China Instrument and Control Society
Instrumentation
OPEN ACCESS
INSTRUMENTATION, Vol. 12, No. 3, September 2025
https://doi.org/10.15878/j.instr.202500291

Review

Cutting-Edge Trends of Ground Robots Transforming Traditional Agriculture: An Overview and Case Studies

Zain Anwar Ali

Department of Electronic Engineering, Maynooth International Engineering College, Maynooth University, Co. Kildare. Ireland

* Corresponding author email: zainanwar.ali@mu.ie

Abstract: The global population is increasing, compelling a greater food supply for survival and agricultural activity to support economic development. On the other hand, traditional farm machinery and activities result in the overuse of fertilizers, irrigation water, and land, thereby undermining environmental sustainability. The current study aims to present advanced ground robots as effective solutions for autonomous operations, enhancing efficiency, productivity, and revenues in agriculture while consuming fewer resources and preserving the environment. In this regard, an overview of diverse imaging sensors and navigation technologies for ground robots is provided as key components that assist in automation and autonomy. Recent trends adopted for deploying ground robots while integrating the internet-of-things (IoT), artificial intelligence (AI), cloud computing, edge computing, collaborative robotics, and energy and resource-efficient systems are elucidated, driving smart and sustainable agriculture. Moreover, state-of-the-art applications of ground robots in three agricultural branches are explored. Three case studies from Ireland are presented as evidence of the transformation of traditional agriculture. Some limitations that necessitates future considerations are highlighted. The current study signifies the importance of employing ground robots to leap from conventional agricultural practices to precision and sustainable operations.

Keywords: agriculture; ground robots; imaging sensors; navigation; sustainability

Citation: Zain Anwar Ali."Cutting-Edge Trends of Ground Robots Transforming Traditional Agriculture: An Overview and Case Studies." Instrumentation 12, no.3 (September 2025). https://doi.org/10.15878/j.instr.202500291

1 Introduction

Agriculture requires human involvement in cultivating land, seeding to harvesting and picking activities, resulting in adverse working conditions, fatigue, labor shortage, and high wages. In addition, the growing demand for food supply due to increasing population paved the way for mechanization in agriculture. Mechanization evolved over the last century with the introduction of tractors[1]. The weight and power of agricultural machines were increased to improve plowing, feeding, harvesting, planting, and other operations. This change optimized farming productivity but resulted in three crucial problems: higher energy consumption, significant soil degradation, and massive investment, exceeding aggregate agricultural production costs. Another key issue in agriculture is traditional practices in which water and agrochemicals are consistently supplied to crops without considering their variety, needs, and conditions[2]. These practices are responsible for unsustainable resource usage and wastage across the globe. Therefore, transforming classical agricultural activities and mechanization paradigms is integral for addressing all the mentioned issues.

Constant advancement in novel strategies and technologies drives increased automation in agriculture. In the 1980s, sensors, computers, and actuators were introduced as agricultural techniques. Later, in the late 1990s, robotic vehicles were deployed with specifically designed subsystems, such as sprayers, harvesters, pruners, and other robotic systems[3]. Developments in navigation, control, and sensing approaches and cutting-edge technologies have exapanded robotic abilities and augmented their applications. The agricultural robot market was valued globally at USD 4082.8 million in 2018 and is projected to reach USD 16,640.4 million by 2026 at a CAGR of 19.2%[4]. Robots are extensively used for automating agricultural tasks to reduce human involvement and enhance crop productivity and yields[5]. The cited study developed an autonomous robot for watering, applying pesticides, and loosening the soil efficaciously. Nowadays, diverse types of robots, including mobile robots, drones, unmanned aerial vehicles (UAVs), and others, are used for capturing data and performing various agricultural tasks. However, airborne platforms are weather-dependent and subject to strict legislative regulations[6]. Conversely, ground mobile robots are paramount as they are not restricted to such limitations and are proficient in acquiring plant data from different viewpoints at closer range.

Broader research bodies have reviewed robots for agriculture from different perspectives. Ref.[7] reviews the research status and diverse applications of robots in agriculture, delineating their components, categories, benefits, and hindrances. Ref. [8] analyzes navigation and guidance founded on machine vision technology for agricultural vehicles and robots. The cited review provides insights into vision sensors and systems, navigation information processing technologies, and their implementations for agricultural robots. Ref. [6] analyzes recent supportive technologies, such as hardware technologies, localization and mapping approaches, path planning strategies, and artificial intelligence (AI) methods for mobile robots to inspect and monitor agricultural plants and crops. Ref. [9] systematically reviews popular AI techniques, intelligent farming processes, and path planning of robots in three farming phases—monitoring, cultivation, and harvesting. Ref. [10] comprehensively reviews development in precision spraying using aerial and terrestrial robots, notably delving into spraying techniques, sensor technologies, the precision agriculture market, and design and development technologies. Table 1 summarizes the contributions and limitations of these review papers and compares these with the present study.

Table 1 Comparative analysis of recent review papers based on robot deployment in agriculture

References	Contributions	Limitations
Ref. [6]	Reviews state-of-the-art technologies, approaches, and AI potentialities for ground mobile robots for autonomous mapping and monitoring agricultural environments	No case study is presented
Ref. [7]	Reviews features, functions, and applications of field, animal husbandry, and fruit and vegetable robots	Lack of explicit discussion on supportive technology; No case study is presented
Ref. [8]	Reviews machine vision-enabled navigation and guidance for autonomous agro robots and vehicles	No case study is presented
Ref. [9]	Reviews implementations of robotics and AI techniques in monitoring, cultivation, and harvesting phases	No case study is presented
Ref. [10]	Reviews advancements in precision spraying technology within agricultural robotics with a brief exploration of AI, ML, and BDA technologies	No case study is presented
This work	Reviews cutting-edge trends of adopting AI, IoT, cloud and edge computing, collaborative robotics, and sustainable systems for ground agricultural robots and applications in horticultural production, arable farming, and animal husbandry	Three case studies are presented

This work differs from the above-mentioned existing reviews as they are confined to specific technology suited to specific agricultural operations in a particular area. Conversely, the current study presents a critical review of emerging trends and applications of ground robots in three agricultural branches: horticultural produce, arable farming, and animal husbandry, with its focus on different imaging sensors and navigation aspects (localization, mapping, vision-based navigation, path planning, obstacle avoidance, and autonomous navigation). Furthermore, real-world applications of agricultural robots are also presented as case studies. The contributions of this study are significant in the following aspects:

i. Evaluating imaging sensors and navigation strategies as essential components and technologies for ground robots.

ii. Discussing recent trends adopted to boost robotic performance and agricultural productivity.

iii. Explaining diverse current applications of ground robots in arable farming, horticulture, and animal husbandry.

iv. Presenting three case studies from Ireland.

v. Exploring some challenges for deploying agricultural robots.

The manuscript encompasses many sections. Section 2 delves into key components and technologies crucial for agricultural robots. Section 3 sheds light on cutting-edge trends adopted to revolutionize the potential of agricultural robots. Section 4 presents current implementations of ground robots in the agriculture subfields. Section 5 elaborates on multiple case studies. Section 6 explores the limitations of deploying agricultural robots, whereas Section 7 concludes the paper. Fig.1 presents an overview of this study.

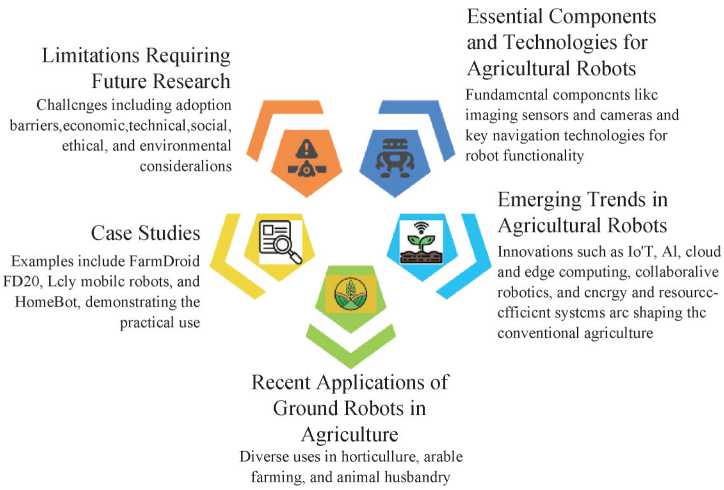

Fig.1 Paper overview

2 Essential Components and Technologies for Agricultural Robots

Unstructured and complex agricultural terrain varies from hilly areas to muddy fields. Therefore, robots require various components and technologies to secure performance effectiveness, precise navigation with outstanding adaptability, and obstacle avoidance ability[7]. The cited study reviews mobile platforms, control systems, mechanical actuators, and vision systems as rudimentary components of agricultural robots. Among these prerequisites, mobile platforms enable mobility, navigation, obstacle avoidance, detection, and task performance. Notably, mechanical actuators are essential for performing operations precisely, such as grippers for picking fruits, sprayers for spraying agrochemicals, etc. Besides these, imaging sensors and navigation technologies have received significant traction as integral components for their influence on agricultural production. A review of these fundamentals is given below,

2.1 Imaging Sensors and Cameras

Robots equipped with imaging sensors and cameras capture data, addressing the laborious and grueling data collection procedures in fields. The imaging sensors and cameras vary based on how they collect images, covering red, green, and blue (RGB), structured light cameras, and spectral and thermal imaging sensors. RGB is an extensively used color imaging sensor for capturing geometrical, texture, or other parametric characteristics in two-dimensional (2D) images[11]. Another camera for detecting structural characteristics of plants, such as volume, size, or height, is a structured light camera. This camera projects infrared (IR) patterns and analyzes the running pattern distortion. Similarly, red-green-blue-depth (RGB-D) sensors capture depth information with color data for creating three-dimensional (3D) vision. The key issue appears when such cameras are deployed under changing ambient lighting, but can be resolved using image processing techniques[12]. However, in certain electromagnetic spectrum bands, radiation reflectance and absorption are affected by or related to physiological parameters covering water stress, nitrogen, or chlorophyll levels. In such cases, spectral imaging cameras, multispectral or hyperspectral, are employed to monitor nutrient levels or stress conditions[13]. Multispectral cameras use a few broad visible near-infrared (NIR) spectral bands (not always continuous), whereas hyperspectral cameras exploit continuous spectral bands for assessing reflectance. Other than the visible spectrum, thermal imagining sensors use temperature as a valuable indicator for diagnosing plant stress, detecting water deficiency, or identifying fruits.

In recent years, imaging sensors and cameras have been extensively reviewed and studied in simulated field and greenhouse environments. Ref. [14] comprehensively reviews IR implications in agriculture and concludes greenhouse solutions obtained using structured-light cameras maximize yields and agricultural well-being. Ref. [15] proposes a novel RGB-D stereo camera, Intel RealSense camera D435i, for collecting depth information and visual perception of strawberries in the simulated field environment, achieving accurate ripened strawberry localization and facilitating the grasping process.

A broader literature body has conducted experiments in real-world fields. Researchers commonly exploit RGB-D cameras for automatic harvesting tasks such as determining the form and color of fruits or vegetables. Ref. [16] mounted a Kinect 2.0 to capture RGB color and re-encoded depth data in wheat fields. The mentioned study captured images in a cloudy environment to avoid degradation caused by bright sunlight and suggested a semantic segmentation technique for improving analysis. Conversely, Ref. [3] exploits multispectral and RGB cameras with three soil multi-depth probes on the wheat and maize field that collect information about soil and crop development monitoring and equips two Wifi high-definition cameras on a robot to identify weed treatment effects and real-time traffic volume. Contrarily, Ref. [17] embraces a low-cost, easy-to-use thermal sensor, AMG8833, for identifying water leakage in a drip irrigation system in undersized or no vegetation fields. The only drawback of the embedded thermal sensor is its low pixel value, 8 x 8, and 60° reading angle, which is crucial to consider while selecting the view distance. Fig.2 highlights imaging sensors, cameras, and navigation technologies employed in [1], [16-20].

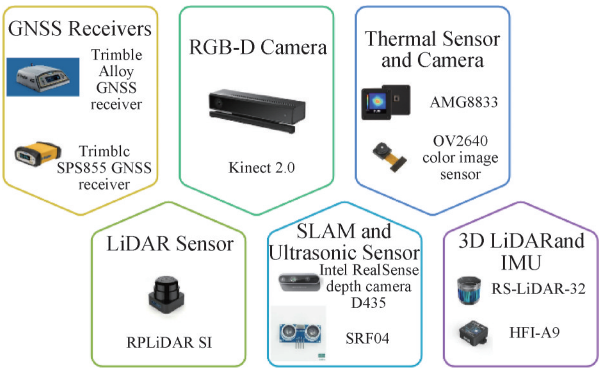

Fig.2 Navigation technologies, imaging sensors, and cameras

2.2 Navigation Technologies

Navigation is a prerequisite capability of robots in agricultural environments. Robots acquire surrounding data from sensors for creating an environmental map, estimating their position and orientation for localization, planning paths, avoiding obstacles, and moving autonomously to accomplish their goal[21]. The cited work indicates that sensors, software, algorithms, and their comprehensive and interdisciplinary integration have broad application potential in perceiving the environment accurately and making informed decisions, ultimately facilitating autonomous navigation and executing tasks with fewer human interventions.

Robots integrate various exteroceptive sensors such as Light Detection and Ranging (LiDAR), Radio Detection and Ranging (Radar), and ultrasonic sensors for collecting information concerning their surroundings, enabling effective navigation decisions. Besides, the global navigation satellite system (GNSS) provides a precise location of up to 2 cm using current satellite signals, for instance, the global positioning system (GPS), Galileo, global orbiting navigation satellite system (GLONASS), and BeiDou[22]. The prime advantage of using GNSS localization is its simple implementation and high accuracy. Furthermore, the exteroceptive sensors and localization systems are synergized, enabling robots to locate themselves in a field area and build a map at the moment without prior knowledge. However, Ref. [18] argues that LiDAR implementation leads to accumulated odometry errors due to prolonged travel and track slipping, while GNSS signals face obstructions in dense cover environments of orchards. To address this concern, the referred study exploits ultra-wideband (UWB) positioning for high-precision positioning information with real-time capabilities, then fuses it with LiDAR and odometry for improving positioning and navigation accuracy with corrected cumulative positioning errors in a kiwifruit orchard.

The faint signals and multiple factors of unstructured agricultural environments obstruct the indispensable preconditions of navigation. A crucial method of enabling robots to map such environments and locate themselves within that map simultaneously is simultaneous localization and mapping (SLAM). However, the repetitive structures (similar tree sizes) and standard planting intervals in large commercial orchards may confuse laser SLAM, as it does not accurately recognize the robot's current position. Thus, multi-sensor fusion technology can be applied by merging data from LiDAR, inertial measurement unit (IMU), and camera, effectively improving a robot's positioning accuracy and tree mapping precision. Ref. [20] focuses on multi-sensor fusion and suggests a 3D LiDAR SLAM for autonomous navigation in a peach orchard. Initially, the robot obtains environmental data using multi-line LiDAR, and then merges IMU data and robot encoder for constructing a 3D point cloud map of a peach orchard, then converts it into a 2D grid map, and incorporates iterative closest point (ICP) with normal distribution transform (NDT) for refining the mapping accuracy. Experimental trials ensure the accomplishment of mapping trajectory with positioning and navigation accuracies, meeting autonomous operational requirements. Similarly, Ref. [23] deploys a robot with 32-line LiDAR, an IMU, and a binocular camera for multi-sensor fusion SLAM in pear and persimmon orchards. The cited study localizes individual fruit trees using the SLAM approach, registers their point clouds to a global map, and globally optimizes previously detected tree positions. Monocular cameras and LiDAR fusion odometry improve odometry accuracy. The overall system provides stable, high-precision, and accurate localization for fruit trees and robots, enhancing the robot's capabilities. Owing to fallen branches and variable lighting conditions, positioning accuracy in a pear orchard is higher than in a persimmon orchard.

Another pitfall of SLAM technology is drift rectification, which improves mapping accuracy. Therefore, mapping unknown environments using visual SLAM is advantageous with a loop closure detection algorithm. Ref.[24] proposes a stereo-visual SLAM system comprised of image enhancing, feature tracking, mapping, and placing the complete process in a loop closure. If tracking a robot fails or any mapped scene is relocalized, the loop closure detection algorithm recognizes a loop based on whether the sensor-equipped robot has visited the recent scene or not. Finally, the distributed drift is adjusted while fusing both loop sides, optimizing the overall map. Testing results show the suggested system is superior in tracking the complete trajectory in challenging agricultural environments (e. g., soybean fields, macadamia orchards). Notably, vision-based navigation is intensively studied due to rich visual information and the low hardware cost of imaging sensors and cameras. Imaging sensors and cameras are promising tools enabling visual navigation in complex environments, facilitating accurate navigation with real-time adaptations. Ref. [8] conducted a review on visual navigation and highlighted the affordability and significant impacts of 2D and 3D vision sensors but asserted that these sensors are sensitive to illumination and rapid changes in viewing angle, necessitating image analysis procedures, including filtering, segmentation, and line-detection-based data computation.

The other crucial navigation element is path planning. Robots are fitted with various algorithms for determining an optimal path to their destination while considering environmental constraints. Ref. [11] categorizes path planning approaches into classical methods and learning-based techniques. The cited work identifies classical methods, such as Dijkstra, A*, etc., appropriate for navigating static environments and learning-based mechanisms, such as reinforcement learning (RL) techniques, suitable for unstructured or dynamic environments. Furthermore, their combination boosts robustness and safety, enabling autonomous navigation. Recently, a broader research body focused on safety maneuvers for avoiding obstacles and transitioning to a state other than the intended one, triggering replanning. Ref. [25] considers human-in-the-loop, uses LiDAR capabilities with landmark-based SLAM for localization and model predictive control (MPC) for navigation, and emphasizes online replanning. The proposed motion planner conducts the replanning of robots to identify obstacles (humans) and then replans the robots to new trajectories. Similarly, Ref. [26] also centralizes online replanning to avoid any identified conflict and task satisfaction with safety. In addition, autonomous navigation of mobile robots is a challenging task, predominantly on bigger farms. Researchers have addressed this issue by implementing various intelligent control algorithms and sensor technologies. Ref. [19] implements a fuzzy controller for row trajectory tracking, an ultrasonic sensor SRF04 for obstacle avoidance, and an Intel RealSense depth camera D435 for SLAM tasks in a greenhouse, resulting in efficient coverage with minimal plant disruption. Table 2 presents an overview of the above-analyzed technologies for different navigation fundamentals.

Table 2 Overview of analyzed technologies for robot navigation in different agricultural environments

Reference	Navigation Technologies	Environment	Opportunities
Ref. [11]	Classical and learning-based methods for path planning	Static and dynamic	Boosts robustness and safety in autonomous navigation
Ref. [18]	UWB- LiDAR-odometry (fused with EKF) for positioning	Kiwifruit orchard	Exhibits promising performance against standalone methods
Ref. [19]	Fuzzy controller for trajectory tracking, an ultrasonic sensor for obstacle avoidance, and a depth camera for SLAM tasks	Tomato greenhouse	Enables efficient coverage of all rows with the least plant disruption, driving autonomous navigation
Ref. [20]	3D LiDAR SLAM and multi-sensor devices for navigation and a multi-threaded cooperative algorithm for obstacle avoidance	Peach orchard	Achieves sufficient accuracy meeting autonomous operational prerequisites
Ref. [21]	Sensors for localization, mapping, SLAM, and obstacle detection and algorithms for waypoint following, sensor fusion, path planning, and collision avoidance	Fields and orchards	Ensures a safe and reliable navigation
Ref. [22]	Visual odometry-GNSS for precise positioning	Arable field	Low-cost visual odometry refines the reliability and accuracy of GNSS readings, yielding affordable solutions for accurate localization
Ref. [26]	Case 1: Sampling-based algorithm for local trajectory generation Case 2: MPC for obstacle avoidance	Dynamic	Online replanning resolves conflicts and handles collisions

All the reviewed sensors are critically compared in Table 3 based on accuracy, cost, and environmental suitability, along with their limitations.

3 Emerging Trends in Agricultural Robots

Robots are evolving explosively with the incorporation of emerging technologies. Advances in agricultural robots make significant impacts on farming practices. Moreover, new approaches are integrated with robots to facilitate more user-friendly and environment-friendly interactions in agriculture.

3.1 IoT-based Connected Decision-making and AI-empowered Processing and Analytics

Internet of Things (IoT) refers to a network of things embedded with software, sensors, and other technologies,

Table 3 Comparative analysis of various analyzed sensors

Sensor	Accuracy	Cost	Suitable Environment with Limitation
RGB	Highly accurate in color (depends on resolution)	Low	Open fields, indoor farms, greenhouses, and vertical farming but sensitive to low-light or extreme conditions
RGB-D	Highly accurate in color and depth data	Low	Open fields especially for indoor use, greenhouses, and vertical farming but depth accuracy depends on the operating environment and sensor type.
Multispectral	Moderate	Low-medium	Outdoor fields, indoor vertical farms, and greenhouses, but may be affected by weather
Hyperspectral	High accuracy (detailed spectral data)	Very high	Versatile for diverse environments but sensitive to platform vibrations and requires stable conditions
Thermal	Moderate to high (depends on resolution)	Fair	Well-suited for controlled environments (indoor farms and greenhouses) and low-light and night conditions but can be used in fields with limited settings.
LiDAR	Very high (mm and cm-level precision)	High	Large open fields, orchards, vineyards, indoor farms, and greenhouses but may be sensitive to weather and reflective surface
RADAR	Medium (meter-level)	Medium	Large open fields, orchards, vineyards, indoor farms, and greenhouses are robust to weather conditions
Ultrasonic	Low	Low	Large open fields, indoor farms, and greenhouses but have a limited range and may be affected by surface material

connecting and enabling data exchange over the Internet. In an IoT architecture, the physical layer collects data using sensors (carbon dioxide, humidity, soil moisture, temperature, and light sensors), actuators, and microcontrollers. The network layer transmits data through various communication protocols (5G, LoRa, ZigBee, Bluetooth, and Wi-Fi), the service layer processes data utilizing different computing services, whereas the application layer monitors and controls data[27]. Incorporating robot controllers into the Internet undertakes demanding tasks, transforming robotic capabilities and exploiting autonomous services in cropland. Ref.[28] shows that integrating IoT offers crucial details of parameters—humidity, ambient temperature, soil moisture level, and power usage—and assists a robot in applying accurate and consistent chemicals, enhancing decision-making and catalyzing wage expense reductions. Thus, IoT enables more intelligent and connected working, ultimately converting the robotic paradigm to the Internet of Robotic Things (IoT) and creating smart farming ecosystems for connected decision-making and holistic farm management.

AI techniques and tools empower robots to obtain human-like intelligence, covering perception, learning, and reasoning skills for thinking and processing problems with efficiency. Robots with onboard AI processors optimize sensor fusion capabilities, process image data, and extract data patterns, delivering onsite insights, analytics, and predictions. Convolutional neural network (CNN) implementations have observed a surge in recent years. Ref. [29] proposes two ResNet50 architectures for extracting visual features from tomato crop images, then merges both architectures using a 2D convolutional layer and passes through a faster region-based convolutional neural network (faster R-CNN) to detect lesions of pest or disease, improving detection rates. Ref. [9] analyzes trends in synergizing AI techniques with robotic applications for solving agricultural problems and realizes fuzzy logic is extensively employed for path planning and cultivation, followed by the genetic algorithm and artificial neural network (ANN). ANN is predominantly favored for the harvesting and monitoring phases. Evidently, AI has been extensively considered a viable solution for converting traditional agriculture into a smart one.

3.2 Digital Twin Simulation and Quantum Technology-magnified Capabilities

Digital twin (DT) is a digital replica of any agricultural system or robot functionalities in real time. DT simulation predicts a robot's performance and operation consequences, enabling efficient path optimization, proactive maintenance, and task execution in complex environments. Furthermore, DT has gained significant traction for monitoring and simulating real-time agricultural practices. For instance, Ref.[15] develops a simulated DT greenhouse environment for testing a mobile autonomous robot with a telescopic arm interacting with crops and the environment, enabling a realistic model and optimizing the robot's performance with no crop damage.

Quantum technology includes quantum communication, computing, and sensors, revolutionizing the computational power of agricultural systems and enabling precise navigation. Quantum algorithms analyze enormous data generated by robots exponentially faster, detecting diseases and pests and coordinating flocking or swarming robots. Ref. [30] integrates quantum computing with robotics and AI technologies for designing advanced self-driving systems. Quantum algorithms process enormous amounts of agricultural data rapidly, making operations more efficient. Manifestly, incorporating DT frameworks and quantum-enhanced data analytics improves robots' efficiency, adaptability, and intelligence in crop yield.

3.3 Cloud and Edge-driven Data Computing

Transitioning to cloud or edge nodes from central computations handles enormous data sets in agricultural robot-based applications. Ref. [3] reveals the benefits of cloud-autonomous robot communication, including safe data storage, easy access, and sharing, no risk of data loss, scalability, and analytics services with AI tools for decision-making. However, the cloud requires initial investments that are recovered instantly but enhance accessibility. Ref. [31] proposes the cloud as a central repository for collecting sensor data through a fixed-based unit and processing it using machine learning (ML) algorithms. The user can easily access and monitor the cloud data via mobile or web browser, benefiting fish farmers greatly.

Latency constraints are vulnerable in unreliable and sparse networks between cloud servers and sensor nodes, which may limit the opportunities. Edge computing is an alternative solution that also accelerates the computing efficiency of any model. Ref. [32] proposes hierarchical federated learning for collaborative learning among edge devices. The suggested architecture involves edge-cloud to embark partial analysis in proximity to sensing devices, providing surplus benefits of deploying ML closer to where data is captured and yielding initial analytics at lower latency and computational cost. Seemingly, cloud computing is suitable for advanced data processing. Conversely, edge devices network processes real-time data, meeting the resource-intensive issues of agriculture operations and accelerating the decision-making of robots.

3.4 Collaborative Robotics

IoRT provides sensing-as-a-service solutions, furnishing optimization, and collaboration with other robots to form swarms and multi-agent systems. Ref. [33]] presents collaborative robots (cobots) as skilled workers for specific viticultural operations, for example, pruning, weed controlling, herbicide use, and topping, and analyzes their economic performance against four conventional cultivars. Findings reveal the efficiency and precision of cobots in viticulture reduce annual equivalent costs by up to 11.53%. Nevertheless, cobots show inefficiency in the defoliation and tying practices.

Web applications and advanced sensors enable intuitive and safe human-robot interactions, performing scalable agricultural operations. Ref. [34] leverages a FarmBot, a precision agriculture robot, with a multi-camera system and garden tools to facilitate citizen engagement in urban gardening using PlantPal, a web application. Results signify that PlantPal allows FarmBot-assisted seeding, weeding, and watering operations, facilitates gardening into daily routine, allows citizens to cultivate diverse crops, and furnishes an engaging experience irrespective of time and user's location and expertise level. Apparently, collaborative robotics exemplifies the groundbreaking potential in proffering agricultural processes.

3.5 Energy and Resource-efficient Systems for Sustainable Robotic Operations

Sustainability is an innovative concept that requires multidisciplinary and holistic approaches for optimizing resources and innovating renewable energy systems, diminishing environmental impacts. In contrast to conventional agricultural operations, sustainable practices integrate advanced solutions, technologies, and eco-friendly approaches. Ref. [28] promotes water pumps founded on real-time moisture levels for water conservation, solar energy using photovoltaic and battery energy storage systems for self-sufficient renewable, clean energy, and IoT-connected robotic applications for resource usage optimization, reducing ecological footprint and increasing efficiency. Ref. [35] proposes a multifunctional agricultural robot with solar power for cotton plants that is substantiated as cost-effective, increases productivity by 30%, and mitigates ecological footprints.

Agriculture robots are a multifaceted management strategy that reduces agrochemical usage and operating costs, ensuring a balance of environmental and economic requirements. Ref. [32] suggests a NIR-hyperspectral imaging system for guiding the pesticide spraying operation of a mobile robot and CNN for image classification, ensuring the least impact on crops. Ref. [32] further demonstrates that enhancing the sensor system's intelligence supports real-time decision-making, reduces carbon emissions, and attains sustainable development goal (SDG) 13. Ref. [33] implements a lifecycle costing approach and analyzes autonomous cobots' performance with conventional workers to lessen operational expenditures. Autonomous cobots outperform in four specific viticultural operations but are inefficient in tying and defoliation practices. Furthermore, cobots reduce salary, energy, and production costs while enhancing efficiency, precision, and competitiveness and address employment shortages, ultimately achieving sustainable development objectives. Apparently, sustainability has become a research hotspot towards more efficient, resilient, and modern agriculture.

In conjunction with AI, IoT, edge and cloud computing, collaborative methodologies, and sustainable systems, robots are revolutionizing the agricultural domain, offering new prospects in automation and innovation.

4 Recent Applications of Ground Robots in Agriculture

Ground robots are of significant value in enhancing management, facilitating production, and saving salary expenses in contemporary agriculture. This section focuses on robot applications in three crucial agricultural branches and demonstrates their effectiveness under separate headings of horticultural production, arable farming, and animal husbandry practices.

4.1 Horticultural Production

Horticulture is a vital agricultural branch that cultivates varied crops, including trees, shrubs, herbs, fruits, vegetables, flowers, and ornamental plants for food, decoration, and medicine[36]. The horticulture crops are cultivated in various gardens, vertical farming, greenhouses, nurseries, and recreational areas. Robots outfitted with sensors and algorithms manage delicate characteristics of horticulture produce with robustness and offer precision in various tasks, including spraying, pruning, harvesting, etc. Treating unwell plants separately and detecting cutting points are crucial for crop protection in greenhouses. In this context, Ref. [37] develops an advanced horticulture robot with embedded ultrasonic sensors and a dynamic camera to detect obstacles, ensuring seamless operations and capturing images. The mentioned study highlights the effectiveness of implementing image processing techniques and ML algorithms, specifically the single shot multibox detector (SSD) combined with MobileNet architecture (SSD-MobileNet) for identifying pests, fungal and bacterial infections, virus threats, and nutritional deficiencies. After detection, the robot dispenses exact treatment and optimizes nutrients in various plants, supporting greenhouse agriculture. Ref. [38] suggests a robot with multiple functions, encompassing harvesting strawberries and truss pruning in a greenhouse. The cited study performs semantic segmentation through the DL model, DeepLabV3+ , and post-processing for removing false recognitions and then identifies cutting points of strawberries efficiently for both operations.

Other horticulture practices are vertical farming and nursery farming. Growing plants vertically in columns and controlled environments allows manual operations, incurring more costs and employment. Furthermore, space limitations also cause bottlenecks in automating vertical farming operations. Ref. [39] presents cobots for automating transplantation and harvesting operations in containerized vertical farming. Experimental results signify the feasibility of deploying a cobot and RGBD imagery for transplanting saplings and harvesting leafy greens, requiring no task-specific programming. Moreover, ornamental nursery farming also faces challenges due to augmented agricultural input costs. Ref. [40] reviews recent sensing and automation technologies applied for various operations, from planting to harvesting for ornamental crops. This review highlights the potential prospects of using robots, sensors, AI, IoT, computer vision, and ML techniques, and identifies the critical need to understand the plant type and its production requirements. This analysis emphasizes that integrating robots and AI with advanced sensing technologies reduces workers' requirements and input costs, as well as ensures efficient management operations for sustainable ornamental crop production.

Another horticulture practice is home gardening, requiring remote monitoring and management. With improvement in living standards, emphasis on aesthetics and innovation has been boosted. Ref.[41] presents an IoT-integrated home garden robot with 3-D feature extraction. The home garden robot lowers the design threshold and efficiently manages various tasks, from growth analysis to cultivation, improving the garden quality and beautification. To increase home gardening productivity, Ref. [42] integrates the NN model for analyzing robotic assistance, plant development, and cloud-connected plant care. NN runs real-time data, and the deployed robot automates watering, pest management, and fertilizing activities. Whereas the cloud allows remote management of gardens to owners, providing superior smart home gardening.

4.2 Arable Farming

Arable farming involves cultivating agricultural land tracts for large-scale crops[43]. Arable farming involves plowing, planting, nurturing, rotating, irrigating, and harvesting oilseeds, cereals, fiber crops, and root vegetables. Various unpredictable factors influence the mechanical sowing process of root crops, declining yield and quality. Ref. [44] designs a specialized PotatoBot for planting potatoes with limited resources. PotatoBot implements principal component analysis (PCA) and Mask R-CNN for potato pose localization. Results demonstrate the system's cost-effectiveness, specifically in a market with restricted profit margins. Another crucial factor during seeding is to consider different plant populations that necessitate variable input rates, as most agricultural soils are highly heterogeneous. In this regard, robot-driven site-specific operations allow crops to grow optimally over varied field zones. Ref.[45] designs a field robot equipped with a precision seeder and nitrogen fertilizer sprayer for performing site-specific operations in a Belgium maize field. Following recommendations based on online calculated multi-layer soil information, the field robot seeds densely in plentiful fertile management zones and then sprays varied nitrogen rates, improving grain yield and increasing gross margin.

Other arable farming practices include weeding, tillage, and irrigation. Agricultural robots perform tillage and smart crop rotation, preventing plants from weeds, pests, and disease. Ref. [46] proposes an RTK-GNSS-supported mobile electric robot for weeding and tilling operations in olive orchards and vineyard inter-rows. Substantial results demonstrate that RTK-GNSS gives precise autonomous navigation, and the electric motor reduces greenhouse gas emissions. The robot upgrades seedbed conditions, breaks down clod size, and augments weed-cutting efficiency by up to 36.81%. Ref.[47] build a fully solar-powered robot that uses an ultrasonic sensor for navigation and Bluetooth or Android app signals for movement and operating various mechanisms. The developed robot tills the entire field. Subsequently, the robot plows and distributes seeds, boosting sowing effectiveness. Furthermore, Robot-based irrigation systems monitor moisture levels, evaluate water requirements, and dispense water using drip irrigation or sprinkler systems. Ref.[48] designed an automatic planting-irrigating robot with machine vision and DL algorithms. The algorithms process images and identify suitable areas for accurate tree planting. The drip irrigation module perceives effective watering operations, ensuring sapling growth.

Estimating a robot's economic and environmental performance during agricultural operations is crucial for operational cost-cutting and well-informed decisions, empowering farmers. Ref. [49] assesses the financial viability, operational aspect, and environmental impacts of deploying a robot with real-time kinematic (RTK) - GPS-based precise navigation against a tractor for seeding and weeding. Findings reveal that the conventional machinery system possesses more field capacity. Nevertheless, the robot outperforms with an increase of 9% in operational efficiency and a decrease of 57% in cost per hour, 63.3% in fuel consumption, and 39.8% in carbon dioxide emissions, causing fewer effects on soil structure and environment.

4.3 Animal Husbandry Practices

Animal husbandry, another significant agricultural branch, focuses on livestock handling, health management, and breeding and includes practices to improve the quality and productivity of animals[7]. Poultry farming, cattle farming, dairy farming, aquaculture, and apiculture fall under the more comprehensive umbrella of animal husbandry. Ground robots are materializing as promising tools for livestock farming. Livestock farming faces life-threatening challenges due to the weeds in open pasture fields and excessive herbicide usage. Ref.[50] draws traction towards Rumex weeding, which may induce oxalate poisoning in livestock from grass fields. In this regard, the cited study furnishes a lightweight mobile robot with a GNSS receiver and IMU sensor, a robotic arm with a weeding tool, and an Intel RealSense D415 3D camera. The RTK/GNSS enables navigation and accurately locates weeds. On the other hand, the 3D camera captures 2D and 3D images, machine vision analyzes images and detects weeds, and the robotic arm efficiently removes weed saplings, illustrating the feasibility of robotic weeding.

Manure scrapers spread manure piles over larger areas, significantly increasing ammonia emissions. Conversely, floor cleaning and manure-removing robots disinfect farms and remove manure in a targeted manner, improving housing conditions. Ref. [51] outlines recent advancements in robotics in poultry farming. The cited review demonstrates that robots reduce human-animal interactions, minimize human-induced disease risks, gather dead birds and eggs, facilitate production, enhance biosecurity by regular disinfection and cleaning, and interact with chicks, supporting their social behavior. However, robot-animal collisions may occur owing to programmed fixed routes. Considering cow-robot encounters, Ref.[52] suggests dynamic path planning using grid-based RL for a manure-cleaning robot, designs heatmap models for locating cows and identifying defecation behaviors, and finally incorporates the obtained information into path planning in a barn-simulated environment. The developed strategy-followed manure robot cleans more efficiently with reduced cow-robot collisions.

Other significant factors improved using ground robots are a more oriented feed supply and enhanced productivity. In cattle farms, stationary equipment supplies feed. To improve the feed supply efficiency, Ref. [53] develops a robot equipped with a total mixed ration for refining efficiency and productivity, LiDAR and camera for recognizing the cowshed environment, and radio-frequency identification (RFID) for enabling users to determine the robot's current location and supply various types of feed. Moreover, traditional aquaculture methods cause fatiguing work, as well as illness and sudden fish death. Ref.[31] designs AquaBot, an IoT-based monitoring system for automatically evaluating pond water quality, proposes a solar-powered mobile robot for collecting parametric values, and integrates cloud-based monitoring and a custom ensemble model, an ML algorithm, to analyze data. The mentioned study reveals significant advantages of the developed system in terms of enhanced productivity, reduced costs, low degree exertion, and a healthy aquatic environment, increasing fish farmer profitability and farming sustainability. Table 4 presents an analysis of robot applications in horticulture, arable farming, and animal husbandry, revealing significant opportunities for precision, smart, and sustainable agriculture. Fig 3. exhibits various robots executing horticultural[39], arable farming[46], and animal husbandry practices[31].

Hence, ground robots play a central role in cultivating crops and raising animals, ultimately securing food and farmers' livelihoods.

Table 4 Analysis of deploying robots with sensors, technologies, and algorithms in horticulture, arable farming, and animal husbandry

Reference	Robot with technologies	Farming Operation	Agricultural Environment	Outcomes
Ref. [31]	Mobile robot, AquaBot (IoT system), and a custom ensemble model	Monitoring water quality and recommending appropriate fish	Pond	Enhances productivity, reduces costs and lowers efforts, creates a healthy aquatic environment, boosting fish farmers' profitability and farming sustainability
Ref. [37]	Advanced horticulture robot with ultrasonic sensors and a dynamic camera	Health management	Horticulture greenhouse	Detects obstacles, identifies diseased plants, applies exact treatment protocols, and optimizes nutrients, limiting environmental impacts and optimizing resource usage
Ref. [38]	Multifunctional agricultural robot and DeepLabV3+	Harvesting and truss pruning	Strawberry greenhouse	Classifies images into appropriate classes to remove false recognitions and identify cutting points
Ref. [39]	Cobot with RGBD imagery	Sapling transplantation and grown plant harvesting	Containerized leafy greens vertical farming	Automates both tasks with an 83.8% success rate without any task-specific programming
Ref. [44]	PotatoBot with PCA and Mask R-CNN	Planting	Potato field	Develops a cost-effective robotic system, specifically for farming markets with packed profit margins
Ref. [46]	Mobile electric robot with RTK-GNSS	Weeding and tilling	Olive orchards and spontaneous vegetation vineyard	Allows autonomous navigation in the 2m inter-row, improves seedbed conditions and weed cutting efficiency, and reduces clod size and emissions
Ref. [49]	Robot with RTK-GPS	Seeding and weeding	Three different fields	Outperforms with increased operational efficiency and reduced cost, fuel consumption, and carbon dioxide emissions
Ref. [51]	Robots	Environmental monitoring for disease control, welfare, and floor egg collection	Poultry farm	Evaluates effective implementation, enhances productivity and welfare, and supports their social behavior
Ref. [53]	Robot with LiDAR, a camera, and RFID	Feeding	Cattle farm	Recognizes the cowshed environment, determines the robot's current location, and supplies various types of feed

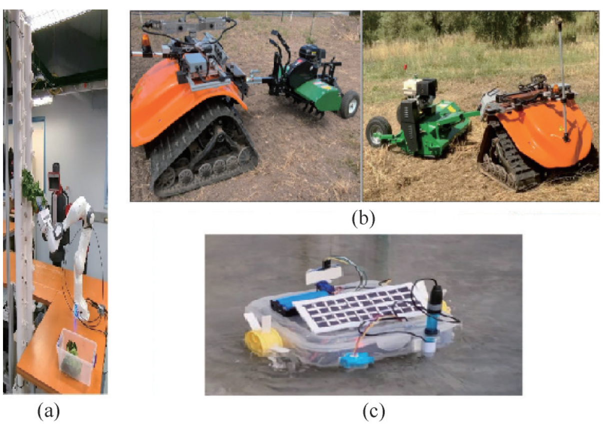

Fig.3 Robots executing various tasks (a) Cobot for harvesting leafy greens (b) Mobile electric tracked robot for weeding and tilling vineyard and olive orchard (c) Designed robotic prototype for monitoring pond water quality

5 Case Studies

Myriad of ground robotic solutions are available for agriculture applications. However, in Ireland's case, robots are not commonly exploited on every farm, but their efficiency and productivity are drawing traction. According to Ref.[54], the Irish Co-operative Organisation Society emphasizes the agri-food sector for synergizing robotics, AI, and IoT technologies, transitioning people's skills towards a super-intelligent society in the LeadFarm 5.0 project final conference. This section explores three real-world examples of deploying robots in Ireland farms.

5.1 FarmDroid FD20: Seed-and-weed Robot

Automation in agricultural operations is crucial for enhancing yield and protecting crops. However, sowing seeds with proper gaps and weeding are challenging for robots. FarmDroid FD20, a fully automatic Danish-manufactured robot, has exhibited superior performance for seeding and weeding beet crops in trials conducted in Co. Kilkenny and displays at the National Ploughing Championships[55]. FarmDroid FD20 uses RTK GPS and sensors for seeding plants with 8mm accuracy and subsequently performing intra-row and inter-row weed control, driving precision[56]. The unprecedented precision weeding eradicates manual weeding requirements, reduces chemical usage, and enhances yield. However, during its testing on the Urlingford-neared mixed farm, some inter-plant gaps were not weed-free due to the flush of weeds[57].

Nevertheless, FarmDroid was engaged in clearing them out. The robot is designed with a lighter weight to cause minimal soil compactness. The FarmDroid FD20 is also fitted with four solar panels to ensure twenty-four hours of continuous operations and reduce costs and carbon dioxide emissions, resulting in efficiency and sustainability in Irish arable farming.

5.2 Lely Mobile Robots: Feeding and Manure Robots

Feeding strategies and cleaning solutions have significant impacts on dairy farming. However, robot-driven feeding and manure solutions automate the barns but may disturb animals. Addressing this issue, Lely, an Irish company, has designed Vector as an automatic feeder, Juno as an automatic feed pusher, and Discovery collector and Discovery scraper as manure robots for dairy farms. Vector and Juno are embedded with advanced software to allow precise stacking of accurate feed weight. These automatic solutions provide frequent feeding for stabilizing the pH level, loading, mixing, and supplying customized feed batches, thus saving labor hours and significantly satisfying cow health, production, fertility, labor, and finances. A new version, Vector MFR, embraces electrical technology for more energy-efficient working, causing less carbon dioxide footprint[58]. On the other hand, the Discovery Collector and Discovery Scraper are equipped with sensors for autonomous navigation. These cleaning solutions ensure consistent and complete manure removal, resulting in cleaner udders, reducing infections and time-consuming, repetitive labor while creating a comfortable environment. A new edition, Juno Max, utilizes a LiDAR laser scanner, virtual farm map, and odometry to navigate autonomously and plan paths optimally while avoiding obstacles[59]. Juno Max contributes to more animal feed intake, better health, and production, thus pertinent for larger farms. All these mobile autonomous robots are managed using Zeta, an AI solution[60]. Zeta uses a camera with LED lighting to capture images. The images undergo AI-based object detection, recognizing mobile robots and cows, as well as their behaviors and locations. Zeta coordinates the robots with their cows' locations, enabling efficient working. Moreover, the collected data is displayed in an app that provides feed-related details and robot locations, fostering efficient farm management. The advisors provide data-driven insights, guidance, and assistance using this app to optimize farming.

5.3 HomeBot: Robot Garden Mower

Mowing is integral to enriching lawn health and protecting against pests and weather. Robots mow the lawn in less time with no sweat. Nonetheless, they may face challenges navigating near ornaments, ponds, and flowerbeds or get blade damage in split-over areas. Identifying this problem, HomeBot, a West Cork-based company, offers Buddy as an AI robotic mower and Chomper as a perimeter-wired robotic mower for manicuring gardens in no time and requiring less maintenance[61]. Chomper uses perimeter boundary wires to set up no-go areas and comprehensively covers immense uninhabited gardens, yielding long-term accuracy[62]. Conversely, Buddy is designed with smart AI features, a camera, and crash sensors, enabling precision navigation around moving and static obstacles, especially in smaller, complicated areas. Both robots mow grass evenly, fertilize gardens using tiny clippings, and return to the charging station automatically. Additionally, in-built rain sensors in both mowers enable them to return to their home base in case of rain, protecting them from damage.

6 Limitations Requiring Future Research

Conventional agriculture is experiencing a transformative phase, marked by a confluence of ground robots integrated with imaging sensors and navigation technologies. This overview underscores several key challenges surrounding economic concerns, technical pitfalls, and social and ethical factors.

Maintenance and fabrication cost considerations for robots are a significant economic concern[7]. Another economic cost consideration is the return on investment (ROI) [63]. ROI cycles vary based on farming scales. Small-scale farms require smaller early investment, harvest faster-growing crops, and offer high-value livestock that can be sold within a shorter period, fetching higher prices and quicker ROI. Conversely, large-scale farms have a more extensive operation scale, the capability of leveraging specialized robots, and cost-sharing opportunities, leading to shorter ROI. Estimation models such as a cost recovery period analysis can be utilized to determine the period in which profits will recover the initial investment. A cost recovery period involves initial farm development cost calculation and comparison with annual revenue. Ref. [64] analyzes the total cost of deploying spraying and harvesting robots on average-sized greenhouses. The purchase price of a robot is higher than that of handheld equipment. Therefore, enhancing production costs would not be feasible from an economic standpoint. Moreover, the evaluation portrays that spraying robots reduce total annual costs for larger surface greenhouses and suggests a robot-as-a-service paradigm through service companies or neighboring farmers.

Various technical pitfalls regarding infrastructure, robots, and sensors hinder their application. Poor infrastructure is a crucial challenge for digitalizing operations in horticulture production[36]. Additionally, restricted battery limits the tested robot autonomy[49], and single robot deployment in a supervised setting restricts the generalizability of deploying multiple robots in larger-scale urban farming to avoid human interaction, coordination, and maintenance issues[34]. Besides, modifications in robots and technologies for efficient and effective delivery, refinement of sensors for capturing data with increased accuracy and reliability are identified as essential technical pitfalls[10]. Simultaneously, capturing single plant images and unpacking and uploading larger image files exceed the time duration. Thus, cameras with optimally configured spectral bands and advanced deep architectures are essential in terms of practical implementations[29].

The potential social and ethical factors stemming from the prerequisite of human expertise to reckon with results and legal framework to assure their compatibility with autonomous systems and employees' safety need future research[36]. Regulations and policies must reflect a credible ethical arrangement of safety and responsibility for deploying farm robots. In this regard, the European Union (EU) safety certification encompasses safety validation and requirements regarding AI usage and human-robot interaction. EU regulation includes compliance with various industry standards, including compliance with farming safety essentials (EN ISO 25119 and EN ISO 12100) and functional safety requirements (IEC 61508) [65]. Hence, EU regulations must be adopted to ensure reliable and safe agricultural robot operations.

Furthermore, issues related to data privacy and ownership are identified as other potential barriers[66]. The routinely generated farm data is collected and stored in various IoT devices, necessitating attention to sensitive data access and control. Technology providers may use or disclose data to other parties, resulting in concerns about farmers' control, privacy, and usage of the generated data. Therefore, control and ownership should be vested in farmers.

These bottlenecks necessitate future research and comprehensive assessment for advancing the agricultural transformative domain, ensuring a precision level that satisfies the nuanced requirements of modern and sustainable farming practices.

7 Conclusion

Motivated by food security, labor scarcity and costs, and global sustainability issues, the ongoing study signifies the transformative impacts of ground robots on conventional agriculture, emphasizing the integration of advanced imaging sensors and navigation technologies. The intensified interest in ground robot research emerges as an imperative and strategic solution to the challenges in the agricultural field. This study is designed to present an overview and explore real-world examples of cutting-edge trends adopted for ground robots revolutionizing the agricultural domain. The drafted area of interest encompasses imaging sensors and navigation elements as integral components and technologies. Analysis of recent literature demonstrates emerging trends in agricultural robots, shedding light on how IoT-driven connected decision-making, AI-enabled processing and analytics, cloud and edge-enabled data computing and safe storage, collaborative robots, as well as energy and resource-efficient systems, evolve autonomous capabilities of robots and optimization of agricultural operations. Examination of current applications involving ground robots for arable farming, horticulture, and animal husbandry reveals robotic applications that automate farming operations from seeding to harvesting plants and feeding to disinfecting animals, improving productivity, quality, and sustainability in agriculture. Exploration of case studies presents insights into Irish farms adopting robots for seed sowing, weed identification and treatment, lawn mowing, animal feeding, and manuring tasks. Finally, adoption reluctance and technical, economic, social, ethical, and environmental concerns are underscored as challenges, necessitating navigation of these issues collectively for transforming the trajectory of smart and modern agriculture.

Insightful observation reveals that ground robots outperform conventional agricultural equipment and tools in terms of efficiency, decision-making, and adaptability. Using key metrics such as labor and time requirement, input (fertilizer or pesticide) usage, environmental impacts, yield, revenue, and economic costs, a quantitative comparison is presented between conventional and robot-enabled agriculture practices. Traditional agriculture leans heavily on human labor, resulting in time-consuming and labor-intensive procedures. Contrarily, robots automate practices and perform repetitive work without fatigue, reducing labor and time requirements. Additionally, classic equipment (manual or handheld) sprays more input resources (fertilizer or pesticide), whereas robots apply precise resources, optimizing resource consumption and minimizing the ecological impacts of pesticide application. Furthermore, traditional machinery (tractors) is powered by fossil fuels, generating more carbon dioxide emissions.

On the other hand, energy-efficient robots save more fuel during operation, mitigating emissions and promoting sustainability. Unlike conventional machinery, robots offer data-driven decision-making and operational efficiency, enhancing farm productivity and generating more revenue. Moreover, traditional practices entail high labor costs, whereas robots reduce human labor costs but exhibit more machinery costs. Summing up, the transformation from conventional agricultural procedures to robot-enabled operations is not simply a technological advancement but a transition toward more efficient, smart, and sustainable agriculture, delivering growing needs for food and environmental stewardship.

Potential areas for future research incorporate cooperative groups of ground and aerial robots, advanced AI models, and image processing techniques- aligning with sustainability goals. Moreover, digital twins could be explored to monitor and simulate real-time agricultural practices, and quantum technology could be analyzed to optimize robot coordination and planting patterns.

Data Availability:

The authors declare that the main data supporting the findings of this study are available within the paper and its Supplementary Information files.

Conflicts of Interest:

The authors declare no competing interests.

Dates:

Received 11 April 2025; Accepted 22 July 2025; Published online 30 September 2025

References

[1] *Ospina, R.* , & Noguchi, N. (**2025**). Real-time work progress estimation based on GIS remote monitoring system for agricultural robot vehicles. Computers and Electronics in Agriculture,234,110313. DOI: 10.1016/j.compag.**2025**.110313

[2] *Sharma, K.* , & Shivandu, S. K. (**2024**). Integrating artificial intelligence and Internet of things (IoT) for enhanced crop monitoring and management in precision agriculture. Sensors International, 100292. DOI: 10.1016/j.sintl.**2024**.100292

[3] Emmi L., Fernández R., Gonzalez-de-Santos P., Francia M., Golfarelli M., Vitali G., Sandmann H., Hustedt M., & Wollweber M. (**2023**). Exploiting the internet resources for autonomous robots in agriculture. *Agriculture* , 13(5), 1005. DOI: 10.3390/agriculture13051005

[4] *Gupta, N.* , & Gupta, P. K. (**2024**). Robotics and Artificial Intelligence (AI) in Agriculture with Major Emphasis on Food Crops. Digital Agriculture: A Solution for Sustainable Food and Nutritional Security, 577-605. DOI: 10.1007/978-3-031-43548-5_19

[5] *Hasan, M.* , & Muda, N. R. S. (**2024**). Design and Develop Autonomous 3 In 1 Agricultural Robots For Farming. IJNRSM Vol4 (5), 56-65. DOI: 10.13140/RG.2.2.30698.53444

[6] Fasiolo D. T., Scalera L., Maset E., & Gasparetto A. (**2023**). Towards autonomous mapping in agriculture: A review of supportive technologies for ground robotics. *Robotics and Autonomous Systems* , 169, 104514. DOI: 10.1016/j.robot.**2023**.104514

[7] Cheng C., Fu J., Su H., & Ren L. (**2023**). Recent advancements in agriculture robots: Benefits and challenges. *Machines* , 11(1), 48. DOI: 10.3390/machines11010048

[8] Bai Y., Zhang B., Xu N., Zhou J., Shi J., & Diao Z. (**2023**). Vision-based navigation and guidance for agricultural autonomous vehicles and robots: A review. *Computers and Electronics in Agriculture* , 205, 107584. DOI: 10.1016/j.compag.**2022**.107584

[9] Wakchaure M., Patle B. K., & Mahindrakar A. K. (**2023**). Application of AI techniques and robotics in agriculture: A review. *Artificial Intelligence in the Life Sciences* , 3, 100057. DOI: 10.1016/j.ailsci.**2023**.100057

[10] Lochan K., Khan A., Elsayed I., Suthar B., Seneviratne L., & Hussain I. (**2024**). Advancements in precision spraying of agricultural robots: A comprehensive Review. IEEE Access. DOI: 10.1109/ACCESS.**2024**.3450904

[11] Wijayathunga L., Rassau A., & Chai D. (**2023**). Challenges and solutions for autonomous ground robot scene understanding and navigation in unstructured outdoor environments: A review. *Applied Sciences* , 13(17), 9877. DOI: 10.3390/app13179877

[12] Wang D., Zhang B., Zhou J., Xiong Y., Liu L., & Tan Q. (**2024**). Three-dimensional mapping and immersive human – robot interfacing utilize Kinect - style depth cameras and virtual reality for agricultural mobile robots. *Journal of Field Robotics* , 41(7), 2413-2426. DOI: 10.1002/rob.22294

[13] Avgoustaki D. D., Avgoustakis I., Miralles C. C., Sohn J., & Xydis G. (**2022**). Autonomous mobile robot with attached multispectral camera to monitor the development of crops and detect nutrient and water deficiencies in vertical farms. *Agronomy* , 12(11), 2691. DOI: 10.3390/agronomy12112691

[14] *Aydin, G. D.* , & Ozer, S. (**2023**, September). Infrared detection technologies in smart agriculture: A review. In 2023 International Aegean Conference on Electrical Machines and Power Electronics (ACEMP) & 2023 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM) (pp. 1-8). IEEE. DOI: 10.1109/ACEMP-OPTIM57845.**2023**.10287033

[15] Singh R., Seneviratne L., & Hussain I. (**2024**). A Deep Learning-Based Approach to Strawberry Grasping using a Telescopic-Link Differential Drive Mobile Robot in ROS-Gazebo for Greenhouse Digital Twin Environments. IEEE Access. DOI: 10.1109/ACCESS.**2024**.3520233

[16] Song Y., Xu F., Yao Q., Liu J., & Yang S. (**2023**). Navigation algorithm based on semantic segmentation in wheat fields using an RGB-D camera. *Information Processing in Agriculture*, 10(4), 475-490. DOI: 10.1016/j.inpa.**2022**.05.002

[17] Türkler L., Akkan T., & Akkan L. Ö. (**2023**). Detection of Water Leakage in Drip Irrigation Systems Using Infrared Technique in Smart Agricultural Robots. *Sensors* , 23(22), 9244. DOI: 10.3390/s23229244

[18] Jia L., Wang Y., Ma L., He Z., Li Z., & Cui Y. (**2023**). Integrated positioning system of kiwifruit orchard mobile robot based on UWB/LiDAR/ODOM. *Sensors* , 23(17), 7570. DOI: 10.3390/s23177570

[19] Mac T. T., Nguyen T. D., Dang H. K., Nguyen D. T., & Nguyen X. T. (**2024**). Intelligent agricultural robotic detection system for greenhouse tomato leaf diseases using soft

computing techniques and deep learning. *Scientific Reports* , 14(1), 23887.DOI: 10.1038/s41598-024-75285-5

[20] Jiang S., Qi P., Han L., Liu L., Li Y., Huang Z., Liu Y., & He X. (**2024**). Navigation system for orchard spraying robot based on 3D LiDAR SLAM with NDT_ICP point cloud registration. *Computers and Electronics in Agriculture* , 220, 108870. DOI: 10.1016/j.compag.**2024**.108870

[21] *Shamshiri, R. R.* (**2025**). Sensors, algorithms, and software for autonomous navigation of agricultural mobile robots. In Mobile Robots for Digital Farming (pp. 1-54). CRC Press. DOI: 10.1201/9781003306283-1

[22] Nijak M., Skrzypczyński P., Ćwian K., Zawada M., Szymczyk S., & Wojciechowski J. (**2024**). On the importance of precise positioning in robotised agriculture. *Remote Sensing* , 16(6), 985. DOI: 10.3390/rs16060985

[23] Tang B., Guo Z., Huang C., Huai S., & Gai J. (**2024**). A fruit-tree mapping system for semi-structured orchards based on multi-sensor-fusion SLAM. IEEE. DOI: 10.1109/ACCESS.**2024**.3408467

[24] Islam R., Habibullah H., & Hossain T. (**2023**). AGRI-SLAM: a real-time stereo visual SLAM for agricultural environment. *Autonomous robots* , 47(6), 649-668. DOI: 10.1007/s10514-023-10110-y

[25] Deka S. A., Phodapol S., Gimenez A. M., Fernandez-Ayala V. N., Wong R., Yu P., Tan X., & Dimarogonas D. V. (**2024**, August). Enhancing precision agriculture through human-in-the-loop planning and control. In *2024 IEEE 20th International Conference on Automation Science and Engineering (CASE)* (pp. 78-83). IEEE. DOI: 10.1109/CASE59546.**2024**.10711319

[26] Yu P., Fedeli G., & Dimarogonas D. V. (**2023**, July). Reactive and human-in-the-loop planning and control of multi-robot systems under LTL specifications in dynamic environments. *In 2023 9th International Conference on Control* , Decision and Information Technologies (CoDIT) (pp. 1862-1867). IEEE. DOI: 10.1109/CoDIT58514.**2023**.10284378

[27] Prakash C., Singh L. P., Gupta A., & Lohan S. K. (**2023**). Advancements in smart farming: A comprehensive review of IoT, wireless communication, sensors, and hardware for agricultural automation. *Sensors and Actuators A: Physical* , **362**, 114605. DOI: 10.1016/j.sna.**2023**.114605

[28] Rehman A. U., Alamoudi Y., Khalid H. M., Morchid A., Muyeen S. M., & Abdelaziz A. Y. (**2024**). Smart agriculture technology: An integrated framework of renewable energy resources, IoT-based energy management, and precision robotics. *Cleaner Energy Systems* , 9, 100132. DOI: 10.1016/j.cles.**2024**.100132

[29] Kounalakis N., Kalykakis E., Kosmopoulos D., Fasoulas J., & Sfakiotakis M. (**2023**, April). A framework leveraging robotics and machine learning technologies for early disease and pest detection in greenhouse tomato crops. *In 2023 International Conference on Control* , Artificial Intelligence, Robotics & Optimization (ICCAIRO) (pp. 74-81). IEEE. DOI: 10.1109/ICCAIRO58903.**2023**.00019

[30] Khobragade P., Dhankar P. K., Titarmare A., Dhone M., Thakur S., & Saraf P. (**2024**, December). Quantum-Enhanced AI Robotics for Sustainable Agriculture: Pioneering Autonomous Systems in Precision Farming. In *2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA)* (pp.1-7).IEEE. DOI: 10.1109/ICAIQSA64000.**2024**.10882412

[31] Hemal M. M., Rahman A., Nurjahan, Islam F., Ahmed S., Kaiser M. S., & Ahmed M. R. (**2024**). An Integrated Smart Pond Water Quality Monitoring and Fish Farming Recommendation Aquabot System. *Sensors* , 24(11), 3682. DOI: 10.3390/s24113682

[32] Ooi M. P. L., Sohail S., Huang V. G., Hudson N., Baughman M., Rana O., Hinze A., Chard K., Chard R., Foster I., & Nagra H. (**2023**). Measurement and applications: Exploring the challenges and opportunities of hierarchical federated learning in sensor applications. *IEEE Instrumentation & Measurement Magazine* , 26(9), 21-31. DOI: 10.1109/MIM.**2023**.10328671

[33] Tziolas E., Karapatzak E., Kalathas I., Karampatea A., Grigoropoulos A., Bajoub A., Pachidis T., & Kaburlasos V. G. (**2023**). Assessing the economic performance of multipurpose collaborative robots toward skillful and sustainable viticultural practices. *Sustainability* , 15(4), 3866. DOI: 10.3390/su15043866

[34] Zeqiri A., Britten J., Schramm C., Jansen P., Rietzler M., & Rukzio E. (**2025**). PlantPal: Leveraging Precision Agriculture Robots to Facilitate Remote Engagement in Urban Gardening. arXiv preprint arXiv: 2502.19171. DOI: 10.1145/3706598.3713180

[35] Poojari M., Hanumanthappa H., Prasad C. D., Jathanna H. M., Ksheerasagar A. R., Shetty P., ... & *Vasudev, H.* (**2024**). Computational modelling for the manufacturing of solar-powered multifunctional agricultural robot. International Journal on Interactive Design and Manufacturing (IJIDeM), 18(8), 5725-5736. DOI: 10.1007/s12008-023-01291-y

[36] Ludwig-Ohm S., Hildner P., Isaak M., Dirksmeyer W., & Schattenberg J. (**2023**). The contribution of Horticulture 4.0 innovations to more sustainable horticulture. *Procedia Computer Science*, 217, 465-477. DOI: 10.1016/j.procs.**2022**.12.242

[37] Hruday P. J., Kiran A. B. V. S., & Reddy V. P. (**2024**, April). Horticulture Robot for Precision Plant Health Management. In *2024 10th International Conference on Communication and Signal Processing (ICCSP)* (pp. 448-452). IEEE. DOI: 10.1109/ICCSP60870.2024.10544096

[38] *Fujinaga, T.* (**2024**). Strawberries recognition and cutting point detection for fruit harvesting and truss pruning. Precision Agriculture, 25(3), 1262-1283. DOI: 10.1007/s11119-023-10110-z

[39] Mahalingam D., Patankar A., Phi K., Chakraborty N., McGann R., & Ramakrishnan I. V. (**2024**, May). Containerized vertical farming using cobots. In *2024 IEEE International Conference on Robotics and Automation (ICRA)*

(pp.17897-17903).IEEE.DOI:10.1109/ICRA57147.2024.10609985

[40] Mahmud M. S., Zahid A., & Das A. K. (**2023**). Sensing and automation technologies for ornamental nursery crop production: current status and future prospects. *Sensors* , 23 (4), 1818. DOI: 10.3390/s23041818

[41] Gao J., Wang S., Hu D., Li Y., Lai Y., Qiu Y., Zhao W., & Yin Z. (**2024**, November). Home garden robot based on Internet of Things technology, plant 3D data features and spherical calibration and registration. In *2024 International Conference on Intelligent Robotics and Automatic Control (IRAC)* (pp. 52-57). IEEE. DOI: 10.1109/IRAC63143.**2024**.10871344

[42] Rajalakshmi P., Dhivya K., Anitha D., Sandhya P., Gnanavel N., & Muthulekshmi M. (**2024**, October). Smart Home Gardening with Robotic Assistance using Cloud-Connected Plant Care and Neural Networks Growth Analysis. *In 2024 First International Conference on Innovations in Communications* , Electrical and Computer Engineering (ICICEC) (pp.1-6).IEEE.DOI: 10.1109/ICICEC62498.**2024**.10808702

[43] Shi J., Bai Y., Diao Z., Zhou J., Yao X., & Zhang B. (**2023**). Row detection BASED navigation and guidance for agricultural robots and autonomous vehicles in row-crop fields: Methods and applications. *Agronomy* , 13(7), 1780. DOI: 10.3390/agronomy13071780

[44] Almanzor E., Birell S., & Iida F. (**2023**, September). Rapid Development and Performance Evaluation of a Potato Planting Robot. *In Annual Conference Towards Autonomous Robotic Systems* (pp. 15-25). Cham: Springer Nature Switzerland. DOI: 10.1007/978-3-031-43360-3_2

[45] Munnaf M. A., Wang Y., & Mouazen A. M. (**2024**). Robot driven combined site-specific maize seeding and N fertilization: An agro-economic investigation. *Computers and Electronics in Agriculture* , 219, 108761. DOI: 10.1016/j.compag.2024.108761

[46] Sara G., Todde G., Pinna D., & Caria M. (**2024**). Evaluating an autonomous electric robot for real farming applications. *Smart Agricultural Technology* , 9, 100595. DOI: 10.1016/j.atech.**2024**.100595

[47] Sujitha S., Meghana N. T., Vandana R., & Vidya G. R. (**2023**, March). Solar Powered Autonomous Multipurpose Agricultural Robot Using Bluetooth. In *2023 Second International Conference on Electronics and Renewable Systems (ICEARS)* (pp. 234-241). IEEE. DOI: 10.1109/ICEARS56392.**2023**.10085122

[48] Liu X., Huang H., Chen M., Fang Y., & Shu Y. (**2025**). Optimization and performance analysis of a novel automatic planting-irrigating integrated robot. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science* , 239(3), 899-929. DOI: 10.1177/09544062241278191

[49] Vahdanjoo M., Gislum R., & Sørensen C. A. G. (**2023**). Operational, economic, and environmental assessment of an agricultural robot in seeding and weeding operations. *AgriEngineering*,5(1),299-324.DOI:10.3390/agriengineering5010020

[50] Kotaniemi J., Känsäkoski N., Halbach E., & Heikkilä T. (**2024**, September). A Weeding Robot for Seedling Removal. In *2024 20th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)* (pp.1-8). IEEE. DOI: 10.1109/MESA61532.2024.10704901

[51] Özentürk U., Chen Z., Jamone L., & Versace E. (**2024**). Robotics for poultry farming: Challenges and opportunities. *Computers and Electronics in Agriculture* , 226, 109411. DOI: 10.1016/j.compag.**2024**.109411

[52] Sun C., van der Tol R., Melenhorst R., Pacheco L. A. P., & Koerkamp P. G. (**2024**). Path planning of manure-robot cleaners using grid-based reinforcement learning. *Computers and Electronics in Agriculture* , 226, 109456. DOI: 10.1016/j.compag.**2024**.109456

[53] Bae J., Park S., Jeon K., & Choi J. Y. (**2023**). Autonomous system of TMR (total mixed ration) feed feeding robot for smart cattle farm. *International Journal of precision Engineering and manufacturing* , 24(3), 423-433. DOI: 10.1007/s12541-022-00742-y

[54] Byrne N., McCarthy O., & Ryan-Doyle M. (**2024**). Leveraging the potential of co-operative agri-advisory services in the transition to sustainable and landscape-based agriculture. *International Food and Agribusiness Management Review* , 27(1), 117-145. DOI: 10.22434/IFAMR2023.0076

[55] Farmers Journal. An innovative seed-n-weed robot, FarDroid FD20, is developed especially for sowing and weeding beet crop. Available at: https://www. farmersjournal. ie/machinery/farm-machinery/ireland-first-autonomous-seed-n-weed-robot-gets-to-work-in-the-southeast-769012

[56] Farmdroid. Automate your agriculture. Available at: https://farmdroid. com/? utm_term=farmdroid&utm_campaign=Brand% 20-% 20FarmDroid&utm_source=adwords&utm_medium=ppc&hsa_acc=2626152131&hsa_cam=22231152858&hsa_grp=180203463972&hsa_ad=733006576936&hsa_src=g&hsa_tgt=kwd-1287786095984&hsa_kw=farmdroid&hsa_mt=e&hsa_net=adwords&hsa_ver=3&gad_source=1&gclid=Cj0KCQjwy46_BhDOARIsAIvmcwPaie-3AMeD_qVkoWOXBEzmIaGpl6To7u467p-ERKdno7veK2Fjr9gaAnvMEALw_wcB

[57] Agriland. First report: Farmdroid robot at work in Kilkenny. Available at: https://www. agriland. ie/farming-news/first-report-farmdroid-robot-at-work-in-kilkenny/

[58] Lely. Lely introduces the Vector MFR Next: less work, more results. Available at: https://www.lely.com/ie/about-lely/news/Lely-introduces-the-Vector-MFR-Next/

[59] Lely. Lely introduces autonomous feed pushing robot for large-scale farms. Available at: https://www.lely.com/ie/about-lely/news/lely-introduces-autonomous-feed-pushing-robot-for-large-scale-farms/

[60] Lely. Lely Zeta: the start of a new chapter in dairy farming. Available at: https://www. lely. com/ie/about-lely/news/lely-zeta-the-start-of-a-new-chapter-in-dairy-farming/

[61] HomeBot Ireland. Robot Lawn Mowers -Giving you back your weekends. Available at: https://homebotireland. ie/robot-

lawn-mowers/

[62] HomeBot Ireland. Which Robot Lawn Mower is best for me? Available at: https://homebotireland. ie/which-robot-lawn-mower-is-best-for-me

[63] Kumar D., Alagarasan I., Kalidas N., Karthik B., & Kashyap S. K. (**2024**, September). Financial Gains from Automated and Robotics in Fields. In *2024 International Conference on Communication, Computing and Energy Efficient Technologies (I3CEET)* (pp. 1313-1317). IEEE. DOI: 10.1109/I3CEET61722.**2024**.10993825

[64] Moreno J. C., Rodríguez F., Sánchez-Hermosilla J., Giménez A., & Sánchez-Molina J. A. (**2024**). Feasibility analysis of robots in greenhouses. A case study in European Mediterranean countries. *Smart Agricultural Technology* , 9, 100638. DOI: 10.1016/j.atech.**2024**.100638

[65] Martins J. J., Silva M., & Santos F. (**2022**, November). Safety standards for collision avoidance systems in agricultural robots-a review. *In Iberian Robotics conference* (pp. 125-138). Cham: Springer International Publishing. DOI: 10.1007/978-3-031-21065-5_11

[66] Holm S., Pedersen S. M., & Tamirat T. W. (**2024**). Robots in agriculture – A case-based discussion of ethical concerns on job loss, responsibility, and data control. *Smart Agricultural Technology* , 9, 100633. DOI: 10.1016/j.atech.**2024**.100633