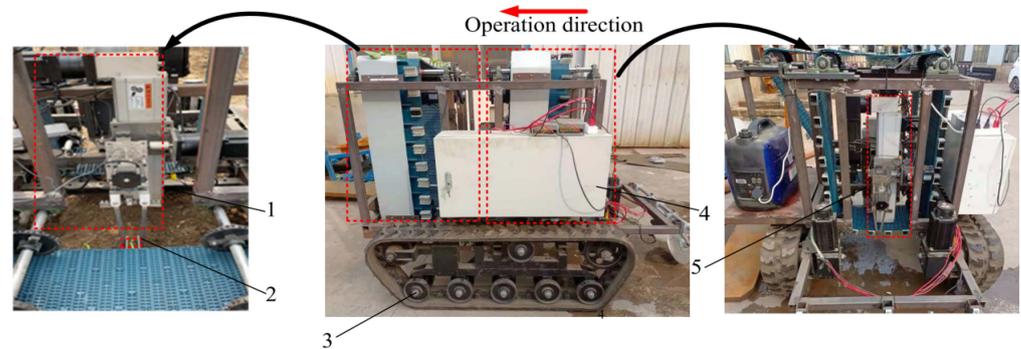

Figure 12. 1. Transplanting robot arm; 2. Transplanting position; 3. Crawler chassis; 4. Control box; 5. Filling robot arm [65].

4.2. Fruit and Vegetable Patrolling Robots

Fruit and vegetable patrolling robots usually navigate autonomously, collect various information, and finally transmit feedback gathered information to farmers. The data they gather incorporates fruit and vegetable maturity, environmental parameters, and pests. Based on colour proportion analysis, Zhou et al. [66] improved a scouting robot to detect tomatoes and measure their maturity using YOLOV4. It is worth mentioning that the identification accuracy rate is extremely high, reaching 95%, and the detection speed is more than 5 frames/s in the natural greenhouse. Iida et al. [67] designed an information-collecting robot to collect environmental information, such as CO_2 content, temperature, and humidity. In addition, they validated the usefulness of the proposed robot through a prototype.

Wang et al. [68] developed a patrolling robot on the basis of the Web of Things, which can send processed warning information to users, thus instructing farmers to plant scientifically. Introducing the Web of Things to agricultural production is beneficial in intelligent planting applications. To detect early pests, Martin et al. [69] developed an ROS-based architecture dubbed Robotframework (Figure 13) that successfully combines various robotic skills, such as navigation and manipulation. These innovative solutions enable the possibility of new mobile robotic manipulators.

Figure 13. GreenPatrol robotic platform entering a greenhouse [69].

4.3. Pesticide Spraying Robots

Similar to spraying pesticides on field crops, spraying pesticides on fruits and vegetables is a burden on the environment due to excessive spraying ranges. Therefore, many pesticide spraying robots have been designed to achieve more precise spraying via various methods, such as servo-controlled nozzles, flow control systems, and ultrasonic sensors. A great deal of research effort and attention has been focused n the area of pesticide spraying robots.

Cantelli et al. [30] invented an autonomous spraying robot containing two parts, a vehicle and a spraying control system. Then, experimental tests were conducted to prove that synergy between the two parts could achieve a safer and more precise spraying operation. Bhat et al. designed a semi-autonomous robot [70] able to climb Areca Nut trees and then spray pesticides using servo-controlled nozzles. In this way, higher quality and output can be attained. This additionally solves problems involving the limitations of human labor. An autonomous pesticide sprayer [71] was developed and implemented to spray pesticides precisely while incorporating obstacle avoidance ability. Moreover, it can be applied to different crops, including pineapples, tomatoes, rock melons, and more. Further exploration was considered from the perspective of spraying pressure, waterproof structure, and upgrading of the monitoring system.

Oberti et al. [14] developed a modular agriculture robot in the CROPS project [14] to achieve autonomous disease detection and selective pesticide spraying operation, which could mitigate pesticide overuse. In addition, they designed the first fully automatic selective system for spraying pesticides geared towards specialty crops. As shown in Figure 14, Seol et al. [72] proposed a flow control system for a smart spraying robot using semantic segmentation. Thereafter, contrastive field experiments were carried out, demonstrating that the proposed system outperformed existing control approaches. Tewari et al. [73] developed a robotic selective sprayer using sensitive ultrasonic sensors. Based on ultrasonic sensing technology, the nozzles spray exclusively toward the tree canopy, reducing pesticide usage in orchards by 26%. A robotic spraying system based on the SegNet model was proposed in [74] to spray pesticides in orchards, composed of hardware configuration, semantic segmentation, and depth data fused with trained RGB data. In field experiments, their environmentally friendly spraying robot showed satisfactory properties.
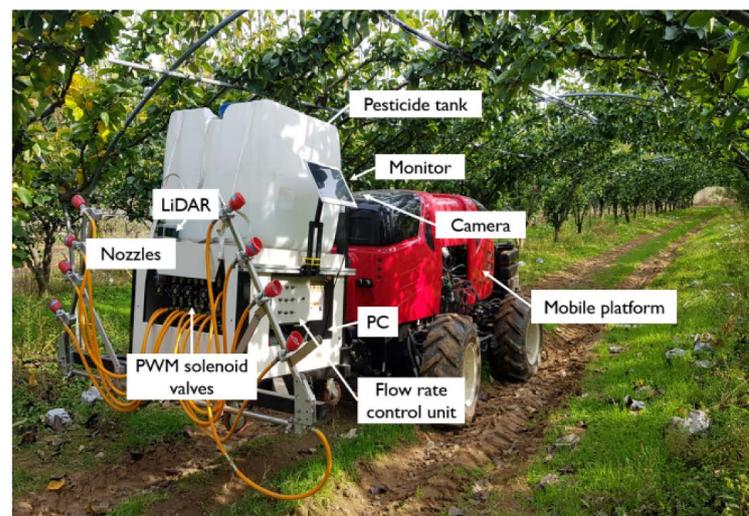

Figure 14. Intelligent spraying system [72].

Compared with typical pesticide-spraying robots, the "X-Bot" designed by Ozgul and Celik is much smaller [75], as shown in Figure 15. The semi-automatic mobile robot presents potential energy savings and can spray pesticides and repel insects without any human assistance.

Figure 15. X-Bot operating in a field [75].

It is worth mentioning that the remote control can be attained through Bluetooth communication. Mane et al. [76] proposed a pesticide spraying robot with an interface controller for feasible remote control. Moreover, they fabricated and tested a prototype that was able to satisfy all major requirements.

4.4. Gardening Robots

Due to the dynamic circumstances generated by seasonal changes and plant growth, a garden with unique characteristics is challenging for autonomous gardening robot systems [77–82]. The garden map for robot navigation applications is influenced during gardening robots' cutting of hedges, because its appearance and geometry are changed at this stage. Hence, the existence of pitches and the gardening robot movements plan should be considered in navigation techniques. A great deal of research attention has been focused on this area.

In the TrimBot 2020 project, a robotic lawn mower was proposed, the first outdoor robot intended to trim bushes and prune roses. Strisciuglio et al. [83] pioneered a prototype using innovative path planning and visual servo systems. A robotic irrigation system [84] was specially developed to irrigate indoor gardens. An Arduino microcontroller increases the water flow when a moisture sensor detects dry soil. Moreover, an automatic fertilizer sprayer was developed to compensate for one deficiency of this work.

In [85], a pruning manipulator with five degrees of freedom was designed for jujube, as shown in Figure 16. Subsequently, a performance test was conducted, verifying the excellent properties of the automatic equipment, with minimal positioning error and an average success rate higher than 85.16%.
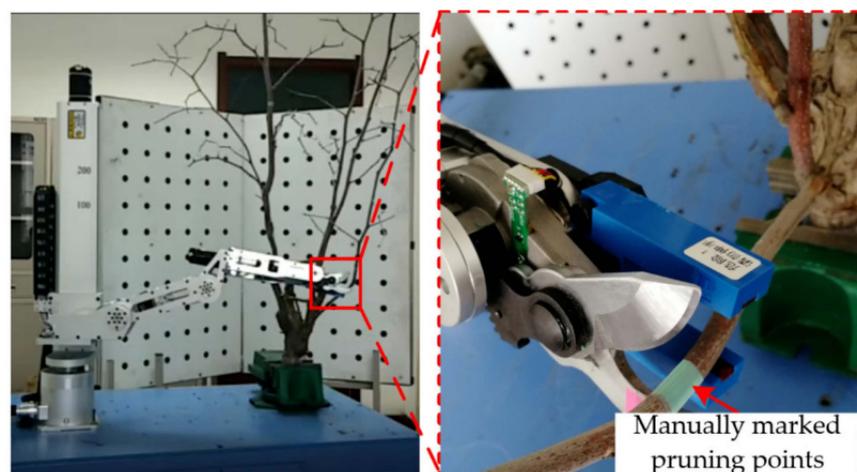

Figure 16. The pruning test [85].

Based on an automatic irrigation system, small-sized gardening robots [86] have been designed and tested to assist people in growing plants, as shown in Figure 17. Thanks to the use of sprinkler controllers and moisture sensors, plants were able to grow faster by as much as 20% under the care of gardening robots. In future work, more sensors are expected to be accessed, and image-based machine learning can be highlighted. Islam et al. [87] designed a multi-functional gardening system that could be implemented on rooftops and nurseries. This semi-autonomous assistance system can supply water and detect leaf disease. However, the gardening robot is limited by the solar charging system, which is unavailable with insufficient daylight. Cheung et al. [88] at the City University of Hong Kong designed an automatic mobile gardening system made up of four parts, namely, a monitoring kit, artificial intelligent classifier, mobile application, and cloud storage, with the aim of increasing planting efficiency.
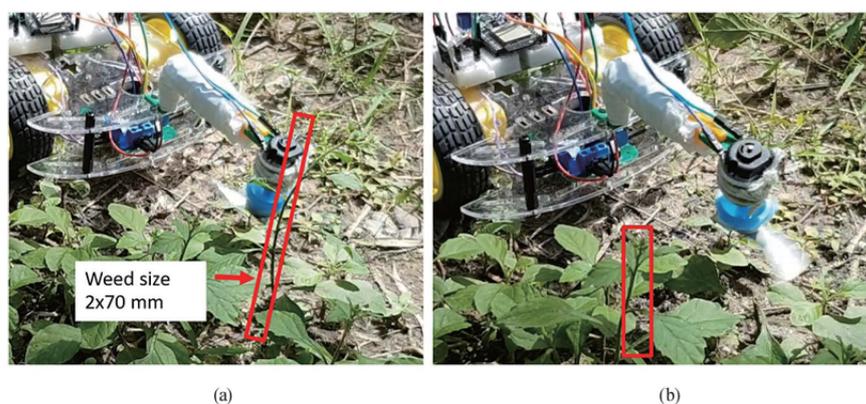

Figure 17. (Color online) Weeds (**a**) before cutting with a cutter blade and (**b**) after cutting with a cutter blade [86].

4.5. Fruit and Vegetable Picking Robots

Fruit and vegetable picking robots usually refer to automatic machines designed for large-scale detection and picking of fruits and vegetables in modern agriculture [89–92]. Robotic harvesters are classified into bulk and selective robotic harvesters [93], and include kiwi-picking robots, apple-picking robots, strawberry-picking robots, tomato-picking robots, and more [11]. In addition, numerous examples have proven that fruit and vegetable picking robots have become a prevalent topic among agriculture robots.

Williams et al. [27] developed a kiwi fruit-picking robot. This type of kiwi fruit-picking robot consists of a machine vision system, end effectors, and four harvesting arms. Specifically, the robot employs a convolution neural network (CNN) which performs semantic segmentation on images of the canopy. However, due to obstructions and loss, only 51% of kiwi fruits were successfully picked by the novel robotic kiwifruit harvesting system in the test orchard.

With regard to apple-harvesting robots, Kuznetsova et al. [94] developed a machine vision system based on a YOLOv3 algorithm with pre- and post-processing for detecting apples. By employing pre-and post-processing, the fruit detection rate increased from 9.1% to 90.8% compared with standard YOLOv3. Notably, only 19ms was required to detect each apple; objects mistaken for apples accounted for 7.8%, while 9.2% of apples were unrecognized. A complete and totally autonomous picking robot [26] was implemented by the agricultural R&D-company Octinion to detect and pick ripe fruits without damaging them. The efficiency of the prototype was high, picking strawberries in only 4 s. Based on RGB-D, Li et al. [95] invented a trustworthy algorithm for harvesting robots (Figure 18) to automatically locate lychee clusters, facilitating collection in large-scale environments. In field experiments, only 0.464 s was required to deal with a single lychee string.
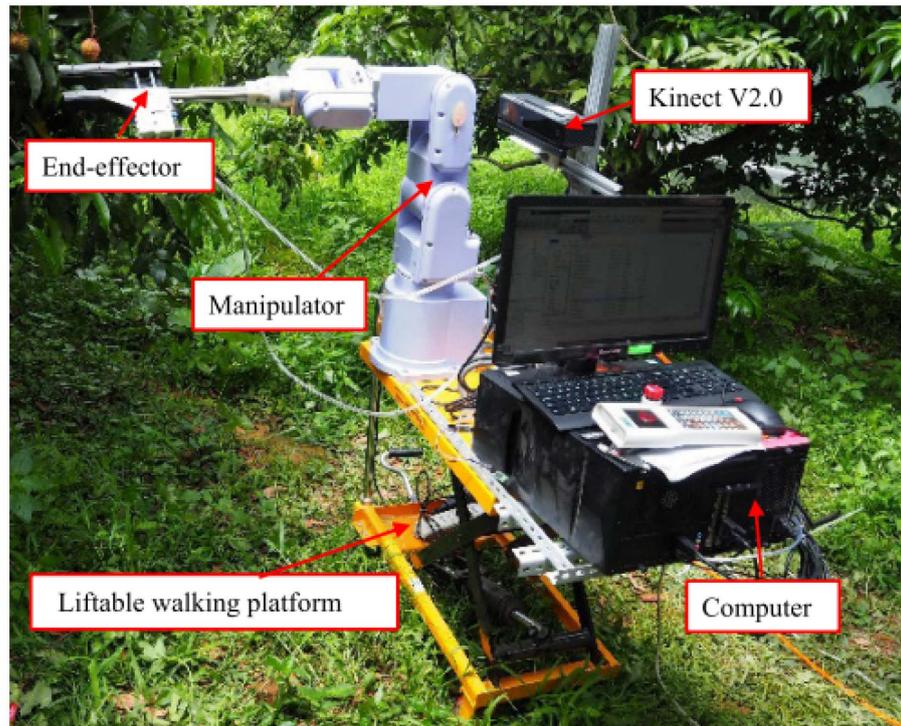
Figure 18. Robotic system for lychee harvesting [26].

Within the overall procedure for harvesting sweet peppers, a new robotic harvester was developed by Lehnert [96]. Using a vision-based algorithm, a 3D localisation and grasp selection method, and an end-effector, it obtained a harvesting success rate of 58%, a grasping success rate of 81%, and a detachment success rate of 90% for the sweet pepper, which represents a breakthrough. Although these results cannot yet satisfy commercial needs, it is possible to foresee a promising future for this autonomous sweet pepper harvester. Based on deep learning, thermal images were used in [20] to detect chili peppers in complex environments, which is more efficient than RGB images. Using thermal cameras can make the harvesting process more efficient; this study opens up new possibilities for harvesting in low-light environments.

Distinct from rigid grippers, flexible soft grippers can gently interact with objects. Peng et al. [97] summarized the advancements and relative excellence of soft robotic grippers in vegetable and fruit picking and their robustness in adapting to different requirements. Then, they briefly introduced the notion and status of soft robotic grippers. They concluded that progress on the development of soft grippers has been made in materials, chemistry, and other multidisciplinary areas, and that challenges remain in manipulating methods, controllability, and mechanical design.

5. Animal Husbandry Robots

Due to lengthy investment cycles and the high stakes of animal husbandry production, animal husbandry tends to suffer massive crises. When a crisis situation occurs, the yield of meat and dairy declines accordingly, increasing the expense of production. Therefore, the need for a more intelligent strategy that can manage farms efficiently has begun to catch the public's eye.

5.1. Breeding Robots

Poultry and livestock breeding is an essential part of agricultural production, with generous profits. Therefore, enhancing poultry and livestock breeding can be of high significance. Disinfection is the most fundamental, valuable, and comprehensive way to

improve breeding, and has attracted extensive attention among the various methods used to improve breeding.

To deal with the labour-intensive work of disinfection, Feng et al. [98] designed an efficient disinfecting robot. Afterwards, an experiment was conducted to test its performance, and the results showed that the disinfecting robot satisfied the basic requirements very well. In 2021, Feng et al. [99] upgraded a robot that can be controlled automatically and remotely for disinfectant-spraying in poultry houses. Accordingly, this research serves as technical support for intelligent production.

Based on the Internet of Things, Li et al. [100] developed an intelligent device to monitor the environment of enclosed henhouses, trying to find the relationship between the production environment and laying rate. In general, they found that suitable temperature and increased ventilation are two key factors for laying hens. Li et al. [101] employed internet technology in chicken breeding. The intelligent and remotely controlled system they developed can monitor the chickens and update real-time information through various sensors. Hence, the chicken house in the woods can become an organic whole through the use of such a network.

5.2. Animal Feeding Robot

Feeding livestock and poultry on time is another labour-intensive assignment, and it is difficult to accurately determine the quantities of fodder. The automation of animal feeding can reduce the costs of both feed and labour while eliminating feed waste. In light of this, roboticizing the process becomes the universal direction in animal feeding.

Peng et al. [102] proposed and designed a robotic pig-feeding system to decrease the demand for artificial labour and guarantee a pleasant environment for pig breeding, leading to a great improvement in production efficiency. In Nepal, Karn et al. [103] introduced a feeding system for cattle that followed the pre-determined trajectory and placed the feed by the fence. In the designed work environment, the developed robotic vehicle enabled successful operation. On the basis of force feedback, Rumba et al. [104] proposed an iterative pile-pushing algorithm to estimate the feed-pushing robot path in dairy cattle farms. Notably, the related change can contribute to intelligent dairy farms.

As shown in Figure 19, Pavkin et al. [105] conceived a robotic feeding pusher to enable robot modernization. Later, they developed an experimental model to test their simulation model; the results showed that the automatic robot can significantly facilitate the process of feeding by conducting labor-intensive operations. However, the animals at the feed table posed a challenge for the accuracy of the vision system. In Figure 20, Tian et al. [106] designed a pusher robot able to navigate automatically using a 3D lidar system. Moreover, they proposed an advanced obstacle avoidance method to overcome problems in complicated open situations. These developments contribute to intelligent dairy farming.

Figure 19. Physical analogue of a robot pusher: 1. Outlet of the feed additive dispenser; 2. Pusher auger; 3. Filler with closer [105].

Figure 20. Pusher robot [106].

5.3. Milking Robots

Usually, milking is performed in specified sessions, and the cows cannot determine the timing of being milked. However, the advent of AMS has revolutionized the process and even the whole dairy industry, helping farmers to gain much more respectable returns. Nowadays, milking robots are available throughout the day, and farm management has evolved in a more organized way. Hence, many scientists have taken an interest in this topic.

Sitkowska et al. [107] developed an automatic robot system (AMS) to allow farmers to monitor cow performance traits. By analyzing the data collected through AMS, researchers were able to find the relationships between performance features and milk yield, improving milk yield and economic benefit. They pointed out that the optimal milking plan referred to milking at a frequency ranging from 2.6 to 2.8 per day and milking speed of 2.6 kg/min. Iweka [108] developed an NIRS sensing system for a milking robot to determine the quality of non-homogenized milk from the perspective of SCC and three main milk constituents. This can provide farmers with feedback control, contributing to high-quality milk and precision dairy farming.

The vision system plays a paramount role in automatic milking. A novel milking robot [109] (Figure 21) with RGBD cameras, image segmentation, and an algorithm was designed for achieving automatic milking. Although elementary, the idea proved feasible in the initial experiment. Nonetheless, further engineering improvements can be expected, and further validation in real scenarios remains required. A new 3D vision system that can locate the milking cups precisely was developed by Akhloufi [110], and was able to improve the performance of milking robots. Pal et al. [111] conceived an intelligent vision system for milking systems using the technologies of RGBD imaging, thermal imaging, and ToF camera imaging. Moreover, the application scenarios of this advanced detection system included the sheds and carousel parlors.
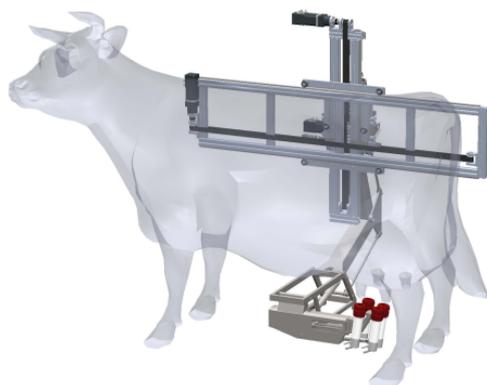

Figure 21. Kinematic model of a milking robot [109].

5.4. Egg Collecting Robots

Collecting eggs in large-scale poultry houses is dirty and dull; autonomous equipment can considerably improve this situation. As shown in Figure 22, Vroegindeweij et al. [112] successfully developed and evaluated a mobile robot that can navigate autonomously, keep an eye on the poultry, avoid obstacles, and collect eggs, which indicates a bright future for intelligent poultry houses.

Figure 22. PoultryBot among hens in the test environment [112].

6. A Comparative Review of Agricultural Robots Based on Several Criteria

In this section, a comparative review of agriculture robots is provided on the basis of several criteria, including the mode of locomotion (wheels, caterpillars, drones), the size of robots (small, medium, large), application scenarios (indoor, outdoor, or both), sensors employed (GPS, RGB, IR, LiDAR, etc.), autonomy (autonomous, semi-autonomous, manual), and the distinction between research prototypes and commercial products.

After conducting a thorough analysis, we find that most agriculture robots are designed to locomote using wheels, while the use of caterpillars and drones is rare, as shown in Table 1.

Table 1. Modes of locomotion used by agriculture robots.

Modes	Robots Reviewed	Main Examples
Wheels	21	[37,43,45,52]
Caterpillars	7	[40,58]
Drones	6	[42,44]

Based on the current study, we find that smaller-sized robots have received the most attention from researchers (Table 2). For example, in [32], Pikulkaew Tangtisanon introduced a small gardening robot with a decision-making watering system. However, larger-sized robots have been studied by many researchers as well.

Table 2. Size of agricultural robots.

Size	Robots Reviewed	Main Examples
Small	25	[32,44,86,113]
Medium	9	[114,115]
Large	17	[116–119]

Indoor agriculture has become a popular research trend in recent years, and indoor robots have consequently received a great deal of attention (Table 3). In [120], Marsela Polic et al. proposed a robotic system for indoor organic farming. A networked

autonomous gardening system with applications in urban/indoor precision agriculture was described by Nikolaus Correll et al. in [121].

Table 3. Application scenarios of agricultural robots.

Scenarios	Robots Reviewed	Main Examples
Indoor	27	[84,120–122]
Outdoor	19	[83,123]
Both	13	[124,125]

All robots perceive signals through a sensor, with RGB (Red-Green-Blue) sensors, vision sensors, and GNSS being the most common (Table 4). There exist other sensors that allow robots to identify their surroundings, such as light detection and ranging (LiDAR) sensors, multispectral sensors, infrared (IR) sensors, etc.

Table 4. Sensors used by agricultural robots.

Sensors	Robots Reviewed	Main Examples
GNSS	18	[32,51,113]
RGB sensor	32	[44,109–111,126–129]
Infrared(IR) sensor	17	[87,108]
Light detection and ranging (LiDAR) sensor	14	[106,126]
Vision sensor	19	[126–128]
Multispectral sensors	8	[56,68,130]

Most of the agriculture robots described in this review are autonomous, as shown in (Table 5). The broad use of fully autonomous agricultural robots reduces labor costs and greatly increases the efficiency of farming work. Meanwhile, semi-autonomous robots are an indispensable element of agricultural robots. For instance, in [75] Ege Ozgul and Ugur Celik offered a semi-autonomous robot named "X-Bot" to improve efficiency and precision in agricultural tasks. On the other hand, manual robots were rarely found in our review.

Table 5. Categorization of agricultural robots based on their degree of autonomy.

Degree of autonomy	Robots Reviewed	Main Examples
Autonomous	78	[31,32,35,38,39,45,46,50,61,64, 71,76,96]
Semi-autonomous	29	[43,75,131,132]
Manual	14	[133,134]

Last but not least, the distinction between research prototypes and commercial products is worth mentioning. Currently, the commercialization of agricultural robots is insufficient and needs further exploration, as shown in (Table 6). In our review, many different research prototypes were found. For instance, in [33] the creation of software for robots intended for spot mechanical tillage was a major focus of researchers Roman N. Panarin and Lubov A. Khvorova. In addition, there has been a great deal of research on the use of commercial robotic products in agriculture, as can be seen in [31,43,135].

Table 6. Commercialization of agriculture robots.

Commercialization	Robots Reviewed	Main Examples
Research prototype	16	[33,34,37,61]
Commercial product	12	[31,43,135]

7. Legislative Aspects of Agriculture Robots

In reviewed publications related to agriculture robots, we have seen the rapid evolution of technologies and the resulting potential economic benefits. However, widespread application is hampered by inconsistent and nonstandard legislative codes, which originate from dynamic and complicated environments, various manipulation objects, and gaps among countries [135–137]. This has led to considerable controversy [138]. In order to manage agriculture robots and boost large-scale applications, efforts are being made to update existing laws [139]. Hence, future work in this area is encouraged, with the aiming of safeguarding effective operation in all cases.

8. Discussion

This section concludes and discusses the recent advancements with respect to agriculture robots, as well as the challenges and present trends in related research work. Nowadays, agricultural robots are being developed rapidly thanks to theoretical innovations and various cutting-edge technologies, including multi-modal perception, decision-making, control, and execution abilities. These advancements presage a bright future for precision agriculture and intelligent farming.

However, because the agricultural environment is complicated and dynamic, many more agricultural robots are either employed in small-scale applications or remain in the prototype phase, including pesticide spraying robots, gardening robots, and strawberry picking robots [26,67,83] described in this review. Moreover, other problems involving agriculture robots have barely been explored or remain in the nascent stage, such as energy consumption, accuracy of GNSS, the cost of robot fabrication, and the maintenance of robots or robotic systems [25,140–144]. For instance, it is well known that the vision system is regarded as the "eyes" of agriculture robots, and there is a considerable tradeoff between the cost and quality of cameras for agriculture use, as stated by Khan et al. [113]. Furthermore, in most developing countries land use for agriculture is usually not as intensive as is the case for large-scale farmland in developed countries. In addition, farmers may not hold sufficient capital to purchase efficient agriculture robots. Therefore, it is reasonable to expect more affordable and high-quality agriculture robots.

Apart from autonomous machinery, advanced control systems, and socioeconomic factors, it is worthwhile to consider interaction with the agri-environment. New approaches are required to facilitate more natural and user-friendly interaction in agricultural production. Breakthroughs have been made in human–robot interaction, such as modelling, semantic action recognition, and risk-averse optimization approaches [145–149]. Nevertheless, further exploration is needed due to unstructured and uncontrollable objects and environments. Moreover, based on the publications reviewed here, future efforts should be devoted to agronomics, sensors, and the realization of full automation.

9. Conclusions

This study has reviewed the current status and applications of various agricultural robots by categorizing three primary types of agricultural robots, namely, field robots, fruit and vegetable robots, and animal husbandry robots. About fourteen kinds of robots have been described in detail in terms of their features, functions, and applications. In addition, we have discussed the challenges accompanying the advancement of agricultural robots. Hopefully, this review can provide inspiration for researchers to grasp the future trends in the study of agricultural robots, which include but are not limited to human–robot interaction, agronomics, sensors, and the realization of full automation.

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