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AI-Driven Robotics in Agriculture: A Review

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ABSTRACT

Artificial intelligence (AI) combined with robotics is changing how agriculture has always been practiced to a more efficient, precise, and sustainable one. The review critically discusses the latest achievements in AI-driven agricultural robotics, including vision-based navigation systems, deep learning-based crop surveillance, and autonomous robots based on hybrid control architectures. It analyses fundamental enabling technologies, such as vision-based navigation systems which use deep learning to compute obstacle avoidance and hybrid control structures which compromise robot autonomy and centralized control. The synthesis finds a prevailing trend of the integration of the state-of-the-art sensors, Light Detection and Range (LiDAR), Global Positioning System (GPS) and hyperspectral imaging with AI-based decisions to automate the precision applications in targeted irrigation, harvesting, and early disease identification. These technologies will ensure that there is optimization in the utilization of resources, increased yields, as well as reduced environmental impact. Nevertheless, the analysis also discloses a considerable amount of barriers to the broad adoption, namely, the high initial costs, technical issues in unstructured settings, and insufficient and robust regulatory frameworks. Moreover, the review does not focus only on technical matters but addresses crucial socio-economic and ethical consequences, i.e., changes in labor market, data privacy, and fair access. It is important that future studies focus on the creation of stronger, low cost, and flexed robots. Such directions as improving the collaboration with the swarm of multi-robots, enhancing AI models with simulation-to-reality (sim2real) systems, and setting up policy-aware safety and data governance standards can be identified. The review reiterates the use of intelligent robotics as an instrumental tool in the formation of a productive and sustainable future in global agriculture.

Keywords: Vision-based navigation, Bio-inspired swarm robotics, Hyperspectral crop monitoring, Autonomous precision irrigation, Deep learning weed detection

Introduction

Agriculture is experiencing unprecedented transformations as there is an increased use of robots and automation in traditional agriculture. The world food demand is going to be on a rise due to rising population, urbanization and global warming. The agricultural reforms should be undertaken so as to ensure maximum productivity, efficiency and sustainability of agriculture. The technologies that are most likely to resolve these problems include automation and robotics as they allow to increase precision, minimize the involvement

of human workforce and optimistically use available resources. The use of robotics and automation is very key in the agricultural sector; this applies to the planting process, processes that follow the harvest and even after harvest management. They make precision agriculture possible by their use of intelligent automation which enables them to manage water, fertiliser and pesticides more efficiently and reduce the impact on the environment, all the whilst increasing agricultural output. Further, farm robots resolve complicated issues of labor shortages in industry by allowing robotic processes to do both repetitive and monotonous jobs all by themselves.

Robot farm mechanization is applied on either simple automated farm tools to an extremely advanced autonomous farming processes using artificial intelligence (AI), machine learning, and sensor capabilities. At the initial phases of mechanization, farm producers used automated irrigations and tractors to reduce the amount of labor required. The farm of today has been able to utilize autonomous equipped machines due to great advancements in robotic technology and the operations of such machines can automatically complete execution of a discrete task with a little human interaction.

Over the last several years, there has been an amazing rise of the use of robotics in farming due to the expansion of the Internet of Things (IoT), computer vision, and machine learning services. Using vision, robots can be used to distinguish and identify crops, approximate plant health, and weed identification. Robots that can make AI decisions can be trained to adapt to changes present in their environment, take data-based interventions, which would increase the productivity of agriculture and the efficiency of operations. Agricultural robots control approaches are the underlying determinants of its operational performance. They control how the robots move, how they interact with the environment and the performance of the tasks in general. Agricultural robots apply varied control structures, including centralized, decentralized, and hybrid structure.

Centralized Control: The Control of a group of robots is done by a single control unit as this ensures maximum efficiency and coordination. The most useful applications in the case of the centralized control system involve situations where high precision coordination is necessary, as in the case of automated harvesting, or in coordinated planting. **Decentralized Control:** Robots apply decentralized control and make decisions based on available circumstantial information. Less centralization is also more adaptable and adequate with a wide-spread activity characterized by different

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regional environmental features. Hybrid Control: Hybrid control systems also possess a unified way which makes it to be highly flexible and efficient since it is the combination of central and decentral control. The hybrid systems entertain a transition between robot autonomy in making of decisions and centralized co-ordination subject to the complexity of task to be performed.

Autonomous farm robots should be able to navigate both in structured areas and in more unstructured regions. Vision based systems make use of cameras and algorithms of vision processing so that the robots can navigate the farmlands. Visual navigation has some intrinsic capabilities compared to the systems of global positioning or LiDAR-based navigation, since it is able to change its behavior based on the prevailing environments, and adapt to those environments in real-time through real-time learning. One of the largest challenges of vision-based navigation is the distortion of the perceptual image caused by the onboard cameras. The variation in illumination, occlusion and independence of field changes usually interfere with the conventional vision-based solutions. Researchers have proposed transformation models which produce top-down projections of images in anticipation of overcoming such distortions and realizing accuracy in navigation. The deep learning algorithms allow one to optimize vision-based systems in terms of obstacle avoidance, route planning and object detection. This is an aptitude that renders them feasible in precision farming.

In nature, phenomena have played an important role in the development and growth of motion control of robots. Bio-inspired motion control (using animal

and insect motion as a model) can help to make agricultural robots more energy effective and flexible. Engaged in using bio-inspired techniques, such robots can now operate in bad conditions, close to crops without damaging them, and harvest energy. Among the various ways of bio-inspiration, swarm intelligence is very useful in agricultural robots as this type of methodology is based on the work of bee and ant colonies. Swarm robotics is a type of system used to complete a collective task through huge quantities of autonomous robots to assess the soil, check crops and identify pests. The coordination of the robots produces fault tolerant, scalable and robust systems and hence would be more appropriate in large scale agriculture. In addition the research in the bio-inspired locomotion system has also spread to the agriculture sector with legged robots that mimic the motion of insects and soft robots that mimic the motion of plant tendrils. The robots allow such techniques that they navigate through rough surfaces, penetrate narrow spaces and precisely distribute actions without causing damages to the crops.

With the ongoing introduction of technology into advancing farm robotics, there are certain trends that are guiding the course of the endeavor in the future:

Integration of AI and Machine Learning: AI robots will be more intelligent and learn how to behave in a new environment and make independent decisions based on real-time information.

Collaborative Robotics: Agricultural robotics will also get human-robot collaboration where farmers will collaborate with robots and bring out the best of each other.

Sustainable Crop Management Practices: As Crop Management practices, robotics will play a great role in creating a sustainable agricultural practice by lowering the use of chemicals, use of an efficient water source, and conservation of soil.

Growth of Precision Agriculture: Robotic precision agriculture will expand further so that data could be used in order to make a decision and interventions could be made with precision to increase crop health and yield.

Improved Sensors: Sensor technology is making better use of AI to combine with better sensors such as hyperspectral imaging and multi-spectral analysis in enhancing the capabilities of farm robots to measure the health of plants and detect disease at young ages.

Literature Review

Evolution and Architectural Trends

The development of agricultural robotics is the shift towards autonomous systems that have AI. The modern systems will include multi-sensor fusion (Light Detection and Range [LiDAR], hyperspectral imaging, Global Positioning System [GPS]), AI-driven decision-making, and the connection will be provided via the IoT. Applications of farm robots emerged in the initial trial mechanisms of farming automation and developed into a complex model that employed AI to enhance efficiencies and green elements of farming process (Figure 1).

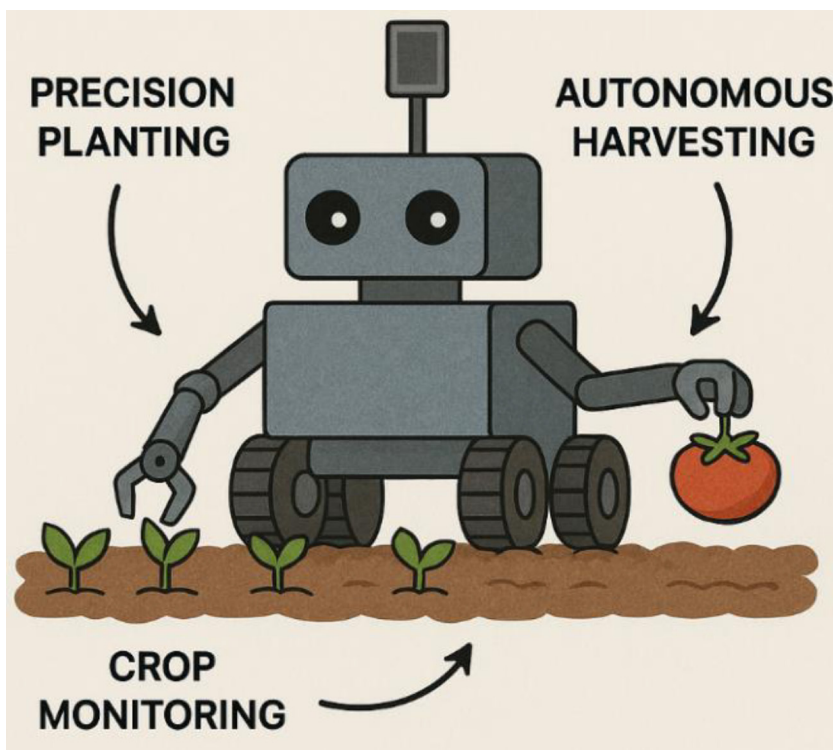


Fig 1 | How efficient robotic systems can be in automatic harvesting and accurate planting

The tractor and the automated irrigation system were among the most revolutionary products in the sense of the value mentioned in mechanical efficiency in production in the agricultural sector resulting to the modernity of the age of robotics. Precision, repeatability and productivity of work force necessitated a change in primitive automation to intelligent automation. Actually the high-tech automation in agriculture arrived with GPS-controlled tractors and completely autonomous irrigation machines, and the prospect of the robotic technology via AI is wide open. Smith et al.¹ mention that the sophisticated agricultural robots are also characterized by integrating the AI, machine learning, and computer vision which visualise rather complicated activities with the minimum engagement of the human aspect. The process has been altered in the farms that have undergone a transformation through the use of the robotic technologies, which have been developed atop the AI, resulting in cost reduction in production and production increments.² Such types as precision in planting and robotization of harvesting describe how farm practice may be improved and such challenges as manpower and climate volatility insufficiency may be fixed through robotic framework.

Farm Robot Control Strategy

The agricultural robots should possess a few control plans to be functional. There are three general groups such as centralized, decentralized, and hybrid control systems in which Liu et al. (2021) can be classified according to the control strategies. In the compilation of such a work, centralized control is useful and in the activity of harvesting, the application of the robot agents

must be adopted due to the fact that it is able to work with each other to attain peak efficiency. Maximum flexibility is achieved as any robot becomes capable of dynamically adapting to the environment changes.³ The best control is the decentralised one which facilitates utmost flexibility that enables the various robots to evolve and respond to alterations in the setting in real-time.³ A compromise between two is implemented in the hybrid control systems where agricultural robots alternate between coordinated and autonomous modes of operation varying on the complexity of tasks (Williams et al., 2022). Auto harvesting involves having robotic arms that pick the fruits autonomously where they relay to a central system to streamline the distribution. Hybrid control is also used in precision irrigation systems, wherein irrigation units respond to variation of soil moisture, but maintains a pre-programmed watering schedule. These control techniques maximize the effectiveness of robots, and, therefore, they are needed in the contemporary agrarian operations.

Vision-Based Navigation in Robot Agriculture

The description of vision-based navigation depicts an inevitable component of farming robots illustrated in Figure 2, the self-driving automobiles equipped to travel both through unstructured and structured settings. The method of navigation based on GPS is weak both in signal jamming and the topographical changes; it is therefore less competitive in dynamic agricultural scenarios.⁴ Deep learning and computer vision have added a great incentive to the area of the robots by enhancing the operability in crop identification, obstacle avoidance, and efficient mobility.⁵ You Only Look Once (YOLO) and Faster Region-based Convolutional Neural Network (R-CNN), convolutional neural networks (CNNs) are ordinarily applied in real-time object recognition in agriculture. The models are useful in the effective identification of the crops by the robots including differentiation between the crops and weeds or any other obstacle, therefore, increasing the levels of accuracy in navigation as well as work efficiency. Zhao and Wang⁶ recognized one of the challenges to be the images perspective distortion through onboard cameras. To address the issue, transformation models projecting images into a top-down image have been suggested to get its resolution corrected, enhancing the level of navigational reliability within the complicated environments. The use of centralized control systems, decentralized control systems and hybrid control systems depend on the complexity of the task. Faster R-CNN Vision-based navigation with deep learning models such as YOLO and Faster R-CNN is capable of operating in unstructured locations.

Bio-Inspired Motion Control in Agricultural Robotics

The new field in agricultural robotics, represented by Figure 3, is bio-inspired motion control, where researchers copy natural ideas to improve robot mobility and efficiency. Based on the idea of using ant colonies and bee swarms, swarm intelligence has been studied to monitor large areas of crops and soil.⁷ Swarm Farm Robotics is one of these applications, whereby a group

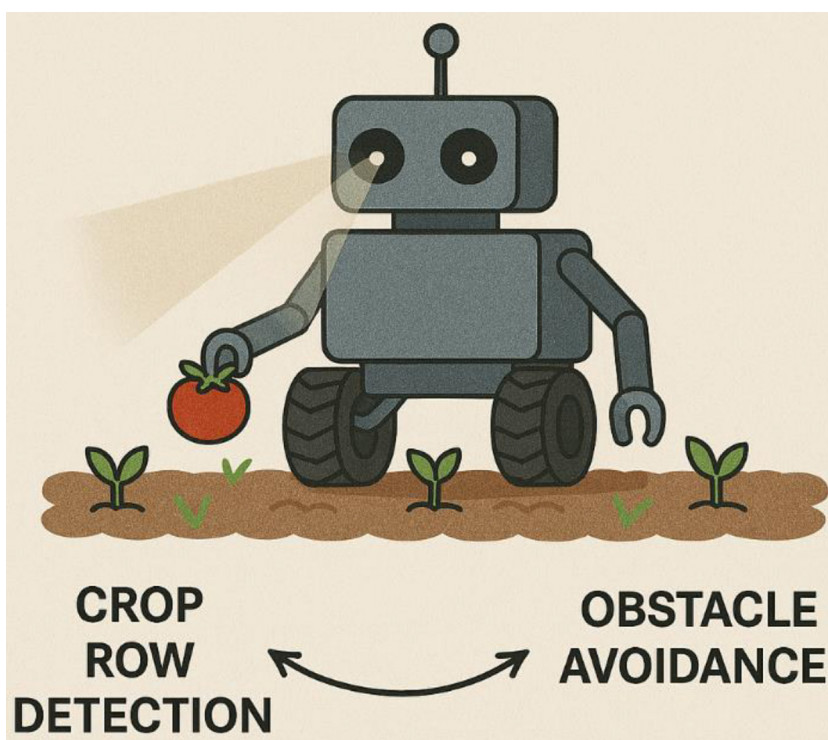


Fig 2 | The vision-based navigation in agricultural robotics

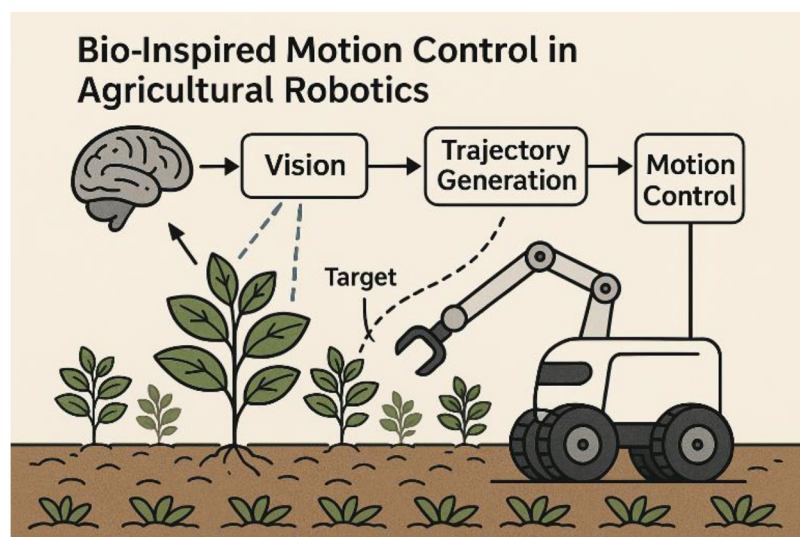


Fig 3 | The bio-inspired motion control in agricultural robotics

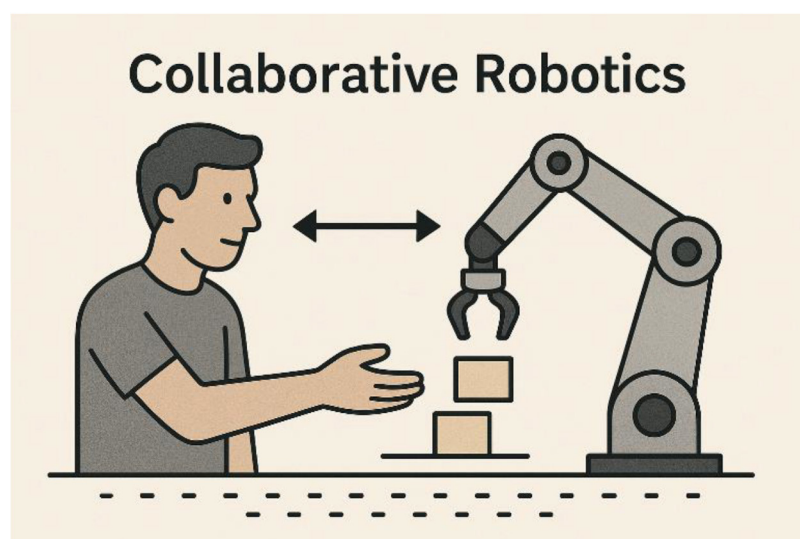


Fig 4 | The collaborative robot

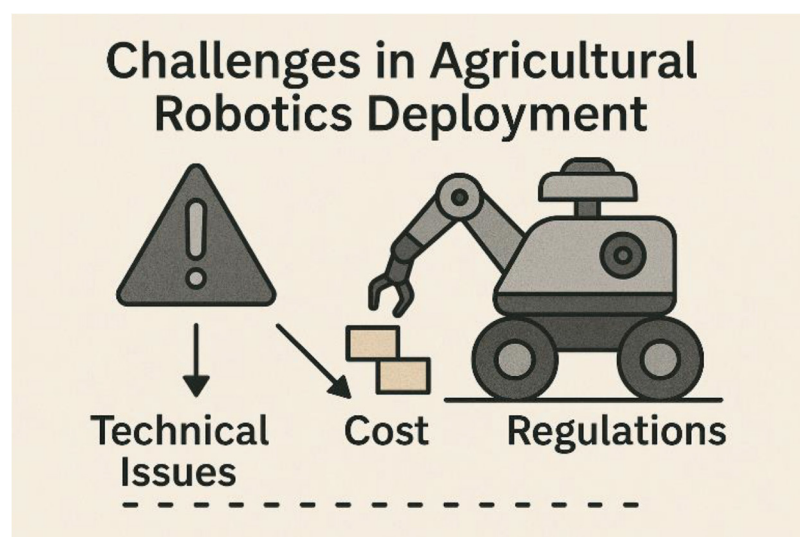


Fig 5 | The challenges in agricultural robotics deployment

of autonomous robots work together to survey crops, identify pests, and deliver precise applications that decrease the amount of resources consumed and increase sustainability. Swarm robotics enhances scalability and fault tolerance and can therefore be used to perform operations autonomously in the field (Kim and Park, 2021). Moreover, insect-inspired legged robots and plant-tendrill-inspired soft robots have been developed to navigate complex terrains and handle crops with caution (Hernandez et al., 2023). These bio-inspired talents make agricultural robots more flexible and enable them to operate better under various farming conditions. Bio-inspired designs enhance the efficiency of energy and versatility and swarm robotics provides a scalable system of large area surveillance and accuracy.

Potential of Agricultural Robots and Applications

As agricultural robotics advances, certain technological trends are becoming dominant in the future of the industry. The goal of these technologies is to be more efficient, likely to sustain, and scale in a manner that agricultural automation can be aligned with the growing demand for food production without imposing much damage on the environment. The following trends point to the future path of transformation:

Integration of AI and Machine learning: AI and machine learning can be integrated, and AI robots are becoming increasingly self-contained, learning within the environment and making real-time decisions (Nguyen et al., 2023).

Collaborative Robotics: Human-robot cooperation (Figure 4) to enhance efficiency in agriculture, as robots are used to plant and harvest (Rodríguez and Patel, 2022).

Sustainable farming: Robotics is also spearheading sustainability through the maximum utilization of resources and the minimal use of chemicals (Singh and Gupta, 2023).

Precision Agriculture Advancement: Robotization of precise agriculture is also increasing, which can be used to conduct interventions directly aimed at improving the health and yield of crops (Lopez et al., 2022). In **Sensor Technologies:** Hyperspectral and multispectral imaging sensors are being developed to improve the capacity of robots in terms of monitoring plant health and early detection of diseases.⁸

Challenges and Sustainability

Although there has been major progress, there are a couple of threats to the proliferation of agricultural robotics, as indicated in Figure 5. Adaptability to different farm conditions is one of the main problems. Studies are mostly limited to samples of large-scale agriculture, whereas small-scale farms cannot afford expensive robotic solutions.⁹ Oliveira et al.¹⁰ asserted that multifunctional robots used in small-scale farming should be able to operate under constrained environments and perform various operations.

Issues of localization precision and maneuverability are also challenging, especially in complicated farm

terrains. Robotic performance depends on uneven terrain, varying weather conditions, and obstruction of visualization.¹¹ Solutions to such problems have been developed to support the improvement of maneuvering precision in dynamic conditions using advanced control models such as the Maneuvering Adaptable Task Processing Model (MATPM).¹² Any type of assistance in resolving such difficulties is required to enhance the use of robotic systems in various agricultural conditions. Major obstacles are the high cost, environmental uncertainty and technical stability. With the help of AI, precision farming will save a huge amount of resources and ensure sustainable development.

Sustainable Agriculture and Robots

The use of farm robots has been of interest, especially in integrated farming, as shown in Figure 6. Practices of precision agriculture that involve AI contribute to minimizing environmental degradation, as they employ the effective use of resources.¹³ Studies have shown that intelligent irrigation, intelligent fertilization, and autonomous robots can reduce agricultural wastage.¹⁴ Moreover, during the initial phases

of crop diseases, hyperspectral sensor-based imaging has already been used in robots to efficiently observe crop health.¹⁵ These technologies reduce the overuse of fertilizers and pesticides leading to sustainable and environment-friendly practices of agriculture which are consistent with international sustainability plans.

Future of Agricultural Robots

Future research will focus on making farm robots stronger, universal, and less expensive. One of the areas of interest is the design of a low-cost robotic platform compatible with small- and medium-sized farms. The next generation of autonomous farming systems will rely on emerging technologies in reinforcement learning, edge computing, and fast high-binary decision frameworks.¹¹ Another feasible research area is swarm robotics in collaborative agricultural work. The literature shows that it is possible to enhance the operational efficiency of multi-robot systems and minimize human involvement in large-scale farming.¹² Moreover, it is believed that digital twin simulations may help to thoroughly test the AI models and prepare them for implementation in the field, so that scientists and researchers can create stronger and more efficient robotic abilities that will serve in future agricultural use.

Critical Comparison of Robotic Architectures and Their Efficacy

An overview of the literature demonstrates that the selection of a robotic system is not only a matter of technology but a factor determined by the complexity of tasks and the size of the farm and financial limitations. The most common architectural paradigms are compared in Table 1.

Synthesis

There is a shift towards flexible, modular platforms being substituted with rigid and single-task automation. Nonetheless, there is a vast divide between designing hardware and middleware with real-world adaptability that can keep up with the software flexibility of AI, enabling one platform to change between radically different physical activities (e.g., between delicate harvesting to violent soil tilling) without reconfiguring it by hand.

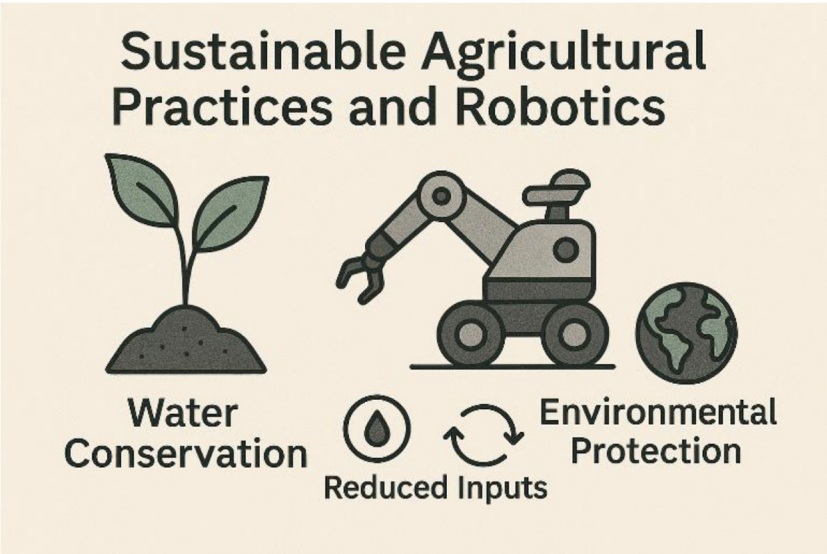


Fig 6 | The sustainable agricultural practices and robotics

Table 1 | Comparative analysis of agricultural robotic system architectures

Architecture	Optimal Use Case	Key Advantages	Major Limitations	Economic Viability	Representative Study
Single-Purpose (e.g., Dedicated Harvester)	Repetitive, high-precision tasks (fruit picking, precision weeding)	High task-specific accuracy and speed; optimized hardware.	Lack of flexibility; low annual utilization; high unit cost per function.	Low for smallholders; justifiable for large monoculture farms.	Jones and Kumar ²
Multi-Purpose (Platform-based)	Diverse, seasonal operations (scouting, spraying, light harvesting)	Improved asset utilization; adaptable to changing needs.	Compromised performance vs. dedicated bots; complex control software.	Higher for medium-scale, diversified farms.	Martinez and Singh ¹⁶
Swarm (Decentralized)	Large-area monitoring, mapping, distributed intervention (e.g., weed control)	Scalability; inherent robustness and fault tolerance.	Complex inter-robot communication; challenges in synchronized complex manipulation.	Promising for very large areas, but coordination costs are high.	Gonzalez et al. ⁷
Human-Collaborative	Tasks requiring dexterity and judgment (selective harvesting, pruning)	Leverages human cognition with robotic endurance; easier integration.	Safety protocols add complexity; speed may be limited.	High for high-value crops where quality is paramount.	Rodriguez and Patel (2022)

Methodology

This review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and methodological rigor.

Data Sources and Search Strategy

A systematic literature search was performed using the following electronic databases:

Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar (used as a supplementary source to capture gray literature and recently published articles)

The search covered publications from January 2015 to December 2024, reflecting recent and relevant advancements in AI-driven agricultural robotics.

Search Keywords

Search strings were constructed using Boolean operators and keywords related to AI, robotics, and agriculture, including:

("agricultural robotics" OR "farm robots" OR "autonomous agricultural systems") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("precision agriculture" OR "crop monitoring" OR "autonomous harvesting" OR "robot navigation")

The keywords were adapted slightly depending on database-specific syntax.

Inclusion and Exclusion Criteria

Inclusion Criteria

Peer-reviewed journal articles and high-quality conference papers, Studies focusing on AI-driven robotics in agriculture, Articles addressing robot design, navigation, control, sensing, or AI-based decision-making, Publications written in English, Studies published within the defined time span (2015–2024).

Exclusion Criteria

Non-peer-reviewed articles, editorials, posters, or abstracts without full text, Studies not directly related to agriculture (e.g., industrial or medical robotics) Papers focusing only on IoT or sensors without robotic or AI integration, Duplicate studies across databases.

Study Selection Process

The study selection was conducted in three stages:

Identification: Records were retrieved from the selected databases using the defined search strings.

Screening: Titles and abstracts were screened to remove duplicates and irrelevant studies.

Eligibility and Inclusion: Full texts of potentially relevant articles were assessed against the inclusion and exclusion criteria.

Disagreements during selection were resolved through discussion among the authors

PRISMA Flow Diagram

A PRISMA flow diagram has been included in Figure 7 as shown:

Number of records identified - 257

Records screened and excluded - 174

Full-text articles assessed - 103

Final number of studies included in the review - 35

This diagram enhances transparency and allows readers to clearly follow the study selection pathway.

Data Extraction and Synthesis

For each included study, the following data were extracted:

Type of agricultural robot
AI/ML techniques used
Sensors and control strategies
Application domain (harvesting, weeding, monitoring, irrigation, etc.)
Key outcomes, advantages, and limitations

A qualitative synthesis was performed to identify trends, challenges, and future research directions in AI-driven agricultural robotics.

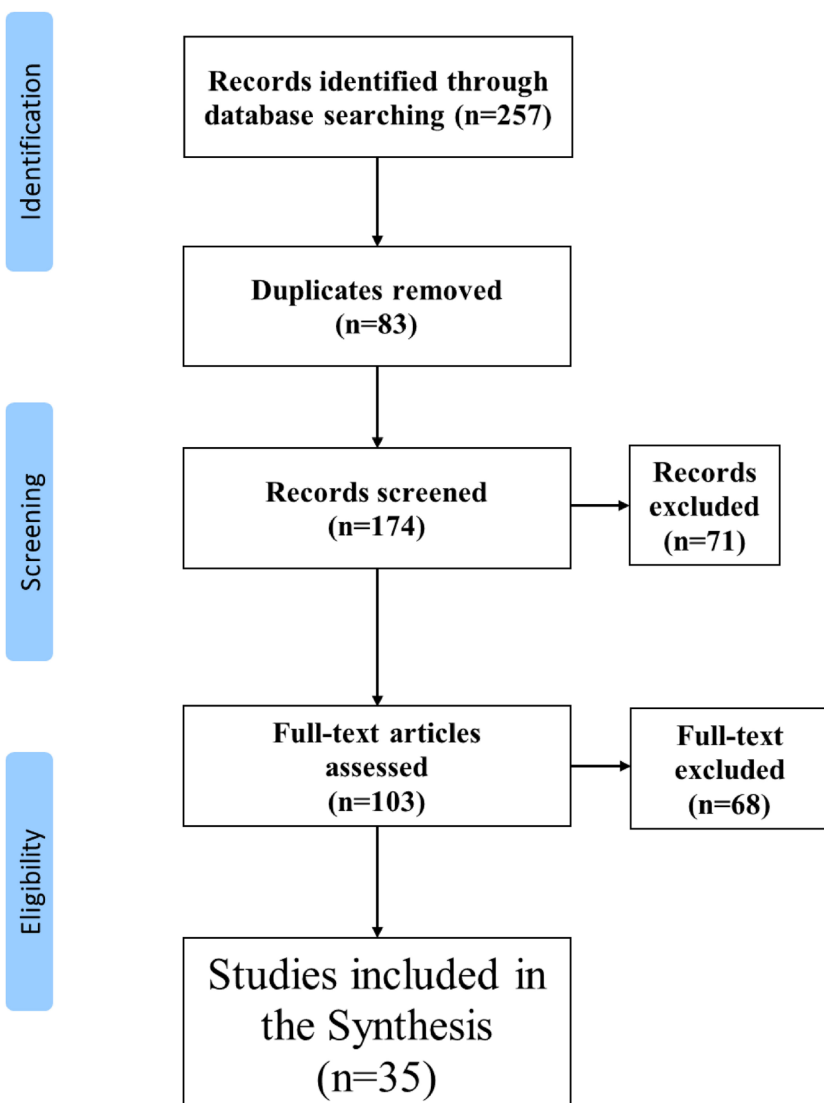


Fig 7 | PRISMA flow diagram for this narrative review

Discussion

Performance and Efficiency of Agricultural Robotics

Presence of robotics in the agricultural practices has enhanced efficiency, accuracy, and at the same time, productivity. Automated systems have improved crop monitoring and irrigation systems, as well as harvesting, making them less prone to human labor and more efficient in terms of yields. The research findings indicate that robotic automation is a technology that maximizes agricultural activities in a sustainable manner. For example, robots that perform weeding independently have resulted in a 90% decrease in the amount of herbicide necessary to control weeds without compromising the control part of the equation.¹ The same can be said for fruit harvesting with robots with more than 85% harvesting accuracy, which means that the amount of loss after harvest is greatly reduced.² This has led to an increased use of resources and reduced effects on the environment. Robots using AI can examine the health of plants, forecast growth patterns, and dynamically adjust farming methods, thereby increasing yields. Automation, on the other hand, enhances efficiency but is an issue of cost, flexibility, and technical reliability.

Synthesis of Conflicting Evidence and Technology Trade-offs

The literature has clear contradictions that demonstrate efficacy depending on the context. As an example, where Brown et al.⁵ claim over 90% navigation accuracy of vision-based implementations in structured orchards, Zhao and Wang⁶ note that the former are vulnerable to sudden changes in illumination in the open field, which LiDAR-based systems demonstrated to resist but cannot differentiate crops color/health. It means that sensor fusion imperative, rather than an excellent single-sensor solution, is needed.

Equally, in the control strategies, centralized control is commended as coordinated efficiency in harvesting (Liu et al., 2021) but denounced as the single point of failure. Swarm methods based on decentralization provide resilience (Kim and Park, 2021) but are poorly divided in terms of the optimum distribution of resources in the world. The new agreement, which is already observed in hybrid systems (Williams et al., 2022), is that hierarchical intelligence has a local reactive autonomy to make immediate decisions (obstacle avoidance) within a global optimization layer to plan tasks and allocate resources. One of the obvious research gaps is the inability to use standardized measures and benchmark conditions (e.g., standardized test fields, simulation situations) in order to objectively evaluate these control paradigms across studies.

Machine Learning and AI Contributions

AI and machine learning (ML) enhance the abilities of agricultural robots. AI-based precision agriculture requires intelligent models to handle tons of sensor data, photos, and IoT data. The application of methodologies such as CNNs and reinforcement learning improves the monitoring of plant health, yield prediction,

and autonomy.⁴ The vision-based navigation system is powered by a combination of the YOLO and Faster R-CNN models to navigate unstructured spaces and avoid obstacles comparable to those that an entire human being has to bypass.⁵ Technologies are less rigid in their operations, resource utilization, and decisions that may be made in a timely manner. Along with predictive analysis aided by AI, precision irrigation is also quite environmentally sustainable and has a very limited loss of resources, such as water, nutrients, and chemicals.¹⁵

Challenges and Limitations

The large-scale application of farm robots has been limited by various problems, irrespective of technological progress. Its greatest disadvantage is the outstanding initial cost, especially for small- and medium-sized agricultural firms.³ Auto tractors and irrigation systems have high prices that cannot be afforded by small-scale farming companies. Second, the soil type and unpredictable weather conditions are typos in the environment affecting the work of the robots. Empirical studies have reported that inclement weather affects the operating performance of sensor-based automation, inducing uneven watering and reducing crop yields.⁶ Technical issues include sensor, landscape navigation, and battery failure, which are also bottlenecks for the large-scale use of agricultural robots. To address these shortcomings, researchers have developed hybrid solar-powered robots that maximize the efficiency of energy expenditure and reduce the consumption of conventional energy sources.⁸

Advanced AI algorithms responsive to the environment, that is, capable of responding to changes in the environment, will also be created, thereby cancelling out the instability of the robot in a diverse range of agricultural conditions. Precision, efficiency and sustainability in agricultural activities have been enhanced significantly as a result of the integration of AI and robotics. Nevertheless, its use is restricted by economic and technical constraints.

Future Trends and Implication

Developments in any kind of AI-based automation, cooperative robotics, and bio-inspired robots will affect the future of farm robots. Swarm robotics, where several robots communicate and are self-organizing, is recommended for precision agriculture on a large scale.⁷ Swarm robotics is the ultimate productivity, where robots are capable of communicating and negotiating operations in the field. Acute morbidity will be described by diseases detected with enhanced hyperspectral images and sensors run time calculations.⁸ Real-time processing will eliminate optimization to a minimum by avoiding the use of the cloud through edge computing with an increased number of AI robots adopting it.¹¹ The work in the future should rely on focusing on cost-effective platforms, dynamically adjusted AI models, human-robot cooperation, and deployment under the guidance of the policy.

Table 2 | The type of robot used and the technologies, advantages, and weaknesses

Type of Robot	Applications	Technology Used	Advantages	Challenges	Reference
Navigation Robots	Autonomous movement in fields	Vision-based navigation, LiDAR, GPS	Efficient route planning, reduced human intervention	Complex environments, sensor limitations	Brown et al. ⁵
Economic Analysis Robots	Cost-benefit evaluation of robotic systems	Economic modeling, return on investment (ROI) analysis	Insights into adoption barriers	High initial cost, uncertain ROI	Chen and Zhao ³
AI Robots	Precision farming, disease prediction	Deep learning, computer vision	Accurate decision-making, yield optimization	Data-hungry models, training complexity	Fernandez and Lee ⁴
Swarm Robots	Large-scale crop monitoring	Multi-agent systems, communication protocols	Scalable, efficient area coverage	Coordination and data aggregation	Gonzalez et al. ⁷
Harvesting Robots	Autonomous fruit picking	Robotic arms, vision systems, deep learning	Labor reduction, consistency in picking	Fragile fruit handling, high development cost	Jones and Kumar ²
Weeding Robots	Automated weed detection and removal	Computer vision, ML classifiers	Reduced chemical usage, eco-friendly	Differentiating crops from weeds	Smith et al. ¹
Sensor Robots	Real-time monitoring of soil and crop health	Hyperspectral imaging, sensor networks	Data-rich, responsive farming	Sensor maintenance, data overload	Yamada et al. ⁸ ; Lee and Torres ¹⁷
All-Purpose Robots	Multi-tasking farm operations	Autonomous platforms, AI decision-making	Versatile, adaptive, farm-wide applications	Complex integration, high cost	Martinez and Singh ¹⁶ ; Fujinaga ¹²
Irrigation Robots	Precision irrigation and water management	ML-based systems, soil moisture sensors	Efficient water usage, crop-specific irrigation	Weather unpredictability, system tuning	Clark and Rivera ¹⁸
Bio-Inspired Robots	Sustainable farming practices	Nature-inspired mechanics, soft robotics	Energy-efficient, adaptable to terrain	New field, durability concerns	Hernandez and Xu ¹⁹
AI-Farming Systems	AI-driven farm planning and simulation	Pretrained models, simulation tools	Scalable decisions, time-saving	Data accuracy, regional variation	Li et al. ¹³ ; Shahab et al. ¹⁴
Small-Scale Robots	Sustainable farming in small fields	Compact robotic platforms	Cost-effective, ideal for smallholders	Limited capacity	Oliveira et al. ¹⁰
Farmer-Assistive Robots	Decision support, preference-driven solutions	Surveys, adaptive control systems	Aligns with real-world needs	Personalization complexity	Spykman et al. ⁹
ML Monitoring Systems	Real-time crop/environmental monitoring	Machine learning, mobile platforms	Fast insights, early issue detection	Model drift, connectivity	Yu et al. ¹¹
Control System Robots	Navigation in specialized environments	Linear-quadratic regulator, motion control systems	Optimized movement, better control in tough terrains	Requires tuning for specific settings	Anderson and Miller ²⁰
Tech Limitation Review	Overcoming technical deployment issues	Review of sensing, autonomy, mechanical design	Broad perspective, roadmap for improvement	Implementation still in progress	Zhao and Wang ⁶

Green and Ecological Sustainability

In a large sense, precision farming methods have improved sustainability in that they do not use as many resources and chemicals as other methods because they depend on AI. To manufacture fertilizers and work independently during irrigation, there is also an opportunity to add nutrition in a very specific way that decreases environmental tension and increases the good status of the soil. AI-based hyperspectral imaging also helps to partially reduce the amount of pesticides used and the probability of contamination due to early detection of diseases.¹⁵ Sustainability in agriculture with the help of robots ensures maximum efficiency during automation. These technologies ensure sustainability in ecology because waste will be eliminated, and as much input as possible can be maximized. However, ethical issues such as data privacy and ensuring agricultural data control must be addressed before the proper application of AI-based solutions becomes feasible.

Future of Agricultural Robotics

Future work in farm robotics will include reliability improvement, scalability, and cost-effectiveness. The output of AI will be real-time, and when this is combined with edge computing, robots will have dominion over decisions. Digital twin simulations will complement

AI training processes, reduce the need for field tests of costly solutions, and accelerate the deployment of smart solutions in agriculture.¹⁴ The co-authoring of engineers, agronomists, and AI specialists will also be required to develop agricultural robotics. Policies, subsidies, and cheap engineering solutions are imperative to overcome financial constraints and offer mass marketability. As more research is conducted, agricultural robotics will modify contemporary agriculture and make it more efficient, sustainable, and secure at the global level. The main focus here is on recent developments; currently, edge AI, digital twins, and soft robotics are being innovated and can further change the landscape.

Identification of Explicit Research Gaps

According to our critical synthesis, we can outline the following specific gaps which can be addressed specifically in the future research:

Gap Level 5 Autonomy in Agriculture: The existing systems follow a high human supervision. The long-term studies are required in the form of autonomy with self-diagnosis, fault recovery and adaptive re-planning when the full growing seasons are developed without human intervention.

Gap in Standardized Evaluation: There are no benchmarks of performance (such as an Agricultural Robot

Kernel to robotic manipulation benchmarks) that can be used to fairly compare performance of different platforms and environments in terms of navigation accuracy, manipulation success, and energy efficiency.

Gap in AI-Generalizability: The vast majority of AI models are trained on small locale-specific data. There is an urgent demand of large-scale, heterogeneous, and open agricultural data and foundation models of agriculture that can be effectively fine-tuned to local conditions.

Disparity in Economic-Integrated Design: There are not many studies that optimize technical performance with Total Cost of Ownership (TCO) models in the case of farmers. There is a huge lack in research that integrates lifecycle analysis, service-based models of robotics (Robotics-as-a-Service), and modular design to make the robots easily repairable.

Disconnect between Policy-informed Safety Frames: Co-evolving policy frameworks are lagging behind technical research on safety (human-robot interaction, data security) frameworks. There should be interdisciplinary efforts in developing certification criteria and liability laws of autonomous field robots.

Practical Implications for Stakeholders

In the case of Farmers and Agri-businesses: Modular, multi-purpose platforms (Table 2) would be a more economically viable investment than single-purpose robots in most non-industrial farms. The established effectiveness of vision-based herbicide reduction weeding robots¹ offers an ROI-positive opportunity of an opportunity to adopt in the near term, particularly among those who grow their production in the organic market.

To Robotics Engineers/Researchers: It should focus more on the robust sensor fusion (vision + LiDAR + radar) and simulation-to-reality (sim2real) transfer methods to address the weaknesses of pure vision systems. The full-day autonomy can only be achieved through the development of energy-conscious algorithms and hybrid (solar + battery) power systems that would help to overcome one of the limitations identified by Yamada et al.⁸

To AI Scientists: It should move towards having the most accurate models on limited data sets to develop robust, explainable, and data-efficient models. By working with agronomists to instantiate domain knowledge in AI (e.g. phenology models in growth predictors) we will produce more credible and usable systems.

To close the adoption chasm among smallholders: Incentives ought to be used to close the chasm between adoption of shared robotics infrastructure (e.g., cooperative-owned robot fleets) and to fund R&D on inexpensive, robust sensing. In addition, launching multi-stakeholder discussions to create safety and data governance standards is an urgent need to create responsible innovation.

Ethical, Socio-economic and Policy Implications

The application of AI-powered robotics will not only resist the technical challenges, it will raise deep ethical,

social, and economic issues that will largely determine the path of its adoption and its perception by society.

1. **Information Ethics, Data Property, and Surveillance.** Precision agriculture is data-intensive over its nature. Robots are gathering high-resolution digital twins of farms by collecting hyperspectral imagery, detailed yield maps, and soil health data. This raises critical issues:

- **Ownership and Control:** Who is the owner of this data? the farmer, the technology provider or the platform aggregator? The terms of contracts usually play in favor of the corporations, which might bring farmers into the proprietary ecosystems and restrict their access to their most valuable resource information about their land.²¹
- **Privacy and Surveillance:** Surveillance may not be limited to crops and may be applied on workers which leads to a privacy issue. There should be clear governance structures to differentiate agronomic data collection and monitoring workers.²²⁻²⁵
- **Algorithmic Bias and Accountability:** AIs that are trained on data of large and industrialized farms in particular areas can be ineffective or do not offer the best options to smallholders or other agroecological units, which may further increase existing inequalities. It is not an easy legal and ethical question to establish accountability of a given miscarriage of justice of AI-driven decisions (e.g. misapplied pesticides).²⁶

2. **Labour Market Change and Social turbulence.** On the one hand, automation offers a solution to the lack of labor, on the other hand, it completely changes agricultural work:

- **Displacement and Deskilling:** The most obvious victims of automation are manual labor (weeding, harvesting), which risks destroying seasonal and migrant laborers. Otherwise, this will deskill the agricultural manpower.
- **Skill Shifts and New Roles:** New positions will be created on the other side in the field of robot fleet management, data analysis and high-level maintenance of mechatronics. The social issue is how to make this transition with re-skilling and education processes to avoid the increased rural unemployment and inequality.
- **Human-Robot Collaboration:** The future of collaborative robotics model (Figure 4) implies that in the future, robots could do the hard and monotonous work, supplementing human work experience in decision-making and manipulation of complex objects rather than substituting it. This model can provide a more sustainable way socially.²⁷⁻³⁰

3. **Market Structure, Economic Viability and Business Models.** Costs this is partly hindered by the high start up cost (usually more than \$100,000 per unit).²² On a further economic examination:

- Beyond Purchase Price: The TCO comprising of maintenance, software license, connectivity and energy should be visibly modeled alongside the benefits of savings in input and yield improvements. The TCO is also prohibitive to many.
 - New Business Models: New Business Models To reduce the cost of entry into the business, robotics-as-a-service (RaaS) models are being introduced, where farmers pay per acre mowed or per operation (e.g., weeding-as-a-service). On the same note, access can be enhanced through cooperative or shared ownership of small holder clusters.
 - Possibility of Market Concentration: This risk may result in fewer large agri-tech companies as a result of the high cost of R&D, resulting in the lack of competition, a dependency of the farmers, and a control over the data streams. The measures to address this trend are the promotion of interoperability standards (e.g., open API to sensor data) and the encouragement of open-source agricultural robotics projects.^{31,32}
4. Well-Balanced Access and the Digital Divide. The advantages of AI-robotics will go to large, capital-intensive farms in developed economies, increasing the digital divide in agriculture.
- Smallholder Exclusion: The existing cost and complexity of systems does not always match up with the small pieces of land, mixed cropping systems, and financial limitations of small holder farmers who yield an important share of the global food supply.
 - Pathways to Inclusivity: To do this, special R&D is needed on low-cost, modular, and robust platforms to apply to operations in small scale. Moreover, the subsidy and investment schemes at the public-sector level, which focus on the inclusive use of technology, and digital literacy education are important to make sure that these ground-breaking tools are involved in global food security and equal development, and not contribute to the existing inequality.^{33,34}
5. Policy and Regulatory Requirements. Existing regulatory systems do not suit autonomous field robots. Key policy needs include:
- Safety and Certification: Regulations of safe work on common areas (with humans, livestock, and other machine work).
 - Data Governance: A law defining who owns, ports and privacies (similar to the GDPR of agricultural data, in the EU).
 - Liability Frameworks: There should be specific rules on liability in malfunction, property damage, or faulty AI advice.
 - Incentive Structures: Tax breaks and subsidies to encourage sustainable automation (e.g. to robots which use less chemical) and to encourage equal access schemes.³⁵

Conclusion

The application of AI-based robotics is a revolutionary technology in the field of agriculture today to improve productivity, efficient use of resources, and environmental sustainability. Although cost, flexibility, and regulation issues persist, further development of intelligent automation, swarm approach and interdisciplinary cooperation will lead to scalable and sustainable solutions in agriculture. The future success will be based on the integration of technological advancement with agronomic skills and conducive policy regimes.

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