

Review Article

REVIEW OF COMMERCIAL AGRICULTURAL ROBOTS UTILIZED IN CROP FIELD OPERATIONS

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Abstract

Certain field procedures in crop production systems are very labor-intensive, either because of their intricacy, because they involve delicate plant/edible product interactions, or because they must be repeated throughout a crop production cycle. The development of agricultural robots is largely dependent on these criteria. This report presents a thorough evaluation of the literature on commercial agricultural robots utilized in crop field operations. This study demonstrated that while disease detection and sowing robots were less studied, harvesting and weeding robotic systems were the most investigated. Quicker processing algorithms, improved communication between the robotic platforms and the implements, and sophisticated sensor systems should all be developed in order to optimize and promote agricultural robotics.

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1. INTRODUCTION

India leads the world in production of a number of important commodities and has the second-largest agricultural land area. India is the world's second-largest producer of sugarcane, rice, wheat, fruits, vegetables, and tea. In order to solve labor shortages, improve accuracy, and increase yields, the Indian agriculture sector is progressively implementing robotics and artificial intelligence. Developing reasonably priced, small-scale agribots for dispersed landholdings, reliable hardware that can manage unstable power grids, and integration with government-backed digital projects are essential criteria. According to Moni Madaswamy, the Farm Extension 4.0 framework is necessary to enable the nation's more than 140 million farm operational holders to embrace Farming as a Service by implementing IOTs, robotics, informatics, and smart farming in rural areas. This will be made possible by AgriTech StartUps, Farmer Producer Organizations, Agricultural Polytechnics, and Agricultural Industrial Training Institutes. Approximately 2.25 lakh Deep AgriTech StartUps might be developed in India with the use

of this Farm Extension 4.0 technology framework, one for each gram panchayat. The first measures toward precision agriculture in India have been proposed by Anil Kumar Singh. Drones should be used as applicators since they can cover more regions and use fewer agrochemicals (fertilizers, pesticides, herbicides, etc.). This would include working out the timing, speed, height, spray characteristics and volumes, and wind concerns to make the application as successful as feasible for each agro-chemical independently. Since smaller quantities are more cost-effective, safe, and efficient, the development of nano-products will accelerate. In the same manner that robots can be used to transplant seedlings to avoid labor-intensive tasks, Mohiuddin (2015) addressed the use of robots in weed management, which will help reduce the use of herbicides and make the food into organic. The work by Sahoo et al. (2022) has concentrated on the interdisciplinary aspects of agronomy, innovative materials, and agricultural robot technology. Quick damage-free operation, autonomous navigation for complex environments, target recognition for complex backdrops, and distinctive design for agricultural robots—with a

development path offered—are seen to be the key technologies of agricultural robot development. The most common tasks for agricultural robots are weeding, hoeing, and fruit harvesting, and they are outperforming people in these tasks. Additionally, robotic platforms with multiple uses have been developed and are being utilized for a variety of agricultural tasks.

Nearly every kind of robot uses a variety of sensors and GPS technologies for navigation. Artificial intelligence is being used more and more at the same time. Robots will undoubtedly be useful in luring the younger generation to agriculture and boosting agricultural output. The robotic industry in agriculture is an emerging area with enormous job and employment possibilities.

1.1. COMMERCIAL AGRICULTURAL ROBOTS

1.1.1. Agrobots

Agrobot creates self-sufficient fruit harvesting devices with accurate picking capabilities. It has 24 separate robotic arms and an AI-powered system that can identify depth and color to select just ripe fruit without causing harm. LiDAR sensors are also used for field navigation (Jiang et al., 2025).

1.1.1. Tractors

An agricultural vehicle that can carry out its duties without direct human assistance is known as an autonomous tractor. It would be an AGV (Automated Guided Vehicle), similar to those seen in factories, although it would operate on land in this instance. In order to avoid obstacles or carry out various tasks like planting, fertilizer application, pesticide spraying, or harvesting, autonomous tractors are outfitted with lasers, cameras, control systems, or GPS navigation (Singha & Kumar, 2024).

1.1.2. Combine Harvesters

Three main areas will be the focus of future autonomous navigation technology development for combine harvesters: deep integration of artificial intelligence (AI), the development of low-cost high-precision sensors, and multi-machine cooperation combined with energy optimization. When taken as a whole, intelligent combine harvester technologies have significantly increased agricultural productivity in terms of automation, accuracy, and efficiency. However, overcoming enduring technological and financial obstacles is necessary to move laboratory technologies to large-scale field applications (Leemans & Destain, 2007)

1.1.3. Rotavators

Three systems make up the rotavator system. First is the detecting rotavator unit, which is integrated into the rotavator. A cage, a controller, and a sensor made up the rotavator unit's component pieces. The input outer shaft of the side gear was where the rotavator unit was installed. A cage was built on the outer shaft to protect the controller linked to the sensor system from the external environment.

The controller is mostly composed of a Hall effect speed sensor, a Bluetooth module, and a battery management system. When the side gear's input shaft, which contains grooves to create a variation in permeability effect, rotates, the speed sensor picks up this difference. The controller then uses a moving average algorithm to process the signal, computes the rotavator blade rpm internally while accounting for the side gear reduction ratio, and uses a Bluetooth module to send the result to the mobile app. Additionally, the Bluetooth module broadcasts the total and current running hours using an internal time clock. The second operating system is a mobile application that flashes sound and vibration notifications when operating in any other zone and uses a green zone to inform the user of the optimal operating zone (Borah et al., 2025).

1.1.4. Seed Drills

It was discovered that the camera mounting had a significant impact on the system's trueness (the mean of the difference between the measurement and the set value). The trueness was less than 30 mm when this camera was installed correctly, primarily because of the drill's trace's aspect. The tractor's comparable figures were 73 and 272 mm, respectively, although the precision (the standard deviation of the aforementioned difference) was 23 mm and the range was 100 mm. These parameters would guarantee that a non-matching width harvesting machine and a seed drill with guiding help are compatible. The driver was instructed to drive sinusoidally for some of the field tests and normally for others. The former driving style has lower precision and range values than the latter. This implies that a smoother driving style is preferable than abrupt direction shifts (Chauhdary et al., 2023).

1.1.5. Sprayers

Depending on crop type and landscape, drone sprayers can reduce pesticide consumption by 30–50%, reducing pesticide drift by 60% and increasing yield by 12–20%. Autonomous navigation systems boost job efficiency, lowering personnel expenses by 40–60% and maximizing input usage. Based on real-time analysis of crop health and field circumstances, image processing also improves decision-making accuracy by 85%. By saving 40–50% of the water used in spraying operations, the convergence of these technologies not only increases precision but also lessens its impact on the environment (Ramesh & Hebbar, 2018).

1.1.6. Sprinklers

A characteristic of the water management decision is the GSM-based automatic irrigation control system for resource efficiency and crop planning utilizing an Android mobile phone. The GSM (RS-232) module is utilized to monitor the entire system. The system can accurately supply the amount of water needed for the plant or tree (crop) by continuously monitoring the water level (water level sensor) in the tank. In order to maintain the soil's nutrient content and promote

healthy plant growth, the system monitors the soil's temperature and humidity (Fang & Ramasamy, 2015).

1.2. PLANT DISEASE DETECTION USING MACHINE LEARNING

To improve the identification rate and accuracy of the outcomes, contemporary techniques like machine learning and deep learning algorithms have been used. Numerous studies have been conducted in the field of machine learning for the detection and diagnosis of plant diseases. Conventional machine learning approaches include random forests, artificial neural networks, support vector machines (SVM), fuzzy logic, K-means method, convolutional neural networks, etc. (Pongnumkul et al., 2015).

1.2.1. Indirect Detection of Plant Disease

Thermography makes it possible to visualize variations in the surface temperature of plant canopies and leaves. Thermographic cameras can record the infrared radiation and assess color differences. Previous studies have shown that phytopathogens would have an impact on the water loss in plants controlled by stomata. Thermographic imaging can be used to track the ensuing illness and measure the volume of water transpired independently of external temperature impacts (Queiroz et al., 2021).

This method measures the amount of chlorophyll fluorescence on leaves as a function of incident light. Based on modifications in the photosynthetic apparatus and photosynthetic electron transport reactions, the change in fluorescence parameters can be utilized to investigate pathogen infections.

Over a broad spectrum between 350 and 2500 nm, hyperspectral imaging can provide valuable information on the health of plants. In large-scale agriculture, hyperspectral imaging is being utilized more and more for crop disease detection and plant phenotyping. The method offers a quick interpretation of the imaging data and is very reliable. Additionally, three-dimensional data gathering is made easier by hyperspectral imaging cameras, which use the X, Y, and Z axes for spatial and spectral data, respectively. This results in more precise and comprehensive data regarding plant health over a wide geographic area (Olson & Anderson, 2021).

The profiling of the sick plants' volatile chemical signature is an entirely separate non-optical indirect method for plant disease identification. Certain volatile organic compounds (VOCs) that are highly suggestive of the kind of stress that plants are under may be released as a result of pathogen infestations. Gas chromatography and mass spectrometry (GC-MS) are frequently used to discover unknown chemicals in the volatile sample in order to improve the performance of compound separation and analysis.

1.3. SENSORS

Ultrasonic sensors and light detection and ranging (LIDAR) sensors are used to differentiate plants based on their height. Andujar *et al.* (2011) proposed the use of an ultrasonic sensor to differentiate broadleaf weeds from grasses based on their heights. The results were promising and indicated the potential for using this technology in autonomous weed control systems.

Fluorescence spectroscopy involves measuring the fluorescence of a target object after emitting radiation (usually ultraviolet radiation). Fluorescence imaging is an advanced form of fluorescence spectroscopy, wherein images are obtained using a charge-coupled device (CCD) camera.

Based on how they work, soil sensors can be classified as electrical and electromagnetic sensors, optical and radiometric sensors, mechanical sensors, acoustic sensors, electrochemical sensors, and pneumatic sensors. The most popular electrical and electromagnetic sensors are those that gauge the soil's apparent electrical conductivity (ECa). Two electrodes were subjected to an electric current, and the potential difference was measured at the other two electrodes. Numerous physical and chemical characteristics of the soil, including salinity, clay content, moisture, density, and organic matter, can affect electrical conductivity.[15]

There are two ways to monitor crops: proximate sensors and remote sensing. In remote sensing, the sensor is located distant from the target, whereas proximal sensors are near or in direct contact with the detected object. In remote sensing, sensors are transported via aerial or orbital platforms.

The MC-100 Chlorophyll Concentration Meter (Apogee Instruments, USA), N-tester (Step Systems, Germany), and SPAD-502 (Konica Minolta Sensing America, USA) are commercial devices for measuring chlorophyll that were used to determine nutritional status. Chlorophyll meters take a lot of time and are not always precise because they are manually operated and only provide estimations (Steeneken et al., 2023).

2. CONCLUSIONS

Agricultural robotics has become a key enabler of precision agriculture by enhancing productivity, reducing labor dependency, and improving resource-use efficiency. This review examined the current state of commercial and research-based agricultural robotic systems employed in field operations such as harvesting, weeding, sowing, spraying, irrigation, and crop health monitoring. The analysis indicates that harvesting and weeding robots have received the greatest research and commercial attention due to their direct impact on operational efficiency and labor cost reduction.

Recent advances in artificial intelligence, machine learning, computer vision, LiDAR, GPS, hyperspectral imaging, and sensor technologies have significantly

improved the autonomy and reliability of agricultural robots. The integration of these technologies enables accurate crop monitoring, disease detection, autonomous navigation, and site-specific input application, thereby supporting sustainable agricultural practices. Furthermore, drone-based spraying systems, intelligent irrigation platforms, and autonomous farm machinery have demonstrated considerable potential for reducing water consumption, agrochemical usage, and environmental impact while maintaining or improving crop yields.

Despite these achievements, several challenges continue to hinder large-scale adoption, including high deployment costs, limited adaptability to diverse field conditions, power and communication constraints, and the complexity of operating in unstructured agricultural environments. These challenges are particularly significant in developing countries, where small and fragmented landholdings necessitate affordable and scalable robotic solutions.

Future developments should focus on improving sensor fusion, real-time decision-making algorithms, multi-robot coordination, energy-efficient robotic platforms, and seamless integration with Internet of Things (IoT) and cloud-based farming systems. Advances in these areas will facilitate the transition toward fully autonomous and intelligent farming ecosystems. Overall, agricultural robotics represents a promising pathway toward sustainable, efficient, and technology-driven agriculture capable of addressing future food security and environmental challenges.

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CONFLICT OF INTEREST

There is no conflict of interest among the authors.

DATA AVAILABILITY

Corresponding authors will provide the data on request

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