A Comprehensive Review of Applications of Robotics and Artificial Intelligence in Agricultural Operations

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Abstract: Robots play a major role in solving problems, especially in the agricultural sector. The uses of agricultural automation and robotics have increased dramatically, which has solved the obstacles and complexities of fields such as agricultural operations from planting to harvesting, giving high effectiveness and efficiency in the fields. The review is divided into four sections: (i) various robotic agricultural processes, in which current robotic technologies in agriculture from planting to harvesting were investigated; (ii) types of robots used in agriculture such as aerial robots, ground robots, special robots, and multi-robot systems; (iii) a study of real applied projects that use agricultural robots, and (iv) Artificial Intelligence (AI) techniques used in agriculture. The study shows that agriculture greatly benefits from robots because they save time and effort, enhance production rates, and reduce costs. The study recommends further improvement and development of agricultural robots, and this should be achieved by creating faster processing algorithms, improving communication between platforms and robotic tools, and advanced sensor systems.

Keywords: Robotics, Agricultural operations, Ground robots, Special robots, Multi-robot systems, RHEA project, Artificial Intelligence.

1. Introduction

Robotics creates autonomous or semi-autonomous systems that work with people, emphasizing adaptability and intelligence in unstructured environments. Robots specifically designed for agricultural applications have been in development since the 1980s. By introducing robots into agriculture, the primary goal is to improve the overall sustainability and consistency of farming tasks. This can lead to higher quality products, reduced costs, and help mitigate environmental issues. Agricultural robots have a wide range of applications, including horticulture, orchards, and field crop tasks such as transplanting, cultivating, spraying, trimming, and harvesting. Livestock farming has also benefited from the introduction of milking robots (Edan et al., 2023). An Agricultural Robotic System (ARS) is a cyber-physical structure that consists of multiple agents that collaborate with monitoring, early detection, and response mechanisms within greenhouses. The system has a collaborative mechanism that detects and prevents errors and conflicts by processing sensor data, which ensures that the system is functioning optimally, while minimizing errors and conflicts (Ajidarma & Nof, 2021). A survey of 506 student and professional respondents from around the world was conducted to determine the current and evolving definition of automation. The term "automation" was reviewed in relation to its purpose, intentions, historical and technological development, progress, benefits, risks, areas, and levels of various applications. The aim was to obtain an accurate definition of automation (Nof, 2023).

Nof (2023) mentioned the advancements in automation technology, particularly in sensors, IoT, robotics, and AI for field, fruit, greenhouse, and livestock production systems. Agriculture and automation have undergone a scale phase change (Figure 1). Early production systems were small farms, with individual production (each farmer attended his own farm) for personal needs, based on available animal and human resources. The introducing of tractor increased productivity (phase 1), extending the farming area and production managed by one worker. Industrial mass production accompanied the mechanization of farm operations with the gradual diffusion of tractors with higher power and machines with higher field capacity (phase 2). As industrialization advanced with the availability of affordable and efficient chemical fertilizers and crop protection products (green revolution), agricultural production boomed, dramatically increasing farm yield and productivity. Large machinery, while enabling fast and homogeneous operations, could not

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cope with the high variability inherent in the biological nature of the product and with the unstructured and dynamic conditions of the natural environment. The onboard integration of sensors and automation technologies, the availability of GPS, and the diffusion of farm computers led to the next generation, enabling the provision of detailed information on field condition (also from remote sensing) and on crop yield, allowing to improved production management and better treatments (phase 3). At this stage, precision agriculture (PA) and precision livestock farming (PLF) became possible, enabling the reduction of the management units from the whole farm field down to the subfield level or from the entire herd to subgroups or single animal and exploiting the maximum potential of productivity better (Berckmans, 2017). PA and PLF aim to optimize the agricultural processes by adapting the operations, to apply what is needed, when, and where. This has further improved the efficiency of farm management by adding data-based digital systems and real-time connection with external information sources that increase farmers' knowledge about their production process and market chains, known as phase 4 or digital farming (Saiz-Rubio & Rovira-Más, 2020). With the advancement of technology and the emergence of applications such as ChatGPT and the metaverse, farming operations are expected to become a luxury and a pleasure to practice (phase 5).

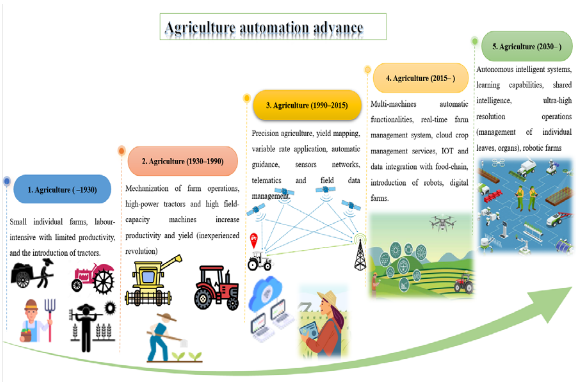


Figure 1. Agriculture automation advance (Nof, 2023)

Agricultural robots with machine vision tech are used to avoid risks, identify crops, and determine harvest time. They handle soil analysis, irrigation, fertilization, growth monitoring, sorting, grading, and packing. Automation, big data analytics, and robotics have boosted agriculture's growth. Evidence from Larkin (2018), who believes that artificial intelligence, analytics, and precision farming robots are among the top industrial possibilities, backs up this mix of agriculture and technology. An industrial robot is a computer-controlled, reprogrammable, multifunctional manipulator with three or more axes that can be fixed or mobile, according to the Robotic Industries Association.

There are very few available review papers on the implementation of AI in the field of agriculture (Jha et al., 2019; Mousazadeh, 2013; Ramin Shamshiri et al., 2018). The available papers highlight the specific area of agriculture, such as weed identification and pesticide spraying, irrigation planning, crop yield monitoring and prediction, greenhouse automation, disease identification, harvesting of crops and fruits, and (Aydan, 2019; Filip et al., 2020) highlighted on soil Monitoring and path planning. None of the available papers have considered the agriculture field's overall processes and activities consisting of various phases such as cultivation, monitoring, and harvesting. It is also seen that there is no systematic review available on the application of AI in the different activities of each phase. In most of the review works, the data is presented neither in a tabular nor in a graphical form for easy understanding. The comparative data between various cited papers is also missing. The available review papers do not provide that depth as they have considered minimal papers for review. The main drawback of the available review papers is the lack of explaining, by using AI, the existing research gap in agriculture, both qualitatively and quantitatively.

Autonomous vehicles with advanced sensor systems, communication tech, GPS, and GIS have been developed for high-value crop management in agriculture. For orchards and horticultural crops such as oranges, strawberries (Kondo et al., 2005), and tomatoes (Peng et al., 2021), several autonomous prototypes have been developed. Furthermore, automated methods for automated harvesting, by using a camera, a GPS navigation and an autonomous Christmas tree weedier have also been created (Hernández et al., 2013).

Here, various robotic technologies used in agriculture, from planting to harvesting, are investigated in section 2. Section 3 describes the types of robots used in agriculture such as aerial robots, ground robots, special robots, and multi-robot systems. Section 4 presents a study of real applied projects using agricultural robots. Section 5 explains Artificial Intelligence (AI) techniques used in agriculture. Section 6 of the paper provides a detailed discussion of applications of robotics and artificial intelligence in agriculture. Section 7 of the paper summarizes the findings and provides suggestions for further research.

2. Agricultural Automation and Robotics: Present Applications

Robotics in agriculture have helped manage crop growth more efficiently while reducing water, energy, and costs. Farming challenges, such as labor shortage, aging population, and higher costs, led to the development of automated systems. Machinery such as tractors and robots are used in agriculture automation systems. Table 1 presents robotic systems and machinery used in agriculture, that require mechanization to increase farming effectiveness.

Table 1. Agriculture robots and machinery

No.	Function	Appearance example	Reference
1.	BoniRob		(Ackerman, 2015)
2.	Chisel cultivator		(Roca et al., 2019)
3.	Combined harvester		(Chaab et al., 2020)

Each structure has its own limitations, which require other machinery to overcome. Due to their sensitivity to water and mud, robots cannot handle severe farming activities. Tractors take over this function, but they are limited to large areas due to their size. Therefore, a mobile robot must handle limited areas. Drones are unsuitable for closed environments like greenhouses. A classification based on agricultural operations helps to understand automation and robotics in agriculture.

2.1 Planting

Planting is the act of putting seeds or seedlings into the ground to grow. Different plants require specific spacing for optimal development. Traditional methods are time-consuming and require consistency. Controlled motion of the planter ensures regular schedule for planting. Table 2 shows planters used to plant different plants. A towed planter is typically used behind a tractor. It plants seeds in a repetitive pattern, but crooked rows may result due to manual operation. An efficient autonomous system is required to create a straight plant row while ensuring no seeds are left behind.

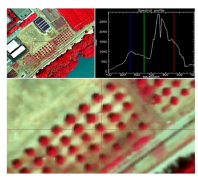
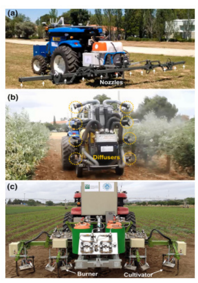
Table 2. Robotics planters used in planting

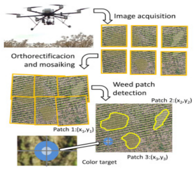
No.	Function	Appearance example	Reference
1.	Minimum-tillage planter		(Shi et al., 2019)
2.	Billet planter		(Saengprachatanarug et al., 2018)

2.2 Inspecting

Plant diseases are the major cause of decreased agricultural productivity, which results in financial losses. Inspection is the process of checking or observing plants for diseases or quality flaws in agriculture. Because the agricultural environment is so dynamic, plants and their products have been affected by a variety of unexpected and unusual stress scenarios, such as changes in temperature, humidity, water levels, disease starts, and pests. If such abnormalities had not been treated swiftly, the severe and irreparable injury could have followed (Adamou Abba Ari et al., 2015) . Table 3 shows robotics used in inspection.

Table 3. Robotics used in inspection

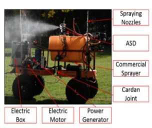
No.	Function	Appearance example	Reference
1.	Sensors on agricultural vehicles		(Vicent & Blasco, 2017)
2.	Weed patch spraying system		(Gonzalez-de-Santos et al., 2017)

3.	Detect Pests and Diseases in Horticultural Crops by Proximal Sensing		(Cubero et al., 2020)
4.	Remote perception system		(Gonzalez-de-Santos et al., 2017)
5.	Robotic Weed Control using Machine Vision		(Zhang et al., 2022)
6.	Ground Robot for vineyArd Monitoring and ProtEction		(Roure et al., 2018)

2.3 Spraying

Spraying is a common method in agriculture to manage plant development and cure diseases. Pesticides are used to control pests uniformly across fields, in order to prevent disease transmission. Table 4 illustrates agricultural robotics used in spraying.

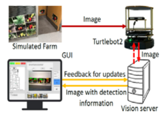
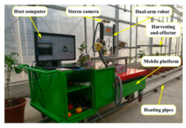
Table 4. Agricultural robotics used in spraying

No.	Function	Appearance example	Reference
1.	Agricultural vineyard sprayer		(Adamides et al., 2017)
2.	Human-robot collaborative site-specific sprayer		(Berenstein & Edan, 2017)
3.	UAV Variable Spray System Based on Neural Networks		(Wen et al., 2019)

2.4 Harvesting

Harvesting in agriculture is the process of gathering crops for consumption, processing, or sale. It's a labor-intensive and time-consuming procedure that requires attention to detail while performing repetitive tasks. As a result, for decades, scientists have been working on developing an autonomous harvesting (Zhou et al., 2022). Table 5 shows harvesting robotics used in agriculture.

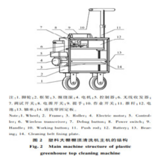
Table 5. Harvesting robotics used in agriculture

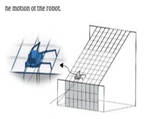
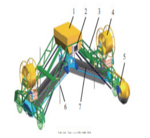
No.	Function	Appearance example	Reference
1.	Human-robot selective harvesting task		(Huang et al., 2020)
2.	Apple Harvesting Arm		(Sarabu et al., 2019)
3.	Tomato harvester		(Williams et al., 2019)

2.5 Cleaning Robots for Greenhouse Roofs

The effectiveness of a greenhouse depends on how clean the cover material is, which allows heat and light to enter the enclosure. Different types of robots in the greenhouse are given in Table 6. Robots are being used successfully in cleaning greenhouse roofs.

Table 6. Different types of cleaning robots for greenhouse roofs

No.	Function	Appearance example	Reference
1.	The glass greenhouse cleaner and multi-span plastic greenhouse cleaning device		(Kong et al., 2015)
2.	The design of plastic greenhouse top cleaning machine		(He et al., 2015)

3.	Four-legged glass cleaning robot		(Çabuk,2023)
4.	Venlo greenhouse roof cleaning machine		(Tianhua et al., 2023)
5.	Robot to clean solar panels without water		(Amin et al., 2023)

3. Types of Robots in Agriculture

Land preparation, planting/sowing, harvesting, plant treatment, and yield calculation, as well as phenotyping, are all considered in the robotics categorization. As a result, the subsections that follow will go over many applications of robotic systems in agricultural contexts, as shown in Figure 2.

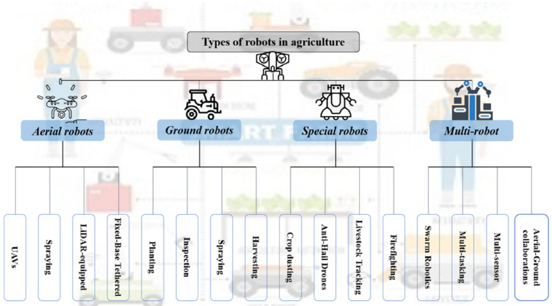


Figure 2. Types of robots in agriculture

3.1 Aerial Robots

In 2013, the Association for Unmanned Vehicle Systems International (AUVSI) released an economic analysis (Vasigh, 2013) on the potential economic impact of the civil use of unmanned aerial vehicles (UAVs) in the United States. Clouds, long data transfer times, the necessity for special clearances, and the expense of some items are only a few of the barriers to their adoption. UAVs, on the other hand, can be launched fast, carry a range of sensors, require no specific approvals, and are rapidly transforming into a cost-effective solution. They used unmanned aerial vehicles (UAVs) to assess water stress in agricultural lands, which was one of the first precision agriculture applications. Fluorescence sensors, as well as thermal and hyperspectral cameras, are now standard. Roldán et al. (2018) carried out an innovative experiment in which they used a controlled irrigation shortage to produce a gradient of water stress in a citrus orchard. The data collected by microthermal and hyperspectral sensors mounted on a fixed-wing unmanned aircraft were compared in their study. The measurements were taken at the depart of the aircraft, in order to confirm the aerial techniques needed for evaluating water stress.

Aerial vehicles are also used in precision agriculture to monitor crops, estimate yields, calculate the right doses of fungicides and fertilizers, and detect pathogens. Gago et al. (2015) used an RGB camera to measure barley growth after two nitrogen treatments. As shown in Figure 3, UAVs outfitted with hyperspectral and thermal cameras offer a cost-effective and practical alternative for increasing the performance of agricultural holdings, while cutting expenses and increasing productivity.

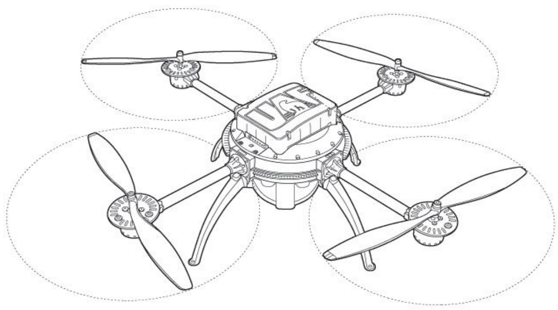


Figure 3. Quadcopter (Model, DJI MINI 3)

3.2 Ground Robots

The platform, manipulator, and end effector employed in a variety of agricultural applications are the focus of several ground robot techniques. GPS, odometer, line guidance (Feng et al., 2012), and path planning are all strategies that can be used in these systems (Sakai et al., 2008). To move around in the field, some robots use irrigation pipes or rails (Irie et al., 2009). Figure 4 shows that many of the end effectors are custom-made (Wan et al., 2010). This design option is due to the diverse variety of tasks to be completed, in addition to the various fruits and vegetables to be handled. It consists of a controller, an arm, an end effector, a mobile platform, a control laptop, and an overhead camera. Furthermore, it is usual to use end-effector behavior to address issues posed by the mobile platform and manipulator; as a result, gripper customization becomes more widespread.

For a complete survey of the specialized literature related to agricultural robotics and more detailed explanation of the ground robot applications, the readers are advised to see the work of (Bonadies et al., 2016).

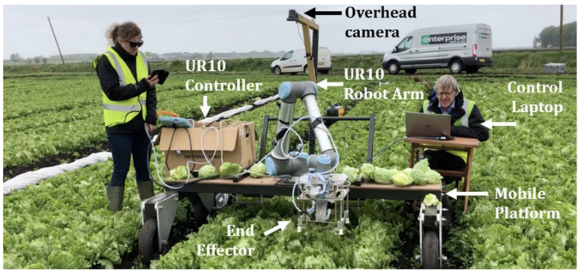


Figure 4. Robots that operate on land (Bechar & Vigneault, 2016)

3.3 Special Robots

The movements of sphere robots are caused by instabilities. Two applications and scenarios where this type of robot is used are exploration (Zhan et al., 2008) and surveillance (Roldán et al., 2018). In uneven terrains, the ROSPHERE robot is significantly lighter and more resilient than wheeled robots of the same size and performance. Several robots have been developed using bioinspiration which seeks to emulate biological progression. For example, engineers have learned that hexapod insects can navigate through a variety of terrains and have duplicated their physiognomies and walking patterns. Prospero, a hexapod robot prototype capable of planting, nurturing, and harvesting on its own, is one example (Gago et al., 2015). Harvard University's RoboBees, which are micro aerial robots inspired by bees, represent another example (Roldán et al., 2018). These robots are being utilized to help with crop pollination and dispersed environmental monitoring.

3.4 Multi-robot Systems

It is often impossible for single robots to complete the required jobs in the provided time, be they simple or complex tasks. In terms of efficacy, robot teams may outperform single robots in efficiency, adaptability, and fault tolerance. In the literature, the bulk of cases of robot teams performing agricultural tasks are similar. The use of a fleet of UAVs rather than a single UAV to collect data over large areas is common, and there is a range of tactics for area distribution and path planning (Avellar et al., 2015). For example, a collection of small UAVs equipped with low-cost cameras can be used to control water extraction and management (Chao et al., 2008), offering the operator more robustness, while getting the same results as a single UAV outfitted with a superior camera.

4. Real Application Projects

More details on two separate multi-robot systems employed in two different agricultural contexts are offered, including outdoor agriculture and greenhouse farming.

4.1 Robot Fleets for Highly Effective Agricultural and Forestry Management (RHEA) Project

The RHEA Project (NMPCPIP 2459862), part of the European Commission's seventh framework program, aimed to improve agricultural and forestry management using robot fleets. The project tested robotic systems for weed management using chemical, mechanical, and thermal methods. Figure 5 shows the ground units with the described actuators, while drones provided aerial imagery assistance.

Figure 5. Ground units for 2014 RHEA project (Roldán et al., 2018)

The system used a fleet of Air Robot's hex copters, which had a high payload and stability, as shown in Figure 6.

Figure 6. Aerial units for 2014 RHEA project (Roldán et al., 2018)

The method used in RHEA eliminates weed plants by combining high-resolution photography with object-based image analysis (OBIA). It takes into account the distance between weeds and crop lines and deems any plant that is not planted on a crop row to be a weed (Torres-Sánchez et al., 2015).

4.2 Monitoring the Environment in Greenhouses

Robots can help monitor the environmental conditions in greenhouses, which is impossible for humans due to the harsh working conditions. Fixed sensors and sensor networks are ineffective alternatives. A multi-robot system can capture spatial and temporal variability of environmental variables. The multi-robot system is organized into small teams that work in specific places, using ground and airborne units, as shown in Figure 7. The first study in the field (Rovira-Más et al., 2008) employed a mini UAV to detect air temperature, humidity, brightness, and carbon dioxide content.

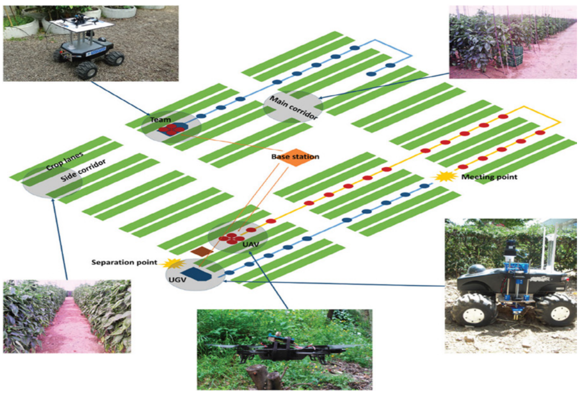


Figure 7. A multi-robot system for monitoring the environmental conditions of the greenhouses (Rovira-Más et al., 2008)

5. Artificial Intelligence (AI) Techniques Used in Agriculture

AI technology has enhanced the target detectability of agricultural robots and helped solve problems in farming activities (Figure 8). Many previous investigations have offered several approaches to tackle related challenges. There are many artificial intelligence techniques used in agriculture. According to the comprehensive study presented by Wakchaure et al. (2023), there are many artificial intelligence techniques used in agriculture, as shown in Figure 9. The present study will focus on the most common artificial intelligence techniques in agriculture, which are: Fuzzy logic (FL) and Artificial neural network (ANN).

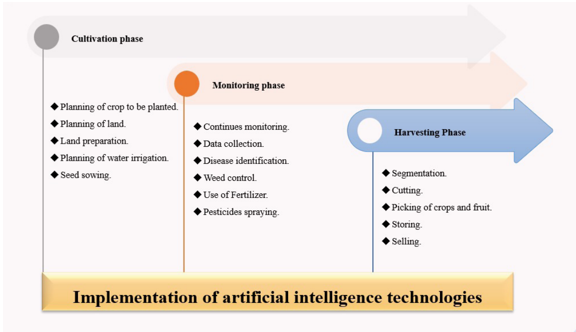


Figure 8. AI implementation in agriculture-related operations

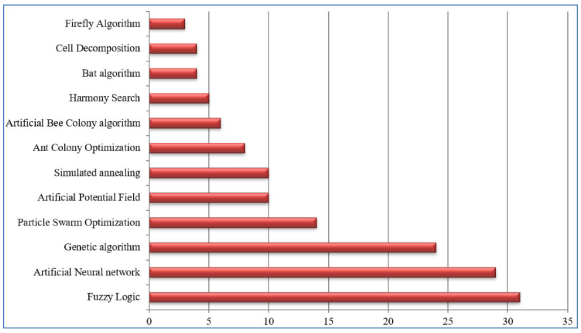


Figure 9. Papers available in the agriculture field related to the use of AI (Wakchaure et al., 2023)

5.1 Fuzzy Logic (FL)

Fuzzy logic (FL) is a precise strategy that measures an ongoing situation with degrees of truth. AI-based controllers use FL to comprehend real-world changes and take accurate actions. FL has improved decision-making abilities and is widely used in agriculture for tasks such as navigation, imaging, robots, monitoring, harvesting, and more.

The FL model has been used by Shahjalal et al. (2021) to examine how climate change will affect agricultural production. Farmers can choose the best crop to plant through this study. Furthermore, Fujiwara (1991) presents the use of FL to comprehend carnation seedlings and the factors that affect their growth cycle, such as form. His work obtains a 97% judgement rate while presenting the FL with an image processing technique. The agricultural procedures are intricate, and it takes a lot of work to complete them on schedule. Nassiri et al. (2022) have worked on the packaging of tomatoes using FL-based classification model by taking this factor into account. The application of FL on agricultural robots has the advantage of reducing human effort in crop harvesting. Spraying pesticides is a crucial step in agriculture engineering for the crop care.

Narendran et al. (2018) present the novel idea of FL-based E-farming. Their work is related to the agriculture robot, which was created utilising FL to control the microcontroller for accurate movement of the motors in executing a variety of tasks in agriculture, including ploughing, dispensing seeds, watering, spraying pesticides, and monitoring temperature. Prema et al. (2012) offer yet another gentle steppingstone in the area of agricultural engineering. FL has also been employed by Upadhya & Mathew (2020) to investigate the potential for vegetable crop development and yield. These findings allow for the planning of efficient irritation remedies. Similar work has been done on FL and SVM (support vector machine) agriculture yield prediction systems by Prabakaran et al. (2021). The forecasting accuracy percentage of the system is 95%.

5.2 Artificial Neural Network (ANN)

ANNs are used to solve complex dynamic problems and are prevalent in agriculture. To distinguish between alive and dead pomegranate fruit, Kumar et al. (2017) created the ANN-based sorting system. A technique created by Dimililer & Kiani (2017) will assist farmers in quickly identifying undesirable plants on their property.

Numerous agricultural researchers have tested out the use of ANN to create a vision system. Standalone ANN has been employed by Dorrer et al. (2020) to offer vision intelligence for precision farming. Deep convolutional neural network (DCNN) data collection techniques were used by Hall et al. (2017) to create a classification model from low-dimensional features. They used it for cotton plants with the help of a mobile platform, where they discovered either cotton-only or weed-only groups. By using lightweight models for agricultural robots based on lightweight DCNN, Champ et al. (2020) provided a related research concept. Ge et al. (2019) used ANN to create a specialised machine vision system on an agricultural robot for harvesting strawberries. Lulio et al. (2009) solved the path-planning issue for agriculture robots using ANN. Zhao et al. (2010) researched path detection for mobile agricultural robots in low-light. Deep learning (DL) is gaining attention to improve target detection. One-stage and two-stage DL algorithms can provide resilience and generalization.

The use of various You Only Look Once (YOLO) or Single Shot MultiBox Detector (SSD) series architecture designs is one common way to implement the one-stage approach. Numerous attempts have been made to change those algorithms to simplify the model structure and speed up processing to fulfil the demand for real-time detection. For instance, by strengthening the multi-scale feature extraction and feature fusion capabilities in YOLO V5, the researchers completed the jujube detection in the field and the detection of vegetable diseases, with mAP reaching 93.1% and 97.2%, respectively (Li et al., 2022).

Deep learning models are extremely effective at classification, intelligent prediction, and decision-making, among other things. A diagnosis support system for plant disease diagnosis utilizing CNN has been reported by Xenakis et al. (2020) on a robotics system. With an out of the box classification rate of 98%, the deep learning system has performed well. By using Faster region-based CNN and data from UAV, Mhango et al. (2021) developed a model for mapping potato plants. Additionally, Khan et al. (2021) have created a deep learning model based on a region-based convolutional neural network (R-CNN) for precision spraying using UAVs. The live experiment correctly identified the area that required spraying 88.57% of the time. Using deep learning neural networks (DLNN), Munir et al. (2020) developed an automatic fruit recognition method for simple harvesting.

6. Discussions

The proposed review paper provides an in-depth analysis on the contribution of robotics and artificial intelligence technologies in the field of agriculture. The specialized literature was presented, from cultivation phase, to harvesting phase. The cultivation phase includes choosing the crops that will be grown, planning the manner in which the land will be used, preparing it for cultivation, organizing irrigation, preparing the seeds, and planting them. Monitoring and regulating the growth of the crops is the primary responsibility of farming, following the cultivation phase. The tasks in this monitoring phase are time-dependent and include planned crop health monitoring, fertilizer application, disease and weed identification, and pesticide application. The harvesting phase, which includes tasks like crop cutting, segmentation, storage, and market sale, is the final and most important stage of the agricultural cycle. All these stages and the robots used in them have been studied, and they have also been studied under the influence of artificial intelligence techniques such as FL and ANN. Although many artificial intelligence technologies are available, the focus was only on the most common artificial intelligence technologies in agricultural activities and applications. According to the literature review, there has been a considerable improvement in crop yield, food quality, farmer income growth, plant care, labor efficiency, farm inspection and monitoring, and selective harvesting employing AI and contemporary instruments. AI is essential for automating the control of temperature, humidity, light, fertilization, and phytosanitary measures in some indoor applications. The commercial robot that incorporates AI can handle the entire agricultural process, from planting to packaging. AI has significantly improved both the technical and financial efficiency of farming and the farmers' health and safety. The present analysis of research articles highlights the widespread use of FL and ANN, offering room for improvement. Path planning for agricultural robots uses AI techniques more frequently than monitoring applications. Urgent improvements are needed in areas such as harvesting and cultivation.

7. Conclusion

In general, in all the robots reviewed, it can be noticed the continued development of agricultural robots to meet the needs of traditional agricultural practices, as agricultural robots are designed to perform agricultural operations, from planting to harvesting. Robots could be beneficial in numerous ways, including commercially, environmentally, and ethically. The results of this review study show that most robotics systems utilized in agriculture are more versatile than traditional systems, reducing labor costs and time to complete tasks. These systems can be remotely linked to GPS and have been developing at a breakneck speed in recent years, as they are preparing for the coming Metaverse era. Finally, the ability of a country to innovate and develop these systems, as well as to adapt them to the economic development and access to leadership of its society determines its growth. The agricultural robotics business is an expanding area with a huge potential for jobs and employment, and robotics will undoubtedly be advantageous in bringing the younger generation into agriculture and enhancing agricultural production. The agriculture robotics is used most in the monitoring and harvesting phases, in comparison to the cultivation phase. For the actions carried out during the cultivation period, robotics technology might be given more attention. The majority of agricultural robot applications are created using FL and ANN. There is also a lot of room for the development of further AI methods for applications involving agricultural robots.

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