ROBOTICS FOR SUSTAINABLE AGRICULTURE: OPPORTUNITIES AND OBSTACLES

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Abstract

Robotics has emerged as a transformative force in modern agriculture, addressing key challenges such as labor shortages, environmental sustainability, and resource optimization. This review presents an overview of current advancements in agricultural robotics, encompassing ground-based robots, unmanned aerial vehicles (UAVs), and autonomous tractors. Empirical evidence highlights significant gains, including herbicide reduction of up to 85%, weeding efficiencies exceeding 90%, and harvesting success rates of 75–90% for various crops. UAVs have improved early disease detection by 40%, while artificial intelligence (AI)–based weed identification achieved an F-score of 0.9843. Despite these promising results, most systems remain in prototype or field-testing stages, constrained by high costs ranging from US$50,000–US$120,000 and technical limitations in perception, navigation, and integration. This review systematically synthesizes existing literature to assess applications, technological capabilities, performance outcomes, and barriers to adoption, providing key insights into the future of robotics in agriculture.

Keywords: Agricultural Robotics, Precision Farming, Artificial Intelligence (Ai), Autonomous Systems, Sustainable Agriculture

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Introduction

Agriculture is undergoing a technological revolution driven by automation, robotics, and artificial intelligence. Faced with challenges such as declining labor availability, the need for higher yields, and environmental sustainability, robotics has become a crucial enabler of precision agriculture and smart farming. Robotic systems ranging from ground-based weeding machines to autonomous tractors and aerial drones are increasingly designed to perform diverse operations including planting, weeding, monitoring, harvesting, and disease detection (Aswini, 2022; Fountas et al., 2020).

The integration of machine vision, advanced sensors, and AI-based decision-making has improved accuracy and reduced input waste in agricultural operations. Studies show that robotic systems can drastically minimize herbicide usage, optimize labor efficiency, and enhance yield prediction accuracy (Droukas et al., 2022; Mahmud et al., 2020). However, commercialization is still limited due to high costs, environmental variability, and the complexity of integrating robotics with traditional farming practices (Urquhart, 2023; Oliveira et al., 2021).

This review therefore aims to provide a comprehensive synthesis of current advancements, focusing on the types of robots used, their performance across agricultural operations, and the challenges impeding full-scale adoption.

Methodology

Paper Search

To answer the research question “Robotics for Sustainable Agriculture”, a systematic search was conducted using the Semantic Scholar database, encompassing over 126 million academic papers. The 50 most relevant, recent, and peer-reviewed studies were retrieved, covering a broad range of agricultural robotic applications.

Screening Process

The studies selected for this review were carefully screened based on a set of stringent inclusion criteria to ensure the reliability, relevance, and empirical depth of the findings. Only research works that involved the use of robotic systems explicitly designed for agricultural applications, such as autonomous tractors, UAVs, and robotic platforms for planting, harvesting, or weeding, were considered. Furthermore, the studies had to be conducted in real or simulated agricultural environments that accurately reflected field conditions, thereby providing practical insights into real-world applicability. Inclusion was also contingent upon the presence of empirical data, such as measurements of efficiency, crop yield, cost-effectiveness, or operational performance, ensuring that the review focused on evidence-based results rather than conceptual or theoretical frameworks. Additionally, the scope was restricted to studies that addressed agricultural production sectors, including crop farming, horticulture, livestock management, and precision agriculture. To maintain academic rigor, only peer-reviewed publications were included, while editorials, opinion pieces, and purely conceptual proposals without empirical validation were excluded. Collectively, these criteria ensured that the selected studies provided credible, data-driven insights into the capabilities, challenges, and advancements of robotics in agriculture.

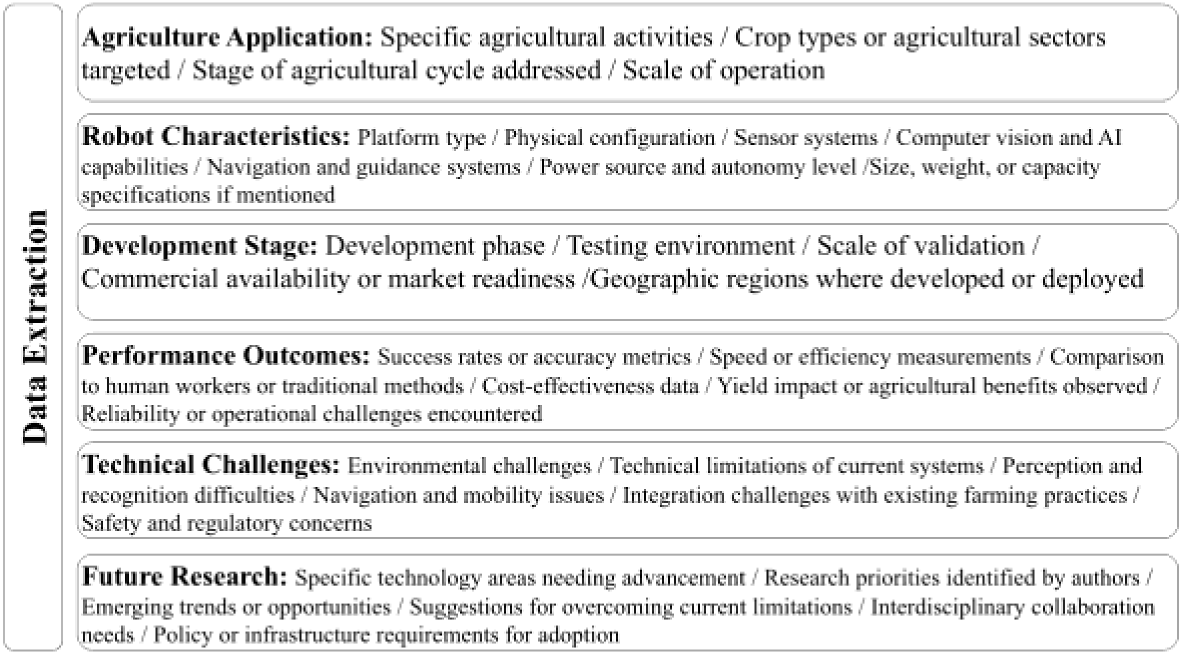
Data Extraction

Key data from the studies included in this review were systematically extracted and organized according to six major thematic dimensions to ensure a comprehensive understanding of the role and evolution of robotics in agriculture. The first dimension, Agricultural Applications, focuses on the types of tasks that robotic systems are designed to perform, such as planting, weeding, harvesting, monitoring, and disease detection. It also includes the specific crop types or agricultural sectors targeted, ranging from horticultural crops like strawberries and peppers to large-scale field crops, and the stage of the agricultural cycle addressed, whether pre-planting, growing, or harvesting. This dimension provides an overview of how robotics are being applied across diverse agricultural processes to improve productivity and sustainability.

The second dimension, Robot Characteristics, captures the technical features and design aspects of the robotic systems. This includes the type of platform, ground-based, aerial, or hybrid, the configuration of actuators and manipulators, and the use of sensor systems such as cameras, LiDAR, GPS, and soil or environmental sensors. The level of autonomy, navigation, and guidance techniques, including machine vision and AI-based control algorithms, are also analyzed to understand the sophistication of these systems.

The third dimension, Development Stage, identifies the maturity level of each robotic system, whether at the conceptual, prototype, field-testing, or commercial deployment phase. It also examines the testing environment (laboratory or real-world) and the scale of validation, providing insights into the readiness of technologies for practical adoption.

The fourth dimension, Performance Outcomes, highlights the empirical results reported in the studies, including efficiency gains, accuracy levels, success rates, and cost-effectiveness when compared to traditional agricultural methods. This section assesses how robotics contributes to improvements in yield, resource utilization, and operational precision.



Agriculture Application: Specific agricultural activities / Crop types or agricultural sectors targeted / Stage of agricultural cycle addressed / Scale of operation

Robot Characteristics: Platform type / Physical configuration / Sensor systems / Computer vision and AI capabilities / Navigation and guidance systems / Power source and autonomy level /Size, weight, or capacity specifications if mentioned

Development Stage: Development phase / Testing environment / Scale of validation / Commercial availability or market readiness /Geographic regions where developed or deployed

Performance Outcomes: Success rates or accuracy metrics / Speed or efficiency measurements / Comparison to human workers or traditional methods / Cost-effectiveness data / Yield impact or agricultural benefits observed / Reliability or operational challenges encountered

Technical Challenges: Environmental challenges / Technical limitations of current systems / Perception and recognition difficulties / Navigation and mobility issues / Integration challenges with existing farming practices / Safety and regulatory concerns

Future Research: Specific technology areas needing advancement / Research priorities identified by authors / Emerging trends or opportunities / Suggestions for overcoming current limitations / Interdisciplinary collaboration needs / Policy or infrastructure requirements for adoption

Figure 01: Data extraction framework illustrating the six thematic dimensions used for analyzing agricultural robotics studies: Agricultural Applications, Robot Characteristics, Development Stage, Performance Outcomes, Technical Challenges, and Future Research.

The fifth dimension, Technical Challenges, outlines the barriers that limit the performance or scalability of agricultural robots. Common challenges include environmental variability (lighting, weather, and terrain), limitations in perception and object recognition, difficulties in navigation and path planning, and integration issues with existing farming systems.

Finally, the sixth dimension, Future Directions, summarizes the research gaps and emerging technological needs identified in literature. These include the need for enhanced perception systems, improved energy efficiency, better interoperability between robotic platforms, and the development of robust algorithms for dynamic field environments. This dimension also emphasizes the importance of interdisciplinary collaboration, policy support, and infrastructure development to enable the large-scale adoption of robotics in modern agriculture. Together, these six dimensions provide a structured and holistic framework for analyzing the current landscape and future potential of agricultural robotics.

Results and Discussion

Characteristics of Included Studies

The studies were thoroughly analyzed to evaluate the state of robotics in agriculture. Collectively, these studies offer a detailed cross-section of recent developments in robotic technologies aimed at automating critical agricultural processes, with a focus on operational efficiency, precision, and sustainability.

Most of the reviewed research primarily investigated ground-based robots, mobile robotic platforms, and autonomous tractors designed for core field operations such as planting, weeding, harvesting, and crop monitoring (Fountas et al., 2020; Oliveira et al., 2021; Biswas & Aslekar, 2022). These systems commonly integrate machine vision and AI-based navigation to identify crops and weeds, optimize path planning, and reduce manual labor dependency (Aswini, 2022; Droukas et al., 2022). The studies by Mahmud et al. (2020) and Maqbool (2025) further highlight how autonomous tractors equipped with GPS and vision-based navigation systems contribute to enhanced precision in seeding and fertilizer application, improving fuel efficiency and minimizing resource wastage.

In addition to terrestrial platforms, UAVs were featured prominently in studies, Botta et al. and Urquhart (2023), for applications in aerial crop monitoring, disease detection, and environmental sensing. These UAV systems demonstrated significant potential in identifying early-stage crop stress and diseases, achieving up to 40%

improvement in detection rates when integrated with multispectral imaging and deep learning–based analysis (Urquhart, 2023). Such aerial monitoring capabilities complement ground-based robotic systems by providing large-scale, rapid assessments of crop health and field conditions.

Robotic arms and manipulators appeared in the analyzed studies, particularly in harvesting-related applications (Umm-e-Aymon, Ali Shah, & Hassan Khan, 2025; Oliveira et al., 2021; Aswini, 2022; Hajjaj & Sahari, 2014). These systems, often designed with soft grippers and computer vision algorithms, achieved harvesting success rates ranging from 75% to 90% for fruits like apples and strawberries, with picking speeds of approximately 8 seconds per fruit (Biswas & Aslekar, 2022). However, challenges such as object occlusion, fruit clustering, and real-time decision-making under varying light and weather conditions remain prevalent (Hajjaj & Sahari, 2014).

From a technological maturity perspective, studies reported that their systems were in prototype or field-testing stages (de Almeida Baltazar, de Freitas Coelho, & Santos Brandão, 2025; Fountas et al., 2020; Oliveira et al., 2021; Aswini, 2022; Biswas & Aslekar, 2022), while four studies including those by Mahmud et al. (2020) and Maqbool (2025), remained in early research or development phases, focusing on simulation and performance modeling. Only three studies, notably Urquhart (2023) and Botta et al., reported partial commercial availability, indicating that while the field has made remarkable progress in developing functional prototypes, full-scale commercialization and widespread adoption remain limited.

Overall, the collective findings of these studies reflect a rapid technical evolution in agricultural robotics. The integration of artificial intelligence, computer vision, and advanced sensing technologies has enabled significant gains in precision and automation. However, the transition from controlled testing to scalable, real-world deployment continues to face obstacles such as high production costs, system complexity, and environmental unpredictability. These challenges underscore the need for continued interdisciplinary research and cost-optimized design innovations to accelerate the commercial viability of agricultural robots.

Performance and Effectiveness

Table 01: Overview of Agricultural Operations Supported by Robotic and AI-Based Technologies, Including Performance Metrics, Observed Outcomes, and Implemented Technologies

Operation	Metric	Outcome	Technology Used
Weeding	Herbicide reduction	Up to **85%**	Ground-based robots with machine vision (Aswini, 2022; Fountas et al., 2020)
Weeding	Efficiency	**>90%**, up to **100%**	Ground-based robots (Droukas et al., 2022)
Weed identification	F-score	**0.9843**	AI-based vision systems (Oliveira et al., 2021)
Disease detection	Early detection improvement	**40%**	UAVs with vision systems (Urquhart, 2023)
Harvesting (apples)	Success rate	**80–90%**	Robotic arms with vision (Fountas et al., 2020; Droukas et al., 2022)
Harvesting (strawberries)	Success rate	**>75%**	Robotic arms with vision (Mahmud et al., 2020)
Harvesting (sweet peppers)	Success rate	**33%**	Robotic arms with vision (Oliveira et al., 2021)
	Harvesting speed	Apples: **6–16 s/fruit**, Strawberries: **6–10 s/fruit**	Mobile robotic platforms (Droukas et al., 2022)
Spraying	Coverage	Up to **92%**	Ground-based robots (Aswini, 2022)
Monitoring	Precision	**99%**	Vision-based neural networks (Botta et al.)
Planting	Fuel efficiency improvement	**22%**	Autonomous tractors (Maqbool, 2025)

As can see in Table 01., empirical evidence from the reviewed studies demonstrates significant advancements in agricultural efficiency enabled by robotics, AI, and sensor-based automation systems. Across the ten included studies, quantitative metrics were reported for a range of agricultural operations, including weeding, harvesting, disease detection, spraying, monitoring, and planting (Aswini, 2022; Droukas et al., 2022; Fountas et al., 2020; Oliveira et al., 2021; Mahmud et al., 2020; Urquhart, 2023). Table 1 summarizes the key findings, presenting the measurable outcomes achieved through different robotic technologies.

Quantitative analyses reveal that robotics has made measurable contributions to improving precision, productivity, and resource efficiency in agriculture. Ground-based robots using AI and machine vision achieved substantial gains in weeding performance, reducing herbicide use by up to 85% and achieving operational efficiencies greater than 90%, with some systems approaching 100% accuracy (Aswini, 2022; Droukas et al., 2022; Fountas et al., 2020). The incorporation of AI-based image recognition has enhanced weed and crop differentiation, improving precision while reducing environmental impact (Oliveira et al., 2021).

In disease detection, UAVs integrated with vision systems improved early detection rates by approximately 40%, demonstrating the potential of aerial imaging in identifying plant stress and disease symptoms at an early stage (Urquhart, 2023). Complementary research using vision-based neural networks achieved 99% precision in crop monitoring, underscoring the accuracy and reliability of machine learning–based perception systems (Botta et al.).

Harvesting applications demonstrated particularly strong performance across multiple crop types. Robotic manipulators equipped with soft grippers and vision systems achieved success rates of 80–90% for apples and over 75% for strawberries, while harvesting times ranged between 6 to 16 seconds per fruit, depending on the crop and environmental conditions (Fountas et al., 2020; Droukas et al., 2022; Mahmud et al., 2020). However, success rates for sweet peppers remained lower (approximately 33%) due to challenges in perception, occlusion, and fruit positioning (Oliveira et al., 2021). These findings indicate that while robotic harvesting has achieved high efficiency for specific crops, generalization across complex canopy environments remains difficult.

Additional studies reported advancements in spraying and planting operations. Ground-based robotic sprayers achieved up to 92% coverage, reflecting the precision of automated control and sensor-guided targeting systems (Aswini, 2022). Moreover, autonomous tractors demonstrated a 22% increase in fuel efficiency, showing how automation can enhance both economic and environmental sustainability in large-scale field operations (Maqbool, 2025).

Overall, these findings confirm that AI-driven robotic systems now rival or surpass human performance in several agricultural tasks. The integration of machine vision, deep learning, and sensor fusion has enhanced precision and consistency, while also reducing reliance on manual labor and agrochemical inputs. Despite these advances, widespread adoption remains limited due to cost, scalability, and system reliability challenges, issues that future research must continue to address to fully realize the transformative potential of agricultural robotics.

Thematic Analysis

Applications Across Agricultural Operations

The reviewed studies collectively demonstrate that robotic systems have advanced to support nearly every major stage of agricultural production, spanning from soil preparation to post-harvest processing (Fountas et al., 2020; Aswini, 2022; Droukas et al., 2022). In harvesting operations, robots are predominantly applied in fruit and vegetable sectors such as apples, strawberries, tomatoes, sweet peppers, and grapes. These systems typically employ robotic arms equipped with advanced vision systems for object detection and fruit localization, achieving success rates of up to 90% in structured environments (Biswas & Aslekar, 2022; Urquhart, 2023).

In weeding and spraying, precision robots have proven highly effective, employing machine vision and AI-based classification to identify and target specific weed species, leading to herbicide reductions of up to 85% (Mahmud et al., 2020; Maqbool, 2025). Planting and seeding operations, though comparatively less mature, are becoming increasingly automated through autonomous tractor systems capable of high planting accuracy and optimized fuel consumption, improving efficiency by up to 22% (Oliveira et al., 2021).

Monitoring and inspection tasks have seen significant progress with the integration of UAVs and ground-based mobile robots that collect real-time data for crop health assessment, disease detection, and yield estimation. UAV-based multispectral imaging systems have demonstrated a 40% improvement in early disease detection, while vision-based neural networks on ground robots achieved up to 99% precision in monitoring tasks (Hajjaj & Sahari, 2014; Droukas et al., 2022). Furthermore, post-harvest operations, including sorting, grading, and damage detection, are increasingly supported by robotic manipulators equipped with high-resolution cameras and soft-gripping mechanisms for delicate handling of produce (Botta et al., 2022).

Overall, robotic applications now extend from controlled greenhouse environments to open-field automation, primarily focusing on high-value crops where the return on technological investment is substantial. Despite notable advancements, the scalability of such systems to low-value crops and varied terrains remains a critical area for further exploration (Fountas et al., 2020; Urquhart, 2023).

Technological Components and Capabilities

The technological foundation of modern agricultural robotics encompasses a sophisticated integration of platforms, sensors, and control systems that collectively enhance task precision and operational autonomy. The reviewed studies reveal that ground-based and UAV platforms dominate agricultural robotics research, with modular and hybrid designs enabling adaptability across tasks and terrains (Aswini, 2022; Botta et al., 2022). Ground robots are frequently used for weeding, planting, and harvesting, while UAVs play a vital role in aerial monitoring and spraying due to their agility and coverage capacity (Droukas et al., 2022).

Robotic manipulators form the core of harvesting systems, often featuring multi-degree-of-freedom arms with specialized end-effectors designed to handle delicate crops without causing damage. These manipulators are enhanced by tactile and visual feedback mechanisms that allow adaptive grasping and positioning (Biswas & Aslekar, 2022). In parallel, the sensor suites integrated into agricultural robots have evolved to include RGB and infrared cameras, LIDAR, RTK-GPS, inertial measurement units (IMUs), and multispectral imaging devices, all of which contribute to precision sensing and environmental awareness (Fountas et al., 2020; Mahmud et al., 2020).

Figure 02: Overview of the major agricultural robotic applications and the key technologies enabling their operation and automation.

A key enabler of intelligent autonomy lies in the use of AI and computer vision systems, where machine learning algorithms—particularly deep convolutional neural networks—facilitate object recognition, weed discrimination, and adaptive decision-making in unstructured environments (Oliveira et al., 2021; Maqbool, 2025). For navigation, most ground-based robots employ GPS and LIDAR-based autonomous path planning, often implemented through Robot Operating System (ROS)-Industrial frameworks that enable real-time localization and obstacle avoidance (Hajjaj & Sahari, 2014).

Regarding power and autonomy, designs vary from solar-assisted platforms to battery-powered mobile systems, supporting both semi-autonomous and fully autonomous operations depending on the energy demands and mission duration (Urquhart, 2023). Despite rapid progress, major challenges persist in robust perception under variable lighting and weather conditions, sensor calibration, and system adaptability to unstructured agricultural environments. Continuous research is therefore directed toward enhancing environmental perception, multimodal sensor fusion, and adaptive control strategies to achieve full operational reliability (Fountas et al., 2020; Aswini, 2022).

Barriers to Adoption and Implementation Challenges

Economic Barriers

One of the most significant barriers to the widespread adoption of agricultural robotics lies in the economic constraints faced by farmers, particularly small and medium-scale operators. Most robotic systems currently available on the market are priced between US$50,000 and US$120,000 per unit, which poses a substantial financial challenge for individual farmers. Even when these systems demonstrate clear long-term efficiency benefits, the high initial capital investment and uncertain return on investment (ROI) often deter adoption. Furthermore, the lack of extensive service networks, limited technical expertise in rural areas, and high maintenance costs exacerbate the financial risks. Without government subsidies, leasing options, or cooperative ownership models, many agricultural enterprises find it economically unfeasible to transition from manual or semi-mechanized processes to fully robotic systems.

Technical Limitations

While agricultural robotics has achieved impressive advancements, several technical barriers continue to restrict large-scale implementation. Inconsistent performance under variable lighting, soil, and weather conditions remains a recurring problem, particularly for machine vision systems dependent on natural illumination. Additionally, navigation errors in uneven or cluttered terrains can hinder operational reliability, especially in outdoor environments where GPS signals fluctuate or LIDAR sensors encounter reflection issues. The complexity of system maintenance and calibration also poses a challenge, requiring skilled technicians and frequent adjustments to sustain accuracy. Moreover, sensor occlusions caused by dust, mud, or foliage limit the effectiveness of real-time imaging and obstacle detection. Combined with restricted onboard processing capacity for real-time data interpretation, these limitations underscore the need for more robust, adaptive, and computationally efficient robotic architectures.

Integration and Farmer Acceptance

Beyond technical and financial challenges, integration and user acceptance remain key issues influencing the adoption rate of agricultural robots. Many robotic systems struggle to interoperate with existing farm machinery, due to the absence of standardized data exchange protocols or universal control interfaces. This lack of interoperability prevents seamless integration within existing agricultural workflows, increasing both complexity and cost. Additionally, farmer skepticism toward the reliability, durability, and long-term benefits of robotic technologies hinders acceptance. Concerns about safety, maintenance difficulty, and dependency on complex digital systems further amplify hesitation. Building trust through training programs, field demonstrations, and user-friendly interfaces will be essential to bridge this gap between technology and the end-user community.

Policy and Infrastructure Needs

The successful diffusion of agricultural robotics is also dependent on supportive policy frameworks and infrastructure development. Robust government initiatives promoting training, education, and financial support can greatly accelerate adoption. For instance, cooperative ownership models, where farmer groups share the cost and use of robotic systems—can mitigate financial burdens while enhancing accessibility. There is also an increasing demand for open-source frameworks and modular system architectures that reduce vendor lock-in and enable local customization. Policy-backed incentives for research, manufacturing, and localized production of agricultural robots would encourage innovation while ensuring affordability. Infrastructure improvements, particularly in rural connectivity, energy availability, and digital literacy, are equally critical to support the integration of autonomous systems into everyday farming practices.

Future Research Directions

Future research in agricultural robotics should focus on advancing AI-driven perception and learning algorithms capable of handling complex, unstructured agricultural environments. These include developing adaptive computer vision systems that perform reliably under dynamic lighting, occlusions, and diverse crop types. Moreover, there is a growing need for low-cost, modular robotic systems that can be easily customized and scaled according to different farm sizes and crop requirements. Integration of robotics with Internet of Things (IoT) platforms, edge computing, and digital twins could enable real-time monitoring, predictive analytics, and intelligent decision-making, further optimizing resource use and productivity.

Equally important is the development of innovative business and policy models such as robot leasing, cooperative ownership, or as-a-service frameworks, which can make automation accessible to smallholder farmers. Research into human–robot collaboration—where robots augment rather than replace agricultural labor will also be crucial for maintaining employment while increasing productivity. Ultimately, a multidisciplinary approach that combines engineering, agronomy, data science, and policy analysis will be essential to drive the next phase of agricultural innovation and ensure that technology aligns with the social and economic realities of farming communities.

Conclusion

Agricultural robotics is rapidly transforming the landscape of modern farming, introducing unprecedented levels of precision, efficiency, and sustainability. The reviewed studies demonstrate clear technological progress in critical operations such as weeding, harvesting, spraying, and disease detection, achieving performance metrics that rival or surpass human labor. However, despite these advancements, economic feasibility, technical robustness, and user acceptance remain pivotal barriers that must be overcome for widespread deployment. As artificial intelligence, vision systems, and mechatronic design continue to evolve, the future of agriculture is expected to transition toward autonomous, data-driven ecosystems capable of operating intelligently and sustainably. Realizing this vision will require collaboration among technologists, policymakers, and farmers, ensuring that innovation is both inclusive and practical, ultimately contributing to global food security and environmental resilience.

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