EAI Endorsed Transactions
on AI and Robotics

Research Article EAI.EU

Robots in Agriculture: Revolutionizing Farming Practices

Ata Jahangir Moshayedi[1,*], Amir Sohail Khan[1],Yiguo Yang[2], Jiandong Hu[3,4], Amin Kolahdooz[5,6]

[1]School of Information Engineering, Jiangxi University of Science and Technology, Ganzhou, Jiangxi, 341000, China
[2]School of Computer Engineering and Science, Shanghai University, 200444, Shanghai China
[3]Key Laboratory of Wheat and Maize Crop Science, Henan Agricultural University, Zhengzhou 450002, China
[4]Department of Electrical Engineering, Henan Agricultural University, Zhengzhou 450002, China
[5]Faculty of Technology, School of Engineering and Sustainable Development, De Montfort University, Leicester, LE1 9BH, UK.
[6]Universitas Negeri Padang, Jl. Prof. Hamka, Padang, Sumatera, Barat 25131, Indonesia

Abstract

Robotics for farming is a game changer for economy and sustainability. Agricultural robots automate activities and help solve industrial difficulties. These robots are designed for precise planting, weeding, and harvesting, automating labor-intensive procedures. Implementing these practices improves productivity, reduces operating costs, and minimises environmental impact by optimising resource use. This research examines the various processes and designs used in agricultural robotic structures to understand their functionality. This study delves into the intricate structure of agricultural robots, highlighting the technical wonders that enable precision farming. From articulated arms to autonomous unmanned aircraft, the study explores a variety of robot designs and their roles in automating jobs crucial to contemporary agriculture.

Received on 11 02 2024; accepted on 28 05 2024; published on 20 06 2024

Keywords: Agricultural robots, Robotic Structures, Precision Farming, Robot Architecture

doi:10.4108/airo.5855

1. Introduction

The advent of agricultural robots marks a transformative era in the realm of traditional farming, heralding a paradigm shift in cultivation methodologies [1]. These cutting-edge machines have emerged as catalysts for innovation, revolutionizing age-old practices by seamlessly integrating automation into the agricultural landscape. With a mission to address the myriad challenges confronting the agriculture sector, these robots stand as technological sentinels, ushering in unprecedented efficiency, precision, and sustainability. Automation, a central theme in this agricultural revolution [2], assumes paramount importance in mitigating the sector's multifaceted challenges. From labor shortages to resource inefficiency, automation emerges as the cornerstone solution, promising to elevate farming practices to new heights [3]. The timeline history of agriculture robots (Figure 1) provides a chronological overview of the integration of robotics in agriculture, delineating key developments from the 1960s to the present and beyond, beginning with the early introduction of basic robotic technologies such as remote-controlled tractors and harvesters [4] in the 1960s. The 1980s mark the emergence of precision agriculture with the utilization of GPS technology for precise mapping. Advancements in the 1990s include the deployment of autonomous tractors and sprayers, revolutionizing tasks such as planting and cultivation.

From the 2000s, specialized robots designed for harvesting fruits, vegetables, and other crops became prominent, whilst the 2010s witnessed the integration of drones equipped with sensors for aerial monitoring, alongside the introduction of swarm robotics for tasks like weed control and pollination. AI and machine learning also made significant strides in data-driven

*Corresponding author. Email: ajm@jxust.edu.cn

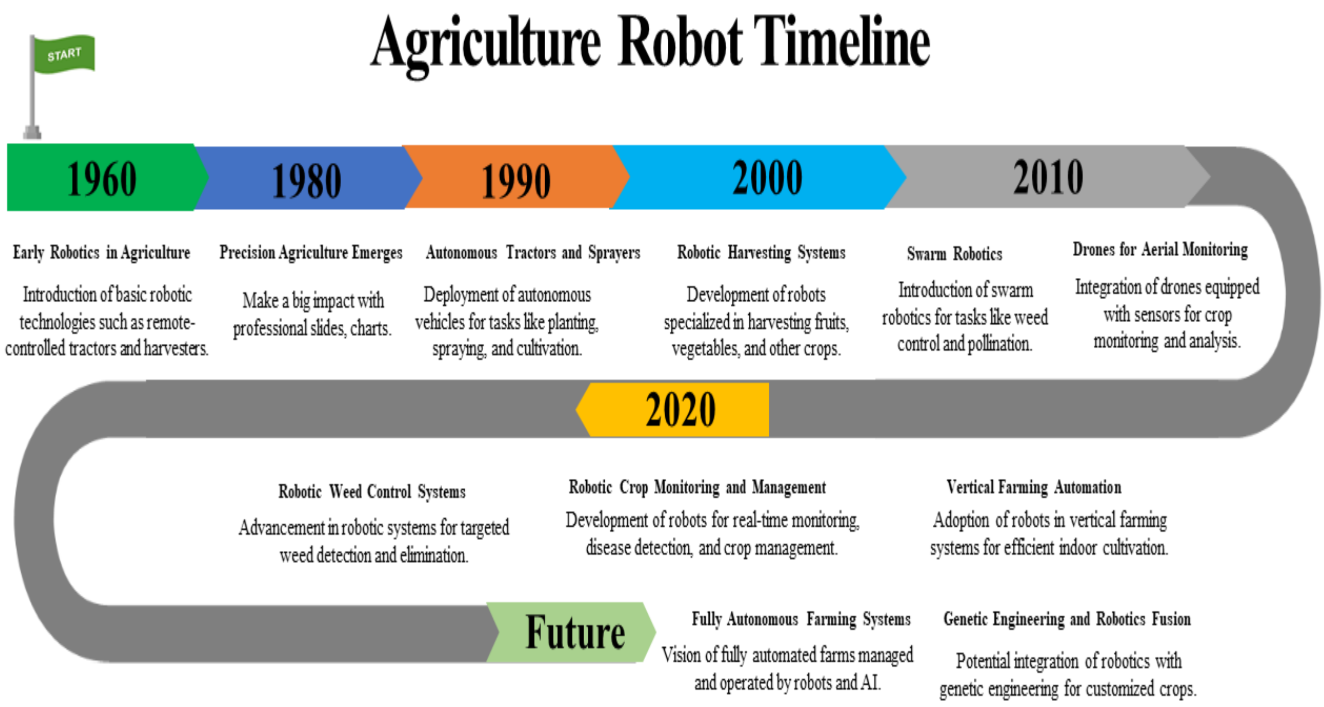

Figure 1. History of Agricultural Robots Used Over The Time

decision-making within agriculture. Recent years, particularly the 2020s, have seen further advancements, with the development of robotic systems for targeted weed detection and elimination, as well as real-time crop monitoring and disease detection. Additionally, robots find application in vertical farming systems for efficient indoor cultivation. Looking ahead, there is excitement about potential integration with genetic engineering for customized crop development and the realization of fully autonomous farming systems, managed and operated by robots and AI. This structured timeline offers a comprehensive glimpse into the evolving landscape of agricultural robotics, showcasing both past achievements and future prospects.
This research paper explores the structure of agricultural robots and their applications across various fields of agriculture. Figure 2 indicates the distribution of surveyed literature in terms of paper type, publisher, and publication year in the review paper analysis.

This review critically examines the latest advancements in the field, drawing insights from a comprehensive analysis of 115 papers. These papers were sourced from various reputable publishers, including IEEE conferences (21 papers), Elsevier (19 papers), MDPI (30 papers), Springer (7 papers), Willey Online (8 papers), and other sources (30 papers). Notably, 84 of the referenced papers were published since 2020, indicating a strong focus on recent developments, while 31 papers predate 2020, contributing historical context to the review. The analysis encompasses a diverse range of sources, with 22 conference papers and 93 journal papers forming the basis of the review's findings and conclusions.

The objective of this paper is to provide an overview of the types of robots used in the field of agriculture. The main aim for this study is to demonstrate the potential of robots in agriculture settings through their design, development, and implementation, thus revolutionising agriculture practices and boosting farm field outcomes. To assure the accuracy of findings, some scientific search engines and databases were used to uncover relevant articles and publications for this study. This study's rigorous research procedure offers a comprehensive review of robots in farmland, including developments, limits, and future possibilities.

The paper is arranged in seven different sections. Following the introduction in Section 1, the evolution of robotics in agriculture is discussed in Section 2. The main focus, the structure of robots, is detailed in Section 3. Section 4 highlights the applications of agricultural robots and the different types of robots used in agricultural are presented in Section 5. The advantages and disadvantages are outlined in Section 6. Finally, the paper concludes in Section 7.

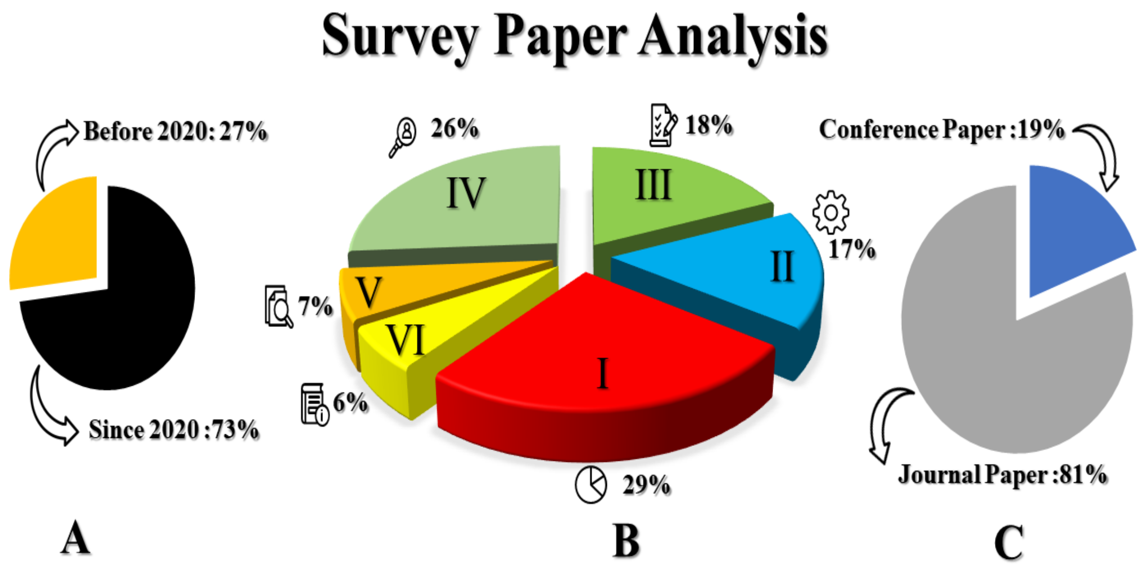

Figure 2. The review paper includes a reference analysis categorized by paper type, publisher, and publication year. A:Percentage of Used Papers Before 2020 (27%)and After 2020(73%). B:Total reviewed paper Percentage Based on Publisher:I)MDPI:(29%), II) Elsevier(17%),III)IEEE Conference Papers (18%) , IV)Others(26%),V)Wiley Online(7%) VI)Springer(6%). C:Percentage of used Journal and Conference paper.

2. Evolution and Advancements in Agricultural Robotics

Sakai et al. (2008) [5] presented a manipulation system tailored for agricultural robots handling heavy materials. This system comprises a mobile platform and manipulator, chosen and designed with innovation in mind. Control systems are meticulously crafted to handle parameter variations and uncertainties. Validation was done through watermelon harvesting experiments, demonstrating a success rates of 86.7% with no damage in both low-gain PID control and switching strategy. The study outlines a design procedure and three essential design tools. Future directions involve refining and optimizing the system for broader agricultural applications. Ball et al. (2016) [6] introduced a robotic solution for sustainable intensification of broad-acre agriculture, utilizing an electric John Deere TE Gator with a 5-meter-wide spray boom and 200 L spray tank. The robot integrates GNSS, inertial navigation, and stereo cameras for localization and obstacle detection. Operating with Ubuntu 12.04 and ROS Fuerte, it employs RTK for precise localization. Field trials showed its capability in task execution, obstacle avoidance, and resilience during GPS outages by visually tracking crop rows. Future research aims to enhance computer vision, obstacle detection algorithms, and scalability for broader agricultural applications.

In 2019 Huang and Chang [7] introduced a bionic electric spraying rod for agricultural applications, mimicking snake vertebrae structures. The robot features a snake bone arm with snake-like muscles controlled by thin wires via a driver module. It includes a water pipe for spraying, connected to a nozzle and operated via remote control through a mobile app interface. In experiments, the robot achieved a bending angle of 133.88 degrees and a jetting distance of up to 60 cm, showing no power issues but facing accuracy challenges beyond 10 cm. Proposed improvements include refining accuracy, enhancing flexibility, and integrating with a mobile app for monitoring and control. Bionic arms offer promise for unmanned field mobile robots, with the possibility of reducing labor and pesticide spraying damage.

Chebrolu et al. (2019) [8] present a precision agriculture localization system merging aerial field maps with crop and weed semantic data to address visual ambiguity. Utilizing a ground robot equipped with wheel encoders, GPS, and a stereo camera, experiments in a sugarbeet field were conducted. Aerial maps, derived from a UAV, achieved 5 mm per pixel resolution. Employing a fully convolutional network (FCN), the system accurately estimates plant stem locations and semantic labels, surpassing traditional visual features. Orthomosaic and landmark-based representations enable robust robot localization, demonstrating efficacy for precision agriculture. Future work includes FCN refinement, broader crop applicability, and integration with autonomous platforms for real-world deployment in agriculture. Also in 2019, Mitra [9] demonstrated a new transformative shift in robotic technology in agriculture, with fruit-picking robots such as Agrobot and Dogtooth Technologies, equipped with up to 24 arms, advance automation and analytics. Robotic weeders, which cost around 120,000–175,000 dollars, offer a lasting solution to specialty crop challenges. Fraunhofer Institute's dual-arm system efficiently harvests cucumbers, while UK's broccoli project reduces costs with 3D cameras. TerraSentia enhances crop trial efficiency, while laser robots aid organic farming by eliminating weeds, contributing to sustainability.

In 2020, Mashhadani and Chandrasekaran [10] proposed integrating robotics into agriculture to meet rising crop production demands. Their study advocated using autonomous aerial and ground robots for monitoring plant health, ripeness, and soil moisture. Gas sensing, a key method discussed, involves employing gas sensors within an IoT network for soil quality measurement. These sensors, functioning as a biological nose, use electronic arrays and neural networks to detect specific odors, aiding in fruit maturation monitoring. Integration with other components like thermal cameras and RGB-D sensors emphasizes a multisensory approach for enhanced agricultural practices. Fountas et al. (2020) [11] explored modern technology's transformative impact on agriculture, focusing on labor-intensive field operations. Their systematic literature review examines agricultural robotics equipped with sensors for tasks like weeding, seeding, disease detection, and harvesting. Challenges include achieving modularity and optimal performance due to hardware and software complexity. Notable achievements include high weeding rates and significant reductions in fungicide use. Vision systems play a crucial role, but challenges such as uniform lighting persist. The study emphasizes the need for improved vision systems, faster image processing, and robust hardware to advance agricultural robotics.

Mahmud et al. (2020) [12] reviewed recent automation and robotics applications in agriculture, focusing on precision farming. Categorized into planting, inspection, spraying, and harvesting operations, technologies like IR sensors and computer vision enhance efficiency and sustainability. Industry 4.0 integration via IoT enables real-time monitoring. Selective spraying systems and vision-based harvesting optimize pesticide use and accuracy. Autonomous systems show potential to address agricultural challenges globally, enhancing productivity and reducing costs. The paper highlights the significance of efficient autonomous agricultural robotics for future implementation.

Ochman et al. (2021) [13] tackled challenges faced by mobile robots in agriculture, particularly autonomous lawn mowers. To improve efficiency and safety RGB-D cameras were used to detect obstacles and define working areas. Evaluating using synthetic and real-world datasets, novel metrics such as $d_{\text{min-}}$obst were used for obstacle detection accuracy. Results show robust performance exceeding 95% accuracy in real-world scenarios. The study emphasizes the importance of spatial metrics for assessing obstacle detection in dynamic outdoor environments. Future work may focus on refining processing pipelines and exploring alternative sensors for improved performance in agricultural settings.

Han et al. (2021) [14] introduced an intelligent mobile picking robot for agriculture, utilizing AI and IoT advancements. Integrated with color, infrared, and ultrasonic sensors on an STM32 board, it identifies fruit maturity, streamlining algorithms for swift picking. Aimed at replacing manual labor during harvest, the robot excels in real-time data collection with reduced power consumption and cost. Meticulous software design ensures successful tests and integration. Future efforts focus on refining capabilities for broader agricultural tasks, enhancing practicality. Chand et al. (2021) [15] introduced the Multi-Purpose Smart Farming Robot (MpSFR) for autonomous water sprinkling and pesticide spraying. Powered by photovoltaic technology, IoT, and computer vision, it monitors soil moisture and plant health, making irrigation decisions based on pest detection. Tested in a Papaya farm in Fiji, the MpSFR effectively senses soil moisture and detects pests, offering farmers a smart solution for remote irrigation scheduling. Future work aims to scale and optimize the MpSFR for broader agricultural applications.

In 2021, Mohammed and Jassim [16] designed and tested an agricultural robot for repotting, excluding seeding and fertilization. Their experiment at the University of Baghdad focused on robot speed and seed depth's impact on mechanical and soil properties. Results showed the second speed treatment enhanced field efficiency, reduced energy consumption, and optimized seed distribution. The highest efficiency (65.03%) was at 6 cm depth and 5 km/h speed. Increased speed led to higher productivity. Future work may explore the robot's applications in remote sensing for precision farming. Kondoyanni et al. (2022) [17] reviewed advancements in agricultural robotics, focusing on biomimetic innovations like soft and swarm robots. They highlighted applications in fruit harvesting and pest control, citing examples like robot bees and precision farming equipment such as RTU. Despite ecological and cost concerns, the bio-inspired agricultural technology market is growing rapidly. Future developments may include affordable robotic grippers for crop harvesting. Despite challenges, the ongoing modernization of agriculture through soft and swarm robotics is expected to continue, promoting sustainable production and economic growth. Moraitis et al. (2022) [18] introduce CityVeg, an economical urban farming robot for automated green space management. Combining Cartesian robot motion and machine vision, it employs advanced computational methods for plant identification and precise watering. CityVeg, designed for balconies or terraces, achieves up to 92% accuracy in identifying lettuce plants, further improving to 95% with soil moisture data integration. The study demonstrates its successful application in lettuce plants, highlighting precise actuator movement and tailored irrigation. Future work may expand capabilities to other crops, enhance efficiency, and integrate additional features for comprehensive urban garden management.

In 2022 Orkweha [19] introduced an agricultural robot platform at Southern Illinois University Edwardsville, based on a law enforcement robot chassis with tracked locomotion for navigating rough terrains. Hardware included specific dimensions, tracks, and four 24V DC motors connected to a gearbox. High-level tasks are managed by a Jetson AGX Xavier computer, while low-level tasks are handled by a Teensy 4.1 microcontroller. The ROS framework incorporates SLAM and navigation packages, with a Model Predictive Controller addressing locomotion challenges. The platform facilitates ongoing exploration and advancement in agricultural robotics to meet self-sufficiency demands. Ghafar et al. (2023) [20] introduced a cost-effective agriculture robot for spraying fertilizers, pesticides, and plant surveillance. The prototype features a two-wheel design with a movable foundation, spraying mechanism, wireless controller, and crop health assessment camera. Despite slightly lower crop coverage productivity than humans, it offers significant labor cost savings due to full autonomy. Test results show resource savings and reduced contamination of water sources, aligning with precision agriculture goals. The prototype boasts excellent battery life and achieves a spraying rate of 20 plants per minute. Future enhancements may include increasing autonomy to further reduce labor requirements and costs. Yang et al. (2023) [21] discussed agricultural robotics as a solution to skilled labor shortages in crop production. They highlighted wheel-type mechanisms as the most common in agricultural robots, particularly those with omnidirectional wheels. These robots are designed for tasks like transplanting, weeding, harvesting, and pruning, sharing core operations such as target identification and operation execution. Field mobile technology is categorized into wheel, track, and leg types, each with its advantages and disadvantages. Adoption of agricultural robots, especially those with wheel mechanisms, promises productivity improvement and labor shortage reduction. Continued research and development are vital for refining these technologies and unlocking their full potential.

Ghobadpour et al. (2023) [22] presented the PV/FC Agricultural Mobile Robot (PV/FCAMR), addressing energy challenges in agricultural robotics. The system combines battery, Fuel Cell (FC), and Photovoltaic (PV) elements for power. Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) algorithms optimize FC and battery sizes. MATLAB/Simulink models energy consumption, showing a 350% autonomy increase. Cost analysis reveals an 8% expense reduction. PV integration extends the robot's range by up to 5%, highlighting potential for enhanced efficiency and sustainability in future agricultural vehicles. Azmi et al. (2023) [23] present a cost-effective agricultural robot for crop seeding, overcoming manual and tractor-based inefficiencies. The robot, with a four-wheel design, employs a crank-slider mechanism for continuous seed injection. Tests show it sows 138 seedlings in 5 minutes with 92% accuracy, outperforming humans by 35%. With a 4-hour operational capacity on a single charge and 1.5-hour recharging time, it minimizes interruptions. Further enhancements, such as full autonomy, could enhance cost-effectiveness by eliminating manual steering. Li et al. (2023) [24] introduced a surveillance and control system for enclosed piggeries, focusing on a check inspection robot. The system includes a mobile monitoring platform, environmental control system, and monitoring terminal. The robot, equipped with infrared sensors, detects harmful gases like NH_3 along tracks. It measures various environmental parameters and employs an adaptive fuzzy PID control algorithm for regulation. Field tests showed effective temperature control within a 2°C range and maintenance of acceptable CO_2, NH_3, and PM2.5 levels. Real-time monitoring and control via wireless communication highlight the robot's adaptive regulation capabilities for comprehensive environmental management.

3. Different Robots Structure used For Agriculture Purposes

Figure 3 shows the different robotic types along with their structures and their merits and demerits. The table shows a comparison across different robots, to facilitate finding the best robot for the most suitable job, with a structure designed for specific agricultural purposes. By integrating these components, agricultural robots contribute to precision farming practices, enhancing efficiency, productivity, and sustainability in modern agriculture.

3.1. Base Platform

The base platform serves as the foundation of the robot and provides stability on various terrains found in agricultural settings. It's typically equipped with wheels or tracks for mobility, allowing the robot to traverse fields efficiently. The base platform of an agricultural robot serves as the foundation or chassis on which the various components, sensors and actuators are mounted [25]. The choice of a base platform depends on the specific requirements of the agricultural task, terrain, and the size of the operation. Here are some common types of base platforms used for agricultural robots:

Tracked Vehicles. Tracked platforms are equipped with continuous tracks instead of wheels, providing better traction and stability, especially in challenging terrains such as muddy or uneven fields. Tracked robots can navigate through rough terrain and maintain stability while carrying heavy payloads [26].

Wheeled Robots. They are commonly used in agricultural robots for their simplicity and ease of navigation. These platforms may have two or more wheels, and they are suitable for operations in relatively flat and well-maintained fields. Wheeled robots are often used for tasks like planting, spraying, and monitoring [27].

Legged robots (LR). LRs are designed with walking or crawling capabilities, providing greater adaptability to uneven terrain. These robots can navigate through fields with crops at different growth stages and are suitable for tasks like monitoring and data collection [28].

Unmanned Aerial Vehicles (UAVs or Drones). Drones serve as aerial base platforms, offering a unique perspective for monitoring and collecting data over large agricultural areas. They are commonly used for crop surveillance, pest detection, and aerial mapping. Drones can cover large areas quickly and provide valuable information for precision agriculture [29, 30].

Autonomous Ground Vehicles (AGVs). Autonomous ground vehicles are wheeled platforms equipped with sensors and navigation systems for autonomous operation. AGVs are used for tasks such as crop scouting, monitoring, and transportation within the field [31].

3.2. Sensor Array

In the realm of agricultural automation, a diverse array of sensor technologies plays a pivotal role in gathering crucial data regarding the surrounding environment and crop conditions [32]. These sensors, encompass:

Visual Sensing Solutions. Agricultural automation systems integrate advanced visual sensing solutions for real-time crop assessment and environmental monitoring. This category includes:

a) **Spectrum Imaging Sensors:** These sensors capture data within various spectra, facilitating detailed observations of crop health and environmental conditions [32].

b) **Thermal Vision Systems:** Employing advanced thermal imaging technology, these systems detect temperature variations indicative of crop stress, diseases, and irrigation issues [32].

c) **Multispectral Perception Sensors:** Sensors capable of capturing data across multiple spectral bands, offering insights into crop health parameters like chlorophyll levels, moisture content, and stress indicators [32].

d) **Depth Perception Sensors:** Utilizing innovative depth perception technology, these sensors provide accurate spatial information crucial for navigation and obstacle avoidance [32].

e) **Advanced Image Analysis Units:** Equipped with sophisticated algorithms and AI capabilities, these units analyze captured images to identify specific features such as pests, diseases, or nutrient deficiencies [32].

Geospatial Positioning Systems. Robust geospatial positioning systems (GPS) combined with inertial measurement units (IMU) enable precise localization and navigation functionalities [33]. Key components in this domain include:

a) **Satellite Positioning Receivers:** Leveraging signals from multiple satellite navigation systems, these receivers ensure accurate positioning even in challenging environments [34].

b) **Precision Positioning Systems:** Utilizing real-time correction signals, these systems achieve centimeter-level accuracy crucial for precision agriculture tasks [35].

Soil Monitoring Technology. Integrated soil monitoring technology provides essential data for optimizing irrigation and fertilization strategies [36]. This includes:

a) **Soil Moisture Monitoring Devices:** These devices employ innovative techniques to measure soil moisture levels accurately, aiding in efficient water management [37].

b) **Soil Composition Analyzers:** Utilizing advanced sensing mechanisms, these analyzers provide insights into soil composition, nutrient levels, and pH balance [38].

c) **Soil Health Sensors:** Equipped with various sensors, these systems assess soil health indicators such as compaction levels and microbial activity [39].

d) **Soil pH Sensors:** These include Glass Electrode pH sensors; these sensors measure the hydrogen ion concentration in the soil, providing information about soil acidity or alkalinity. Glass electrode sensors are commonly used for pH measurement [40].

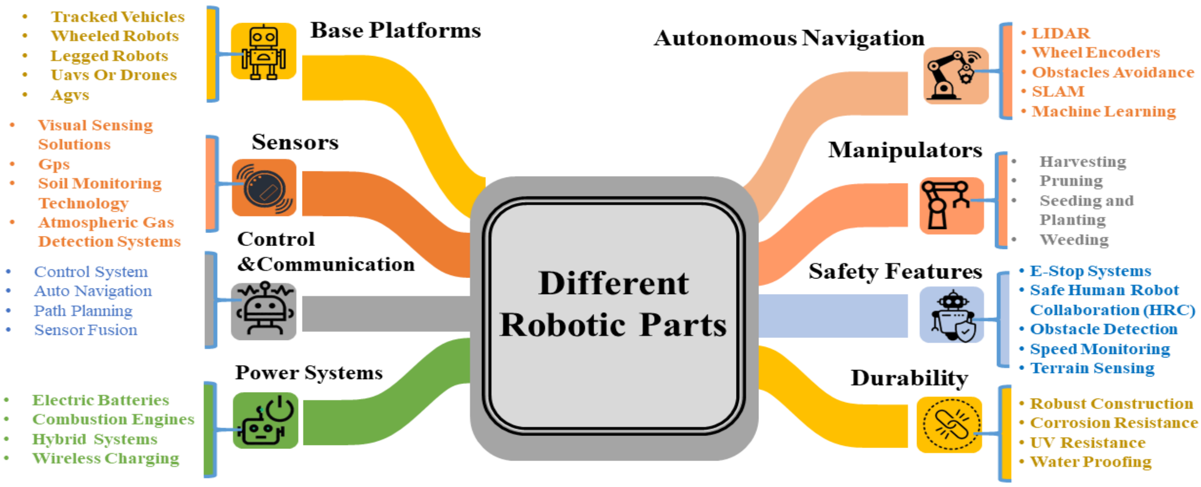

Figure 3. Different Robot Structures used for Agriculture Purposes

e) **Soil Compaction Sensors:** These contain penetrometers measure soil compaction by assessing the resistance the soil exerts against a probe as it penetrates the ground. Higher resistance indicates greater soil compaction [41].

f) **Soil Gas Sensors:** They include different Gas Sensors (e.g., for Oxygen and Carbon Dioxide). These sensors measure the concentration of gases in the soil, providing information about soil aeration and microbial activity [42].

Atmospheric Gas Detection Systems. Monitoring atmospheric gases is essential for early detection of potential threats to crop health [43]. This category includes:

a) **Gas Sensing Networks:** These networks comprise sensors strategically placed to detect gases emitted by pests, diseases, or environmental factors [44, 45].

b) **Air Quality Analyzers:** Employing advanced gas detection technology, these analyzers provide real-time data on air quality parameters such as CO2, NH3 levels and VOC concentrations [46, 47].

c) **Infrared Gas Sensors:** They can detect gases such as methane and carbon dioxide. They operate based on the absorption of infrared light by the target gas molecules [48].

3.3. Manipulators

Robotic arms or manipulators are used for various tasks. These robots and applications are presented in figure 4.

Harvesting. In the realm of agricultural automation, gentle harvesting of fruits, vegetables, or crops is a critical task [49]. Here's how robotic manipulators are employed for this purpose:

a) **Visual Perception and Detection:** Robotic harvesting systems integrate camera and vision systems to identify ripe produce. Advanced algorithms analyze images to determine the size, maturity, and location of the target crops [49].

b) **Manipulator End-Tool Design:** Specialized grippers or suction cups are crucial for gentle picking. These tools are delicately designed to grasp or suction fruits without causing damage, considering factors like fruit type and size [49].

c) **Force Sensing Mechanisms:** Integrated force sensors measure the force exerted during picking, allowing the robot to adjust its grip accordingly. This ensures a gentle touch to prevent bruising or damage to the crops [49].

d) **Path Planning:** Prior to harvesting, the robotic system plans an optimal path through the crop field. Path planning factors in obstacles, crop distribution, and the most efficient route to minimize travel time and maximize efficiency [49].

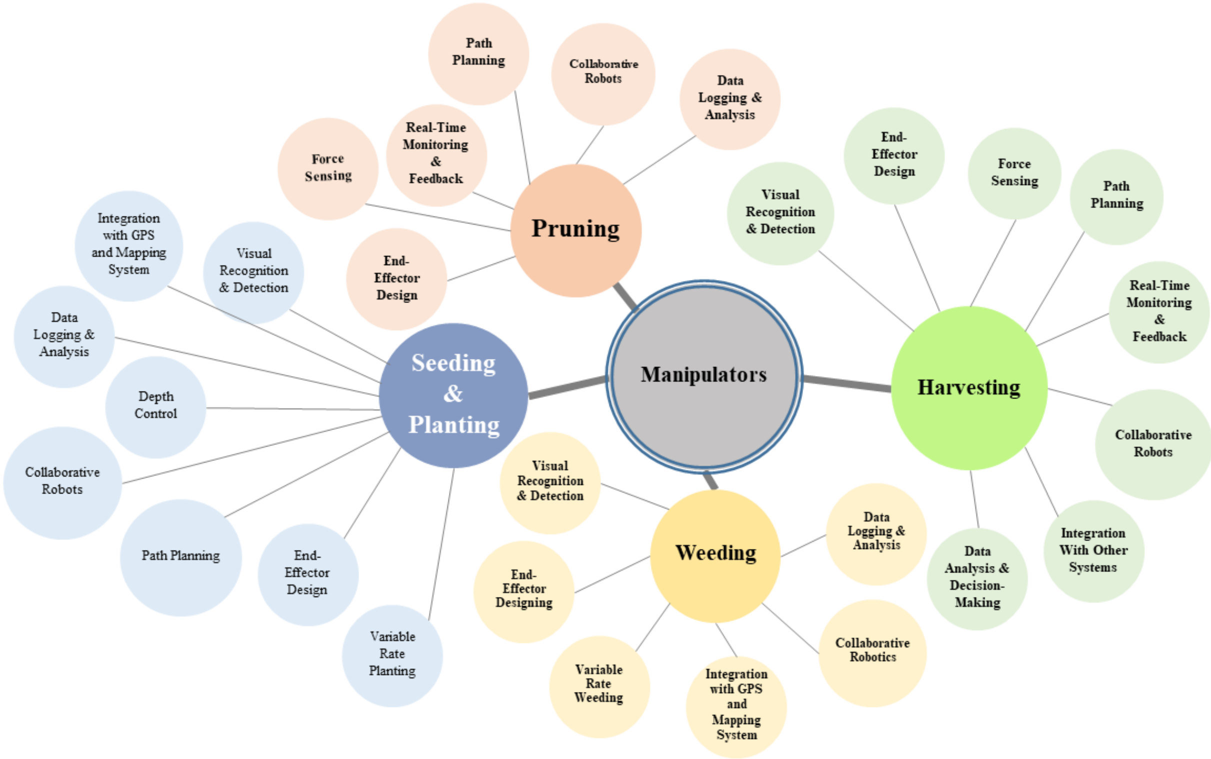

Figure 4. Manipulators (Robots Arm) Application in agriculture

e) **Real-Time Monitoring and Adjustment:** Continuous monitoring of the environment and crop status enables the robot to adapt its movements in real-time. This ensures accurate and gentle harvesting even in changing conditions [49].

f) **Collaborative Robotics:** Robots can work alongside human laborers to harvest crops efficiently. Collaborative robots, equipped with advanced sensing and safety features, ensure safe operation in close proximity to humans [49].

g) **Integration with Agricultural Systems:** Robotic harvesting systems can integrate with GPS and mapping technologies. This integration aids in efficient navigation through the field, ensuring thorough harvesting of ripe produce [49].

h) **Data Analysis for Decision-Making:** The robotic system may utilize data analytics to assess crop health and ripeness. Decision-making algorithms determine the optimal time for harvesting to maximize yield and quality [49].

Pruning. Pruning, the process of trimming or cutting unwanted parts of plants, is essential for promoting growth [50]. Here's how robotic manipulators are utilized for pruning:

a) **Visual Recognition and Detection:** Robotic pruning systems utilize advanced computer vision to identify areas of the plant requiring pruning. Cameras and image processing algorithms detect branches, shoots, and specific plant areas [50].

b) **Manipulator End-Tool Design:** Precision pruning requires specialized cutting tools attached to the robotic arm. These tools, such as robotic pruning shears or blades, ensure accurate and clean cuts while minimizing damage [50].

c) **Force Sensing Mechanisms:** Integrated force sensors provide feedback on the resistance encountered during pruning. This allows the robot to adjust the force applied, ensuring cuts are made with the right amount of force to avoid undue stress [50].

d) **Path Planning:** Before initiating pruning, the robotic system plans the optimal path for the manipulator. Path planning considers branch locations, plant structure, and obstacles to ensure efficient and systematic pruning [50].

e) **Real-Time Monitoring and Adjustment:** Continuous monitoring of plant condition and cutting process enables real-time feedback. The robot adjusts its movements based on plant response, ensuring accurate and appropriate pruning [50].

f) **Collaborative Robotics:** Robots can collaborate with human workers in pruning tasks. Collaborative robots are designed for safe operation near humans, providing flexibility and adaptability in different pruning scenarios [50].

Seeding and Planting. Seeding and planting operations in agriculture benefit greatly from automation [51]. Here's how robotic manipulators are utilized in seeding and planting tasks:

a) **Visual Recognition and Detection:** Robotic seeding systems employ computer vision to recognize suitable planting locations. Cameras identify soil surfaces and detect existing plants, weeds, or obstacles [51].

b) **Manipulator End-Tool Design:** The end-tool of the robotic arm is designed to handle seeds or seedlings with precision. Specialized grippers or suction devices ensure proper seed placement at the correct depth in the soil [51].

c) **Variable Rate Planting:** Some robotic planting systems adjust planting density based on soil conditions and crop requirements. This ensures optimal seed placement and spacing for improved crop yields [51].

d) **Depth Control:** Sensors and control mechanisms adjust planting depth to ensure optimal germination and growth conditions [51].

e) **Path Planning:** Prior to planting, the robotic system plans the optimal path for the manipulator. Path planning considers field layout, existing crops, and obstacles to ensure efficient coverage [51].

f) **Integration with GPS and Mapping Systems:** Robotic planting systems integrate with GPS and mapping technologies for accurate navigation. This ensures seeds are planted in the right locations, optimizing planting efficiency [51].

g) **Collaborative Robotics:** Collaborative robots can assist in planting tasks, working alongside human workers. This collaboration allows flexibility in addressing various field conditions [51].

h) **Data Logging and Analysis:** The robotic system may log planting data for analysis. This includes seed placement, planting density, and other factors, aiding in optimizing planting strategies and overall crop management [51].

Weeding. Weeding, the removal of unwanted vegetation, is crucial for crop health [52]. Here's how robotic manipulators are employed for this task:

a) **Visual Recognition and Detection:** Robotic weeding systems utilize cameras and computer vision to identify crop rows and distinguish weeds from crops. Advanced algorithms analyze images to target and remove weeds effectively [52].

b) **Manipulator End-Tool Design:** The end-tool of the robotic arm is designed for precise weed removal. Various tools, including mechanical implements and non-contact methods like lasers, ensure effective weed control with minimal crop damage [52].

c) **Variable Rate Weeding:** Some robotic weeding systems adjust weeding intensity based on weed density and type. This targeted approach ensures efficient weed control while minimizing herbicide use [52].

d) **Integration with GPS and Mapping Systems:** Robotic weeding systems integrate with GPS and mapping technologies for accurate navigation. This allows robots to follow predefined paths and target areas with high weed density [52].

e) **Collaborative Robotics:** Collaborative robots can assist in weeding tasks alongside human workers. This collaborative approach offers flexibility in handling different field conditions and types of weeds [52].

f) **Data Logging and Analysis:** The robotic system may log weeding data for analysis. Information such as weed density and effectiveness of weeding strategies can be used to refine techniques and improve overall weeding efficiency [52].

3.4. Power Systems

Agricultural robots use various power systems to operate autonomously and perform tasks in the field. The choice of a power system depends on factors such as the type of robot, its size, the nature of the tasks it performs, and the duration of its operation [53]. Here are some common types of power systems used in agricultural robots:

Electric Batteries. Electric batteries, such as lithium-ion or lead-acid batteries, are commonly used in agricultural robots. They provide a clean and quiet power source, making them suitable for electric motors that drive wheels or other actuators. Battery-powered robots are rechargeable and are often used for tasks like monitoring, spraying, and precision agriculture [54].

Internal Combustion Engines. Some larger agricultural robots, especially those designed for heavy-duty tasks like plowing or harvesting, may be equipped with internal combustion engines powered by gasoline or diesel fuel. These engines provide high power output and are suitable for extended periods of operation [55].

Hybrid Systems. Hybrid power systems combine multiple sources of energy, often integrating an internal combustion engine with an electric generator or batteries. Hybrid systems aim to optimize fuel efficiency and reduce emissions by using the internal combustion engine for peak power demands and the electric system for lower power requirements or during idle times [56].

Wireless Charging. Wireless charging technology is being explored in some agricultural robots. It allows the robot to charge its batteries without physical contact with a charging station. This can enhance the convenience and autonomy of the robot, especially during downtime between tasks [57].

3.5. Control and Communication

Control and communication systems in agricultural robots are essential components that enable the robots to operate autonomously, make decisions, and communicate with other devices or systems. The design of these systems depends on the complexity of the robot's tasks, the level of autonomy required, and the nature of the agricultural environment [58]. Here are some common types of control and communication systems used in agricultural robots:

3.6. On-Board Control Systems

Agricultural robots are equipped with on-board control systems that manage the robot's operations, interpret sensor data, and execute tasks. These systems often include micro-controllers or microprocessors that run algorithms for navigation, perception, and decision-making [59].

Autonomous Navigation Systems. Autonomous navigation systems enable robots to move through the field without human intervention. These systems use sensors such as GPS, LiDAR, cameras, and inertial measurement units (IMUs) to perceive the environment, plan paths, and control the robot's movements [60].

Path Planning Algorithms. Path planning algorithms are used to determine the optimal route for the robot to follow while performing tasks. These algorithms consider factors such as obstacle avoidance, terrain conditions, and task requirements. They contribute to efficient and safe navigation [61].

Sensor Fusion. Sensor fusion involves combining data from multiple sensors to create a more comprehensive understanding of the environment. In agricultural robots, sensor fusion helps improve accuracy in perception tasks, such as detecting crops, obstacles, or changes in soil conditions [62].

3.7. Autonomous Navigation

Autonomous navigation is a critical aspect of agricultural robots, allowing them to operate in the field without constant human intervention [63]. These robots use various sensors, algorithms, and control systems to perceive their environment, plan optimal paths, and execute tasks autonomously. Here's an overview of the components and technologies involved in autonomous navigation for agricultural robots:

LiDAR (Light Detection and Ranging). LiDAR technology uses lasers to measure distances and create detailed 3D maps of the environment. LiDAR is commonly used in agricultural robots for terrain mapping, obstacle detection, and localization [64].

Wheel Encoders. Wheel encoders measure the rotation of the robot's wheels, providing information about its movement. This data is used for odometry, helping the robot estimate its position and distance traveled [65].

Obstacle Avoidance Systems. Obstacle avoidance systems use sensor data and algorithms to detect and navigate around obstacles in the robot's path. This ensures safe and efficient navigation in dynamic environments [66].

Simultaneous Localization and Mapping (SLAM). SLAM algorithms enable the robot to create a map of its surroundings while simultaneously determining its own location within that map. This is particularly useful for robots operating in unknown or changing environments [67].

Machine Learning. Machine learning techniques, such as reinforcement learning, can be used to enhance the navigation capabilities of agricultural robots. These systems can learn from experience, adapting their behavior based on the success of previous navigation attempts [68].

3.8. Safety Features

Safety features in agricultural robots are critical to ensure the well-being of operators, bystanders, and the robot itself. Agricultural environments can be dynamic and pose various challenges, making it essential to implement safety measures to prevent accidents and mitigate risks [69]. Here are some common safety features found in agricultural robots:

Emergency Stop (E-Stop) Systems. Emergency stop buttons or switches allow operators to quickly halt the robot's operation in case of an emergency or when an unsafe condition is observed. This immediate shutdown helps prevent accidents and provides a rapid response to unforeseen situations [70].

Safe Human-Robot Collaboration (HRC). These robots contain force sensors and torque limiters that allow them to detect and react to human contact, ensuring that the robot stops or operates at a reduced speed when a human is in close proximity [71].

Obstacle Detection Systems. Sensors strategically placed on the robot detect obstacles, people, or other vehicles in the vicinity. The robot's control system can then adjust its movements to avoid collisions and ensure the safety of both the robot and the surrounding environment [71].

Speed Monitoring and Limiting. Monitoring the robot's speed is crucial for safety. Speed-limiting features can be implemented to ensure that the robot operates within safe speed limits, particularly in areas with high foot traffic or when performing delicate tasks [72].

Terrain Sensing and Adaptation. Some agricultural robots are equipped with terrain sensing capabilities to adapt their movements to uneven or challenging surfaces. This feature helps prevent tipping or getting stuck in difficult terrain conditions [73].

3.9. Durability

Durability and weather resistance are crucial considerations in the design of agricultural robots, as they operate in challenging outdoor environments and are subjected to various weather conditions [74]. Here are key factors and features related to durability and weather resistance in agricultural robots:

Robust Construction. Agricultural robots are built with robust and durable materials to withstand the physical demands of outdoor use. This includes sturdy frames, reinforced chassis, and durable components to endure the rigors of field operations [75].

Corrosion Resistance. Exposure to moisture, rain, and various chemicals in the agricultural environment can lead to corrosion. Using corrosion-resistant materials and coatings helps protect the robot's components from deterioration and extends its lifespan [76].

Waterproofing. Sealing critical electronic components, connectors, and joints against water ingress is essential for ensuring the robot's functionality during rain or when operating in wet conditions. Many agricultural robots are designed to be at least partially waterproof [77].

UV Resistance. Prolonged exposure to sunlight can cause materials and surfaces to degrade over time. UV-resistant coatings and materials help prevent deterioration, maintaining the robot's appearance and structural integrity [78].

4. Applications and Tasks Automated by Agricultural Robots

Agricultural robots, with their diverse robotic structures, revolutionize farming by automating a spectrum of tasks. Autonomous drones equipped with precision sensors navigate fields for crop monitoring and disease detection, showcasing the synergy of robotics and aerial technology. Ground-based robots, featuring articulated arms and advanced computer vision, excel in tasks like selective harvesting and targeted weed control. The integration of robotic structures extends to the automated deployment of robotic tractors, adept at precision planting and cultivating vast expanses with unprecedented accuracy [79]. This paper intricately explores how these varied robotic structures redefine and automate essential agricultural tasks, illuminating the transformative potential of advanced technologies in reshaping traditional farming methodologies. Agricultural robots designed for corn farms play a vital role in improving efficiency, precision, and yield. These robots are equipped with various technologies to perform tasks such as planting, monitoring, harvesting, and crop maintenance. The integration of these diverse robot designs in corn farming contributes to increased productivity, resource efficiency, and sustainability in agriculture [79]. As technology continues to advance, the role of robots in corn farming is likely to expand, offering innovative solutions to challenges faced by modern farmers. Agricultural robots are revolutionizing modern farming by reducing labor demands, optimizing resource utilization, and increasing productivity and sustainability in the agricultural sector. Robots used in agriculture are designed to assist and automate various tasks, enhancing efficiency and precision in farming practices [80]. Some common types of robots used in agriculture are shown in figure 5.

All of the mentioned robot applications shown in figure 5 are mentioned below;

4.1. Crop Spraying Robot (CSR)

Robotic sprayers equipped with precision nozzles and sensors can apply fertilizers, pesticides, and herbicides with high accuracy [81]. They adjust application rates based on real-time data, reducing chemical usage and ensuring even coverage while minimizing runoff and environmental contamination.

4.2. Livestock Monitoring Robot (LMR)

Livestock monitoring robots can vary in design but often include sensors, processing units, and cameras for monitoring livestock [82]. They are used to keep track of the health, behavior, and location of animals. Real-time data provided by these robots on factors

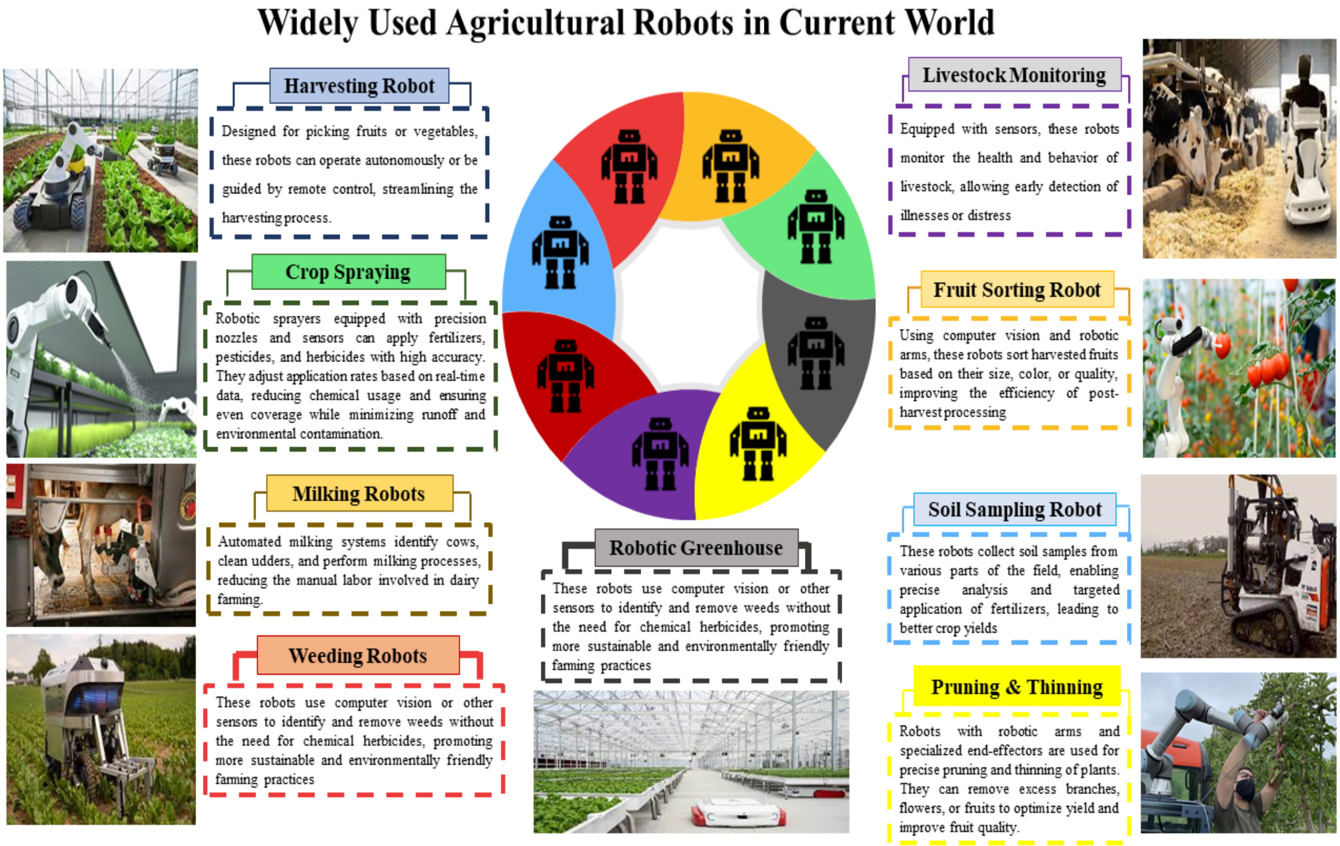

Figure 5. Revolutionizing Agriculture: Cutting-Edge Robot Designs

like temperature, feeding habits, and overall well-being helps farmers detect illnesses early, optimize feeding schedules, and ensure the overall welfare of the livestock.

4.3. Soil Sampling Robot (SSR)

Soil sampling robots are typically equipped with sensors and tools such as a sampling module and anchoring module for collecting soil samples [83]. These robots navigate through fields and collect soil samples at predetermined locations. The samples are then analyzed for nutrient levels, moisture content, and other relevant parameters. Farmers use this data to make informed decisions about fertilization and irrigation, optimizing crop yield.

4.4. Milking Robots (MiR)

Milking robots consist of robotic arms, teat-cleaning mechanisms, and milking units such as quarter milk tubes, milk sensors, milk meters, milk receiver cans, etc. [84]. Automated milking systems allow cows to be milked without human intervention. The robots identify and clean the teats, attach milking units, and monitor milk flow. This technology improves efficiency, provides individualized care for each cow, and allows for continuous monitoring of milk quality.

4.5. Fruit Sorting Robots (FSR)

Fruit sorting robots typically include cameras, sensors, and robotic arms for handling fruits [85]. These robots are used in fruit processing facilities to sort fruits based on size, color, ripeness, and quality. Cameras and sensors identify characteristics, and robotic arms perform the sorting. This automation improves accuracy and efficiency in fruit processing operations.

4.6. Pruning and Thinning (P&T)

Robots with robotic arms and specialized end-effectors are used for precise pruning and thinning of plants [86]. They can remove excess branches, flowers, or fruits to optimize yield and improve fruit quality.

4.7. Greenhouse Robots (GR)

Greenhouse robots can have various designs but often include wheels or tracks for mobility, LIDAR, surveillance cameras, along with sensors and actuators [87].

These robots are employed for tasks like monitoring environmental conditions (temperature, humidity, etc.), applying pesticides, and transporting materials within greenhouses. They help create optimized growing conditions and reduce manual labor.

4.8. Weeding Robots (WR)

Weeding robots may have wheels or tracks for mobility and are equipped with cameras, GPS, and tools for identifying and removing weeds [88]. These robots use computer vision and machine learning algorithms to identify weeds among crops. Once identified, they employ mechanical or chemical means to remove the weeds. This reduces the need for herbicides and manual labor while minimizing damage to crops.

4.9. Harvesting Robots (HR)

Harvesting robots have arms, grippers, RGB-D cameras, autonomous vehicles, and sensors for identifying ripe crops [89]. These robots are designed to harvest fruits, vegetables, or other crops. They use sensors to identify the ripeness of the produce and robotic arms equipped with grippers to pick the crops. Harvesting robots increase efficiency, reduce labor costs, and address labor shortages during peak harvesting seasons.

Each of these robots contributes to precision agriculture, helping farmers make data-driven decisions, optimize resource usage, and improve overall efficiency in farming operations. In the comprehensive analysis of various agricultural robots, distinct robot types emerge with specific advantages, disadvantages, applications, and other influential factors are shown in table 1.

The table 1 explains that, pruning and thinning efficiently handle large-scale operations, yet integration complexities and a learning curve may hinder adoption. Crop Spraying offer accurate crop growth management in orchards, yet their adaptability to varying crops remains a challenge. Milking robots promise continuous operations but are accompanied by high upfront and maintenance costs. Weeding robots, with precision in weed removal, navigate technical challenges in diverse terrains. Harvesting robots, renowned for their ability to reduce manual labor, face challenges such as high initial costs and potential impact on crop quality. The harvesting mainly consists of an RGB-D camera, end effector and robotic arm. Robotic greenhouse system detects environmental issues early, but diagnostic limitations and ethical considerations arise. Soil sampling robots, equipped with advanced sensors and robotic arms, excel in providing accurate data on soil health and nutrient levels, revolutionizing the precision agriculture landscape. Fruit sorting robots bring efficiency to post-harvest processes, streamlining the labor-intensive task of categorizing and packaging fruits based on size, color, and quality. Livestock monitoring robots, equipped with sensors and cameras, facilitate real-time tracking of animal health and behavior, transforming the way farmers manage and care for their herds. Each of these robots, while offering unique advantages, navigates challenges such as technical complexities, initial costs, and the need for seamless integration into existing farming practices.

5. Different Robots for Agriculture Harmful Gas Detections

Various robot designs are employed for this purpose, leveraging different technologies and mechanisms to detect and manage different harmful gases, such as ammonia levels. Here are a few designs used in agricultural settings for the detection of these harmful gases:

5.1. Drone-based Ammonia Detectors

The based robots used for agriculture purposes are shown in figure 6. These robots can be used for different purposes like spraying, pest control, ammonia detection, monitoring of crops and detection of other harmful gases [90].

Fixed-wing Drones. Fixed-wing drones resemble traditional airplanes with wings. They are efficient for covering large agricultural areas due to their longer flight endurance and higher speed compared to multirotor drones. Fixed-wing drones are often used for mapping, surveying, and monitoring large farms [91].

Multirotor Drones. Multirotor drones have multiple rotors and are known for their vertical take-off and landing capabilities, as well as their ability to hover in place. They are versatile and maneuverable, making them suitable for close-range aerial imaging, crop scouting, and monitoring small to medium-sized fields [92].

Hybrid Drones. Hybrid unmanned aerial vehicles amalgamate characteristics from both fixed-wing and multirotor drones, providing advantages from both designs. These drones have the capability to vertically ascend and descend, akin to multirotor drones, while seamlessly transitioning to fixed-wing flight for extended endurance and broader coverage. Applications demanding a combination of agility and endurance, such as expansive mapping and surveillance tasks, find suitability in the deployment of hybrid drones [93].

Spraying Drones. Specialized drones equipped with spraying systems are used for aerial application of pesticides, herbicides, fertilizers, and other agrochemicals.

Table 1. Robotic Type along with their advantages and disadvantages using applications and other factors. (P&T= Prunning and Thinning, CSR= Crop Spraying Robot, LMR= Livestock Monitoring Robot, SSR=Soil Sampling Robot, MiR= Milking Robots, FSR= Fruit Sorting Robots, GR= Greenhouse Robots, WR= Weeding Robots, HR= Harvesting Robots)

Robot Type	Advantages	Disadvantages	Applications	Other Factors
P&T	Increased efficiency and precision in farming. Reduced labor requirements.	High initial investment costs. Requires skilled technicians for maintenance.	Planting, harvesting, plowing, and tilling. Navigation and operations in large fields.	Reduces labor requirements.
CSR	minimizing runoff and environmental contamination. Quick and efficient data collection.	Need high payload capacity. Weather conditions can impact spraying.	Crop monitoring, pest control. Surveillance and mapping of large fields.	Provides real-time data for decision-making.
MiR	Automated milking process, less labor-intensive. Individualized milking and health monitoring.	High initial installation and maintenance costs. Requires regular cleaning and calibration.	Milking in dairy farms. Data collection for dairy herd management.	Improves milking consistency and efficiency.
WR	Reduces chemical herbicide use, eco-friendly. Increased weed removal efficiency.	Limited ability to differentiate crops from weeds. High initial investment and maintenance costs.	Precise and targeted weed control. Organic and sustainable farming practices.	Improves crop yield and reduces environmental harm.
HR	Faster and more efficient harvesting. Reduces labor costs and harvest time.	Initial setup and customization for each crop. May have limitations in handling delicate crops.	Picking fruits and vegetables. Post-harvest processing and sorting.	Addresses labor shortage in harvesting.
GR	Precise control of environmental conditions. Optimizes resource utilization and yields.	High initial investment and energy consumption. Requires specialized knowledge for setup and use.	Controlled environment agriculture. Monitoring and maintaining optimal conditions.	Increases crop quality and year-round production.
SSR	Accurate soil sampling for precise fertilization. Reduces labor and time required for sampling.	Limited sampling depth depending on robot design. May have difficulty in rough terrains.	Soil analysis and nutrient management. Precision agriculture and variable-rate fertilization.	Reduces fertilizer waste and improves yields.
FSR	Fast and consistent sorting based on quality. Reduces human errors and labor in sorting.	High upfront costs and specific fruit compatibility. Limited adaptability to different fruit types.	Post-harvest processing in fruit industries.	Reduces waste and improves product quality.
LMR	Continuous monitoring of livestock health.	Limited autonomy and potential for malfunctions.	Monitoring animal health and behavior.	Early detection of illness or distress in livestock.

These drones can cover uneven terrain and hard-to-reach areas more efficiently than traditional ground-based spraying equipment, reducing chemical usage and minimizing environmental impact [94].

Mapping and Surveying Drones. Drones equipped with high-resolution cameras, multispectral sensors, LiDAR, and GPS systems are used for mapping, surveying, and creating detailed aerial imagery of agricultural fields. They provide valuable data for crop monitoring, yield estimation, soil analysis, and precision agriculture applications [95].

Monitoring and Surveying Drones. Drones equipped with thermal imaging cameras, hyperspectral sensors, and other specialized payloads are used for monitoring crop health, detecting pests, diseases, and irrigation issues. They can provide real-time insights into plant stress, water stress, and nutrient deficiencies, enabling proactive management decisions [96].

Livestock Monitoring Drones. Drones equipped with cameras and sensors are used for monitoring livestock behavior, health, and grazing patterns. They can help farmers track the movement of animals, identify sick or injured individuals, and assess pasture conditions from aerial perspectives [97].

5.2. Harvesting Drones

Harvesting drones are designed to autonomously collect ripe fruits or crops from the fields. Equipped

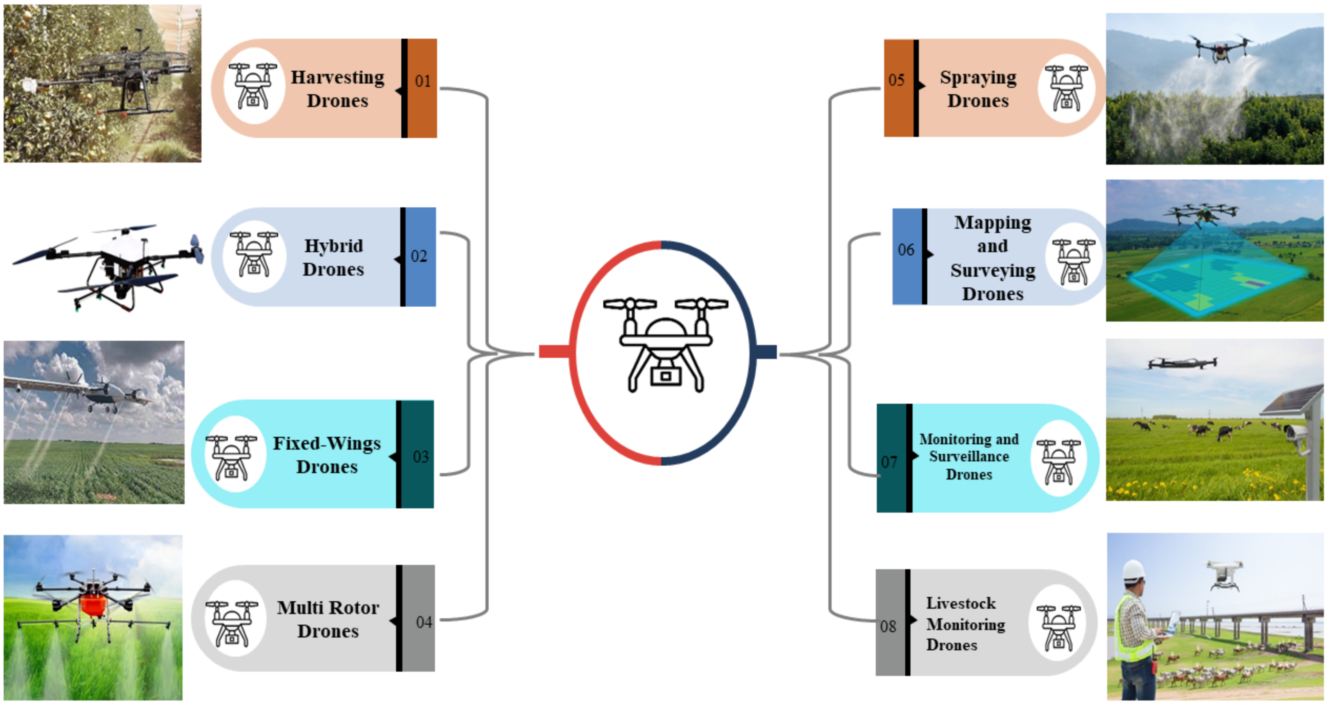

Figure 6. Diverse Drone Solutions: Transforming Agriculture

with advanced computer vision systems and robotic arms, these drones can identify and pick fruits with precision, reducing the labor-intensive process of manual harvesting. Harvesting drones contribute to increased efficiency in crop harvesting, especially in large orchards or fields, and help address labor shortages in agriculture. They can be programmed to navigate through the crops, identify the optimal harvesting time, and gently collect the produce without causing damage [98].

5.3. Ground-based Ammonia Detection Robots

Ground-based Ammonia Detection Robots are innovative machines designed to monitor and detect ammonia levels in various environments. Equipped with advanced sensors and technology, these robots navigate through spaces such as industrial facilities, agricultural areas, or storage units, providing real-time data on ammonia concentrations [99]. This technology enhances safety measures by enabling prompt identification of leaks or hazardous levels, ultimately contributing to environmental and workplace safety. The different types of ground-based robots for ammonia detection are shown in figure 7.

Autonomous Rovers. These are wheeled robots equipped with various sensors and navigation systems. They roam through fields or barns, continuously monitoring and collecting data on ammonia levels. Some models are capable of autonomous navigation using AI and machine learning algorithms [100].

Sensor-Integrated Tractors. Modern tractors are equipped with ammonia sensors that detect gas levels as they move through the fields. They can provide real-time data about ammonia concentration across larger agricultural areas. The integration of ammonia detection sensors into various types of ground-based robots and autonomous vehicles is a feasible approach [101].

Autonomous Ground Vehicles (AGVs). AGVs are wheeled robotic platforms designed for autonomous navigation. They can be equipped with ammonia gas sensors, environmental sensors, and GPS for mapping and localization. AGVs are versatile and can be programmed to follow predefined paths or navigate dynamically in response to detected ammonia concentrations [102].

Unmanned Ground Vehicles (UGVs). UGVs are robotic vehicles designed for various applications, including agriculture. These robots can be customized with ammonia detection sensors and other relevant tools. UGVs equipped with advanced sensors and control systems can contribute to precision agriculture practices [103].

Robotics Platforms for Precision Agriculture. Some companies offer robotics platforms designed for precision

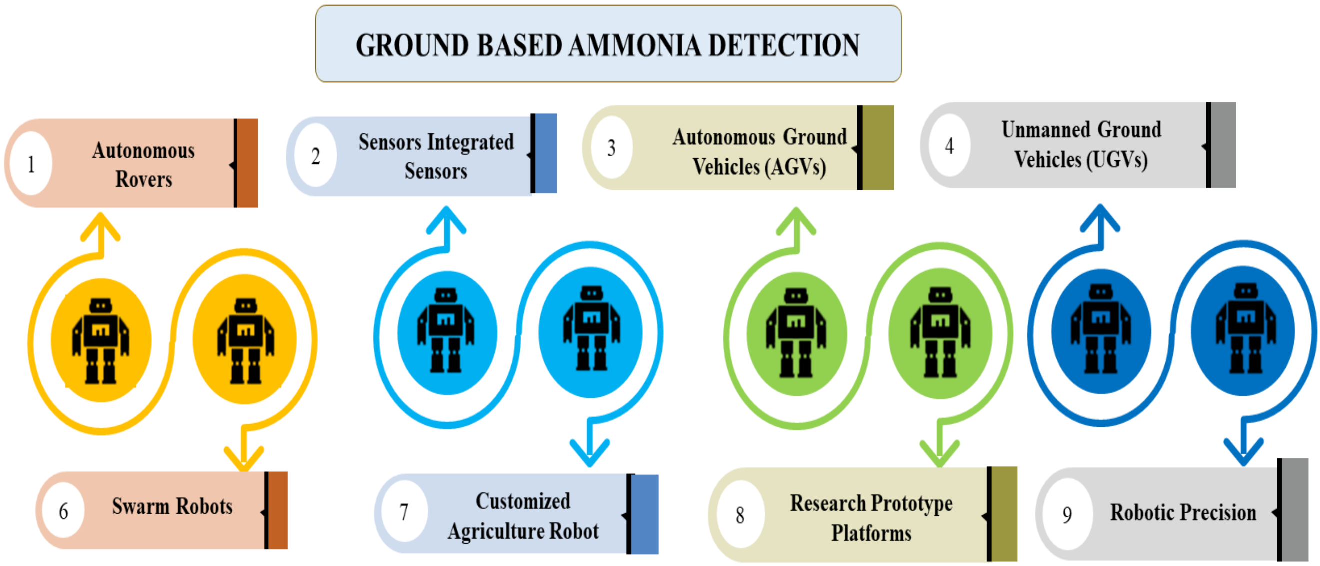

Figure 7. Ammonia Detection Robots: Ground-Based Precision

agriculture applications. These platforms may include ground-based robots equipped with a variety of sensors, including those capable of detecting ammonia levels. These robots can be integrated into broader precision agriculture systems for comprehensive farm management [104].

Swarm Robotics. These involves the collaboration of multiple robots working together. Ground-based robots operating in a swarm can be equipped with ammonia sensors to collectively monitor large agricultural areas. Swarm robotics enhances coverage and data collection efficiency [105].

Customized Agricultural Robots. Some agricultural robotics companies provide customizable solutions tailored to specific tasks. These robots can be adapted for ammonia detection by integrating specialized gas sensors. The customization allows farmers and researchers to address their unique requirements for monitoring ammonia levels in the field [106].

Research and Prototype Platforms. Academic and research institutions may develop ground-based robot prototypes for specific applications, including ammonia detection in agriculture. These platforms often serve as testbeds for exploring new technologies and sensor integration methods [107].

5.4. AI-Driven Centralized Systems

AI-Driven Centralized Systems represent a cutting-edge approach to managing and optimizing complex networks. Utilizing artificial intelligence algorithms, these systems centralize control over diverse processes, from data management to resource allocation. By intelligently analyzing vast datasets and making data-driven decisions, AI-Driven Centralized Systems enhance efficiency, reduce costs, and streamline operations across various sectors, including telecommunications, energy distribution, and smart cities [108].

Centralized Monitoring Systems. Utilizing data from drones, ground robots, and stationary sensors, these systems employ AI algorithms to analyze and predict ammonia levels. They offer real-time monitoring, historical data analysis, and predictive modeling for better decision-making [109].

Mobile Applications and Dashboards. Farm managers and workers can access information through user-friendly interfaces on their mobile devices or computers. These interfaces display current ammonia levels, trends, and alerts for immediate action [110].

E-Nose. Electronic Nose (E-Nose) is a sensor technology used in agriculture to detect gases such as ammonia. Equipped with an array of chemical sensors. The sensors in Enose are sensitive to various volatile organic compounds (VOCs) emitted by ammonia, enabling precise detection. These electronic noses utilize a combination of metal oxide sensors, conducting polymers, and other specialized detectors to analyze the composition of the air. When exposed to the presence of ammonia, the sensors undergo specific changes in electrical resistance, which are then interpreted by the system's software to determine the concentration of the gas. This real-time monitoring capability allows farmers to promptly address ammonia emissions, optimizing agricultural practices and minimizing environmental impact [111].

6. Advantages and Challenges of Agricultural Robotics

The significance of robotics in agriculture extends beyond mere automation; it encompasses the potential to address the pressing issues of global food security and labor shortages. By leveraging cutting-edge technologies, such as computer vision and artificial intelligence, these robots can navigate complex agricultural landscapes with precision, ensuring targeted and resource-efficient interventions [112]. Consequently, the adoption of agricultural robots stands as a transformative force, reshaping the industry and fostering a more sustainable and resilient future for global food production.

6.1. Advantages of Implementing Agricultural Robots

The integration of robotic technologies in agriculture yields a multitude of benefits, ranging from heightened efficiency to substantial cost savings, and enhanced productivity. Automated systems in various agricultural processes, such as harvesting, monitoring, and maintenance, significantly reduce the reliance on manual labor, leading to increased operational efficiency and decreased labor costs. Precision and accuracy inherent in robotic structures result in improved productivity, as tasks are executed with unparalleled consistency and effectiveness [112].

A prominent example of reducing reliance on manual labor in harvesting is the use of robotic fruit-picking systems. These robots, often equipped with advanced computer vision and robotic arms, can identify ripe fruits, assess their readiness for harvest, and delicately pick them without causing damage. Traditional fruit harvesting involves extensive manual labor, but with the deployment of such robots, the need for a large seasonal workforce is significantly diminished, resulting in reduced labor costs. In monitoring, drones equipped with sensors and cameras have proven effective. These aerial robots can cover vast agricultural fields in a short amount of time, capturing high-resolution images and collecting data on crop health. Manual monitoring, on the other hand, would require substantial human labor and time. The use of drones not only streamlines the monitoring process but also reduces the need for a labor-intensive workforce. For maintenance tasks, robotic systems like automated weeding robots showcase labor-saving capabilities. These robots, often guided by computer vision and machine learning algorithms, can distinguish between crops and weeds, allowing them to autonomously navigate through fields and remove unwanted plants. This targeted approach minimizes the need for manual weeding, decreasing labor costs and improving operational efficiency.

The adoption of these specific types of robots exemplifies how automation reduces the reliance on manual labor in various agricultural processes, leading to increased operational efficiency and decreased labor costs. Beyond economic advantages, the environmental impact and sustainability of agriculture are profoundly influenced by robotic interventions. Targeted and precise operations, enabled by sophisticated sensors and algorithms, minimize resource usage, mitigating waste and reducing the overall ecological footprint. Robotic systems excel in optimizing inputs like water, fertilizers, and pesticides, contributing to more sustainable farming practices. The reduction in chemical usage, as facilitated by precise interventions, further aligns with environmentally conscious approaches, promoting ecosystem health and biodiversity [113].

6.2. Challenges and Limitations

The integration of agricultural robots, while promising transformative benefits, is not without its challenges and limitations. One significant hurdle is the cost associated with acquiring and implementing robotic technologies. Initial investment and maintenance expenses can be prohibitive for small-scale farmers, limiting widespread adoption. Additionally, the technical complexities of integrating diverse robotic systems into existing farming practices pose challenges. Farmers often face a learning curve in adapting to new technologies, and compatibility issues may arise when integrating robots with conventional equipment or systems [114].

Regulatory frameworks and ethical considerations are crucial aspects that demand attention. The deployment of agricultural robots raises questions about data ownership, privacy, and the responsible use of autonomous technologies. Striking a balance between innovation and regulatory safeguards is essential to ensure ethical and fair practices in the agricultural sector. Notably, certain types of robots pose more challenges and limitations. Autonomous robots designed for tasks such as selective harvesting or delicate operations like fruit picking face technical hurdles in accurately identifying and handling crops. The intricacies of navigating diverse terrains and responding to unpredictable environmental conditions make the development of these robots more challenging [115].

7. Conclusion and Discussion

As we delve into the intricate structures of various agricultural robots, each type presents a unique amalgamation of functionality, advantages, and considerations are shown in table 2. This illustrates the different robotic types along with their structures and their merits and demerits. The table provides a comprehensive comparison of various robots, facilitating the selection of the most suitable robot for specific tasks. Soil sampling robots, with their advanced sensors and robotic arms, offer precise data on soil health, contributing to optimized farming practices. Fruit sorting robots, designed with efficient sorting algorithms and conveyor systems, enhance post-harvest operations, though they may face challenges in adapting to varying fruit types. Autonomous seed planting robots, leveraging precision technology and GPS systems, ensure optimal seed placement; their adaptability to diverse soil conditions may require further refinement, however. Livestock monitoring robots, equipped with sensors and cameras, provide real-time insights into animal health and behavior, revolutionizing herd management. Advantages and disadvantages span across the board, with soil sampling robots excelling in accuracy but potentially facing challenges in adapting to complex terrains. Fruit sorting robots streamline post-harvest processes but may require specific configurations for different fruits. Autonomous seed planting robots optimize planting but may encounter challenges in adapting to varied soil conditions. Livestock monitoring robots offer real-time insights but may face constraints in certain environmental conditions. Cost and return on investment (ROI) considerations vary, with factors like initial investment and maintenance costs playing a crucial role. Ease of use and integration depend on the complexity of each robot's design, with some requiring more training and adaptability to existing farming practices. Environmental impact considerations factor in the efficiency of operations and resource utilization. Robustness and reliability are critical, especially in demanding agricultural environments. The availability and utilization of data and analytics contribute to the scalability and flexibility of these robotic solutions, with considerations for support and maintenance varying based on the complexity of the robot. Regulatory and safety compliance are paramount, and farm-specific factors play a significant role in the successful integration of these robotic technologies into diverse agricultural landscapes. The abbreviations of table 2 are; App= Applications, Eco=Ecosystem, AT=Autonomous Tractors, UAVs=Unmanned Aerial Vehicles, MR=Milking Robots, WR=Weeding Robots, HR=Harvesting Robots, RGS=Robotic Greenhouse Systems, SSR=Soil Sampling Robots, FSR=Fruit Sorting Robots, LM=Livestock Monitoring.

While agricultural robots hold immense potential, addressing challenges related to cost, technical complexities, and ethical considerations is imperative for their successful integration into existing farming practices. Certain types of robots, particularly those involving intricate tasks and varied environments, present heightened challenges, emphasizing the need for targeted research and development efforts in these areas. The exploration of agricultural robots and their diverse

Table 2. A general comparison of the controlling methods and their suitability for different scenarios.

Type	App	Pros & Cons	Cost	Integration	Eco Impact	Resilience & Reliability	Analytics	Flexibility	Service & Upkeep	Safety Compliance	Farm-Specifics
AT	Navigation and operations in fields.	Increased efficiency and precision in farming.	High initial investment costs.	Requires skilled technicians for setup.	Reduces fuel consumption, eco-friendly.	Robust for outdoor use, weatherproof.	Collects field data for decision-making.	Suitable for large-scale farms.	Regular maintenance needed.	Complies with safety regulations.	Field size and crop types.
UAVs	Crop monitoring, pest detection, efficient data collection.	Surveillance and mapping of fields, Faster data acquisition.	Relatively lower cost, quick ROI.	Remote-controlled, easy to operate.	Reduced chemical usage, eco-friendly.	Prone to weather conditions.	Provides real-time data for analysis.	Versatile for various crop types.	Periodic maintenance required.	Complies with aviation regulations.	Field size, weather, and crop types.
MR	Automated milking process.	Individualized milking and health monitoring.	High initial installation costs.	Integrated milking and data management.	Reduces labor, improves milking efficiency.	Regular maintenance required.	Monitors cow health and milk quality.	Suitable for dairy farms of all sizes.	Requires skilled technicians for service.	Complies with safety regulations.	Number of cows and milking frequency.
WR	Precise and targeted weed control.	Reduces chemical herbicide use, eco-friendly.	High initial investment costs.	Autonomous operation, minimal intervention.	Reduces environmental impact of chemicals.	Navigation in varying terrains.	Data-driven weed detection and control.	Scalable to different field sizes.	Regular maintenance needed.	Complies with safety regulations.	Crop type and weed infestation.
HR	Picking fruits and vegetables.	Faster and more efficient harvesting, reduces labor costs.	High initial investment costs.	Automation reduces manual labor.	Reduces labor, improves harvest efficiency.	Adaptable to various crop types.	Data collection during harvesting.	Scalable to different crop types.	Regular maintenance required.	Complies with safety regulations.	Crop type and harvesting frequency.
RGS	Controlled environment agriculture, Monitoring and maintaining conditions.	Precise control of environmental conditions, improves yield and quality, Optimizes resource utilization, year-round production.	High initial investment costs, Initial investment pays off in the long term.	Integrates with greenhouse infrastructure, Automated control and monitoring.	Reduces resource wastage, energy-efficient.	Stable and consistent performance, Stable performance in controlled settings.	Monitors environmental variables, Real-time data for decision-making.	Scalable to greenhouse sizes, Adaptable to various greenhouse sizes.	Regular monitoring and calibration, Regular maintenance required.	Complies with safety regulations, Complies with safety regulations.	Greenhouse size and crop type, Crop type and greenhouse size.
SSR	Soil analysis and nutrient management.	Accurate soil sampling for precise fertilization.	High initial investment costs.	Reduces manual labor in sampling.	Optimizes fertilization, reduces waste.	Navigates challenging terrains.	Provides valuable soil data.	Scalable to different field sizes.	Regular maintenance required.	Complies with safety regulations.	Field size and soil variability.
FSR	Post-harvest processing in fruit industries.	Fast and consistent sorting based on quality.	High initial investment costs.	Automates fruit sorting process.	Reduces manual labor and waste.	Efficient and accurate sorting.	Collects data on fruit quality.	Scalable to various fruit types.	Regular maintenance required.	Complies with safety regulations.	Fruit type and processing volume.
LM	Monitoring animal health and behavior.	Continuous monitoring and early detection of illness or distress.	High initial investment costs.	Automated health monitoring.	Improves livestock welfare and management.	Operates in livestock settings.	Collects data for health analysis.	Suitable for different livestock sizes.	Regular maintenance required.	Complies with safety regulations.	Livestock size and type.

applications underscores the transformative impact of robotics on modern farming practices. By delving more deeply into the intricate structure, advantages, and operational mechanisms of these robots, we can shed light on their pivotal role in enhancing efficiency, sustainability, and precision in agriculture.

The foundation of agricultural robots lies in their base platforms, with options ranging from tracked vehicles offering stability in challenging terrains to wheeled robots suitable for well-maintained fields. Legged robots and unmanned aerial vehicles (UAVs), including drones, provide adaptability to uneven terrain and unique perspectives for monitoring large agricultural areas. Autonomous ground vehicles (AGVs) further contribute to tasks like crop scouting and monitoring.

A crucial component of agricultural robots is their sensor array, which encompasses cameras, GPS systems, and soil sensors. These sensors play a vital role in data collection for various purposes, from visual inspection of crops to measuring soil moisture, pH levels, and nutrient content. Gas sensors, including those for ammonia detection, provide early warnings for potential hazards, contributing to environmental and workplace safety.

Manipulators, represented by robotic arms, enable agricultural robots to perform tasks such as harvesting, pruning, seeding, and weeding with precision. Power systems, ranging from electric batteries to internal combustion engines and even wireless charging, offer flexibility based on the robot's size, tasks, and operational requirements. Control and communication systems, incorporating on-board control systems, autonomous navigation, and path planning algorithms, empower robots to operate autonomously, making data-driven decisions.

The integration of autonomous navigation technologies, including LiDAR and wheel encoders, ensures that agricultural robots can move through fields without constant human intervention. Machine learning techniques further enhance navigation capabilities, allowing robots to adapt their behavior based on experience. Data analysis and decision support systems provide farmers with valuable insights for optimizing crop yield, resource utilization, and overall farm management.

The paper also explores specialized applications, such as drone-based ammonia detectors and ground-based ammonia detection robots, addressing the critical need for monitoring harmful gases in agriculture. Additionally, AI-driven centralized systems exemplify a forward-looking approach to managing complex agricultural networks.

As agriculture embraces technology, the durability, modularity, and scalability of robotic designs become paramount considerations. The evolution of agricultural robots, from crop spraying robots to milking robots and greenhouse robots, demonstrates their versatility across various farming tasks. Each robot type contributes uniquely to precision agriculture, allowing for data-driven decision-making, optimized resource usage, and increased overall efficiency.

In conclusion, the integration of diverse robotic structures in agriculture marks a significant paradigm shift, offering innovative solutions to challenges faced by modern farmers. The continuous advancement of technology is poised to expand the role of robots in farming, further revolutionizing traditional methodologies and promoting sustainable, efficient, and productive agricultural practices.

References

[1] Lagnelöv, O., Dhillon, S., Larsson, G., Nilsson, D., Larsolle, A., & Hansson, P. A. (2021). Cost analysis of autonomous battery electric field tractors in agriculture. biosystems engineering, 204, 358-376.

[2] Del Cerro, J., Cruz Ulloa, C., Barrientos, A., & de León Rivas, J. (2021). Unmanned aerial vehicles in agriculture: A survey. Agronomy, 11(2), 203.

[3] Oliveira, L. F., Moreira, A. P., & Silva, M. F. (2021). Advances in agriculture robotics: A state-of-the-art review and challenges ahead. Robotics, 10(2), 52.

[4] Tudor, E., Matache, M. G., Vasile, I., Sburlan, I. C., & Stefan, V. (2022). Automation and Remote Control of an Aquatic Harvester Electric Vehicle. Sustainability, 14(10), 6360.

[5] Sakai, S., Iida, M., Osuka, K., & Umeda, M. (2008). Design and control of a heavy material handling manipulator for agricultural robots. Autonomous Robots, 25, 189-204.

[6] Ball, D., Upcroft, B., Wyeth, G., Corke, P., English, A., Ross, P., & Bate, A. (2016). Vision-based obstacle detection and navigation for an agricultural robot. Journal of field robotics, 33(8), 1107-1130.

[7] Huang, C. C., & Chang, C. L. (2019). Design and implementation of bio-inspired snake bone-armed robot for agricultural irrigation application. IFAC-PapersOnLine, 52(30), 98-101.

[8] Chebrolu, N., Lottes, P., Läbe, T., & Stachniss, C. (2019, May). Robot localization based on aerial images for precision agriculture tasks in crop fields. In 2019 International Conference on Robotics and Automation (ICRA) (pp. 1787-1793). IEEE.

[9] Mitra, M. (2019). Robotic farmers in agriculture. Advances in Robotics & Mechanical Engineering, (5), 91-93.

[10] Al-Mashhadani, Z., & Chandrasekaran, B. (2020, November). Survey of Agricultural Robot Applications and Implementation. In 2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) (pp. 0076-0081). IEEE.

[11] Fountas, S., Mylonas, N., Malounas, I., Rodias, E., Hellmann Santos, C., & Pekkeriet, E. (2020). Agricultural robotics for field operations. Sensors, 20(9), 2672.

[12] Mahmud, M. S. A., Abidin, M. S. Z., Emmanuel, A. A., & Hasan, H. S. (2020). Robotics and automation in agriculture: present and future applications. Applications of Modelling and Simulation, 4, 130-140.

[13] Skoczeń, M., Ochman, M., Spyra, K., Nikodem, M., Krata, D., Panek, M., & Pawłowski, A. (2021). Obstacle detection system for agricultural mobile robot application using RGB-D cameras. Sensors, 21(16), 5292.

[14] Han, J., Liu, L., & Zeng, H. (2021). Design and implementation of intelligent agricultural picking mobile robot based on color sensor. In Journal of Physics: Conference Series (Vol. 1757, No. 1, p. 012157). IOP Publishing.

[15] Chand, A. A., Prasad, K. A., Mar, E., Dakai, S., Mamun, K. A., Islam, F. R., & Kumar, N. M. (2021). Design and analysis of photovoltaic powered battery-operated computer vision-based multi-purpose smart farming robot. Agronomy, 11(3), 530.

[16] Mohammed, I. I., & Jassim, A. R. A. L. (2021). Design and Testing of an Agricultural Robot to Operate a Combined Seeding Machine. Annals of the Romanian Society for Cell Biology, 25(7), 92-106.

[17] Kondoyanni, M., Loukatos, D., Maraveas, C., Drosos, C., & Arvanitis, K. G. (2022). Bio-inspired robots and structures toward fostering the modernization of agriculture. Biomimetics, 7(2), 69.

[18] Moraitis, M., Vaiopoulos, K., & Balafoutis, A. T. (2022). Design and implementation of an urban farming robot. Micromachines, 13(2), 250.

[19] Orkweha, P. (2022). Trajectory Control Design for a Custom-Built Agricultural Robot Considering Slippage Effects (Doctoral dissertation, Southern Illinois University at Edwardsville).

[20] Ghafar, A. S. A., Hajjaj, S. S. H., Gsangaya, K. R., Sultan, M. T. H., Mail, M. F., & Hua, L. S. (2023). Design and development of a robot for spraying fertilizers and pesticides for agriculture. Materials Today: Proceedings, 81, 242-248.

[21] Yang, Q., Du, X., Wang, Z., Meng, Z., Ma, Z., & Zhang, Q. (2023). A review of core agricultural robot technologies for crop productions. Computers and Electronics in Agriculture, 206, 107701.

[22] Ghobadpour, A., Cardenas, A., Monsalve, G., & Mousazadeh, H. (2023). Optimal Design of Energy Sources for a Photovoltaic/Fuel Cell Extended-Range Agricultural Mobile Robot. Robotics, 12(1), 1

[23] Azmi, H. N., Hajjaj, S. S. H., Gsangaya, K. R., Sultan, M. T. H., Mail, M. F., & Hua, L. S. (2023). Design and fabrication of an agricultural robot for crop seeding. Materials Today: Proceedings, 81, 283-289.

[24] Li, Y., Fu, C., Yang, H., Li, H., Zhang, R., Zhang, Y., & Wang, Z. (2023). Design of a Closed Piggery Environmental Monitoring and Control System Based on a Track Inspection Robot. Agriculture, 13(8), 1501.

[25] Duckett, T., Pearson, S., Blackmore, S., Grieve, B., Chen, W. H., Cielniak, G., ... & Yang, G. Z. (2018). Agricultural robotics: the future of robotic agriculture. arXiv preprint arXiv:1806.06762.

[26] Vineet, S., Deshmukh, D., Pratihar, D. K., Deb, A. K., Ray, H., & Bhattacharyya, N. (2021, December). Dynamic Analysis of Tracked Mobile Manipulator Used in Agriculture. In 2021 IEEE 18th India Council International Conference (INDICON) (pp. 1-6). IEEE.

[27] Gao, X., Li, J., Fan, L., Zhou, Q., Yin, K., Wang, J., ... & Wang, Z. (2018). Review of wheeled mobile robots' navigation problems and application prospects in agriculture. Ieee Access, 6, 49248-49268.

[28] Bellicoso, C. D., Bjelonic, M., Wellhausen, L., Holtmann, K., Günther, F., Tranzatto, M., ... & Hutter, M. (2018). Advances in real-world applications for legged robots. Journal of Field Robotics, 35(8), 1311-1326.

[29] Degieter, M., De Steur, H., Tran, D., Gellynck, X., & Schouteten, J. J. (2023). Farmers' acceptance of robotics and unmanned aerial vehicles: A systematic review. Agronomy Journal, 115(5), 2159-2173.

[30] Zarei, M., Moshayedi, A. J., Zhong, Y., Khan, A. S., Kolahdooz, A., & Andani, M. E. (2023, January). Indoor UAV object detection algorithms on three processors: implementation test and comparison. In 2023 3rd International Conference on Consumer Electronics and Computer Engineering (ICCECE) (pp. 812-819). IEEE.

[31] Moshayedi, A. J., Reza, K. S., Khan, A. S., & Nawaz, A. (2023). Integrating virtual reality and robotic operation system (ROS) for AGV navigation. EAI Endorsed Transactions on AI and Robotics, 2.

[32] Xie, D., Chen, L., Liu, L., Chen, L., & Wang, H. (2022). Actuators and sensors for application in agricultural robots: A review. Machines, 10(10), 913.

[33] Khan, N., Medlock, G., Graves, S., & Anwar, S. (2018). GPS guided autonomous navigation of a small agricultural robot with automated fertilizing system (No. 2018-01-0031). SAE Technical Paper.

[34] Radočaj, D., Plaščak, I., & Jurišić, M. (2023). Global navigation satellite systems as state-of-the-art solutions in precision agriculture: A review of studies indexed in the web of science. Agriculture, 13(7), 1417.

[35] Hiraoka, R., Aoyagi, Y., & Kobayashi, K. (2023). Automatic travelling of agricultural support robot for a fruit farm. Verification of effectiveness of real-time kinematic-global navigation satellite system and developed a simulator for specification design. Journal of Agricultural Engineering, 54(1).

[36] Moshayedi, A. J., Kazemi, E., Tabatabaei, M., & Liao, L. (2020). Brief modeling equation for metal-oxide; TGS type gas sensors. Filomat, 34(15), 4997-5008.

[37] Senthil, P., & Akila, I. S. (2018, August). Automated robotic moisture monitoring in agricultural fields. In 2018 International Seminar on Intelligent Technology and Its Applications (ISITIA) (pp. 375-380). IEEE.

[38] Shivaprasad, B. S., Ravishankara, M. N., & Shoba, B. N. (2014). Design and implementation of seeding and fertilizing agriculture robot. International Journal of Application or Innovation in Engineering & Management (IJAIEM), 3(6), 251-255.

[39] Kitić, G., Krklješ, D., Panić, M., Petes, C., Birgermajer, S., & Crnojević, V. (2022). Agrobot Lala—An Autonomous Robotic System for Real-Time, In-Field Soil Sampling, and Analysis of Nitrates. Sensors, 22(11), 4207.

[40] Rakhra, M., Singh, A., Fadhaeel, T., Al Ahdal, A., & Pandey, N. (2022, October). Design, Fabrication, and Implementation of an Agriculture robot. In 2022 10th International Conference on Reliability, Infocom

Technologies and Optimization (Trends and Future Directions) (ICRITO) (pp. 1-6). IEEE.
[41] Fentanes, J. P., Gould, I., Duckett, T., Pearson, S., & Cielniak, G. (2018). 3-d soil compaction mapping through kriging-based exploration with a mobile robot. IEEE Robotics and Automation Letters, 3(4), 3066-3072.
[42] Pobkrut, T., & Kerdcharoen, T. (2014, October). Soil sensing survey robots based on electronic nose. In 2014 14th International Conference on Control, Automation and Systems (ICCAS 2014) (pp. 1604-1609). IEEE.
[43] Xing, Y., Vincent, T. A., Cole, M., & Gardner, J. W. (2019). Real-time thermal modulation of high bandwidth MOX gas sensors for mobile robot applications. Sensors, 19(5), 1180.
[44] Moshayedi, A. J., Khan, A. S., Shuxin, Y., Kuan, G., Jiandong, H., Soleimani, M., & Razi, A. (2023). E-Nose design and structures from statistical analysis to application in robotic: a compressive review. EAI Endorsed Transactions on AI and Robotics, 2(1), e1-e1.
[45] Moshayedi, A. J., Sohail Khan, A., Hu, J., Nawaz, A., & Zhu, J. (2023). E-nose-driven advancements in ammonia gas detection: a comprehensive review from traditional to cutting-edge systems in indoor to outdoor agriculture. Sustainability, 15(15), 11601.
[46] Arroyo, P., Gómez-Suárez, J., Herrero, J. L., & Lozano, J. (2022). Electrochemical gas sensing module combined with unmanned aerial vehicles for air quality monitoring. Sensors and Actuators B: Chemical, 364, 131815.
[47] Fumian, F., Di Giovanni, D., Martellucci, L., Rossi, R., & Gaudio, P. (2020). Application of miniaturized sensors to unmanned aerial systems, a new pathway for the survey of polluted areas: Preliminary results. Atmosphere, 11(5), 471.
[48] Al-Mashhadani, Z., & Chandrasekaran, B. (2020, November). Survey of Agricultural Robot Applications and Implementation. In 2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) (pp. 0076-0081). IEEE.
[49] Moshayedi, A. J., Roy, A. S., Liao, L., Khan, A. S., Kolahdooz, A., & Eftekhari, A. (2024). Design and Development of Foodiebot Robot: from Simulation to Design. IEEE Access.
[50] Tinoco, V., Silva, M. F., Santos, F. N., Valente, A., Rocha, L. F., Magalhães, S. A., & Santos, L. C. (2022). An overview of pruning and harvesting manipulators. Industrial Robot: the international journal of robotics research and application, 49(4), 688-695.
[51] Bechar, A., & Vigneault, C. (2017). Agricultural robots for field operations. Part 2: Operations and systems. Biosystems engineering, 153, 110-128.
[52] Bawden, O., Kulk, J., Russell, R., McCool, C., English, A., Dayoub, F., ... & Perez, T. (2017). Robot for weed species plant-specific management. Journal of Field Robotics, 34(6), 1179-1199.
[53] Moshayedi, A. J., Roy, A. S., Liao, L., & Li, S. (2019, December). Raspberry Pi SCADA zonal based system for agricultural plant monitoring. In 2019 6th International Conference on Information Science and Control Engineering (ICISCE) (pp. 427-433). IEEE.
[54] Vyas, S. D., Subash, V. K., Mepani, M., Venkatesh, S., Sinha, A., Guha, A., & Dey, S. (2024). Energy-and Safety-Aware Operation of Battery-Powered Autonomous Robots in Agriculture. IEEE Transactions on AgriFood Electronics
[55] Gonzalez-de-Soto, M., Emmi, L., Benavides, C., Garcia, I., & Gonzalez-de-Santos, P. (2016). Reducing air pollution with hybrid-powered robotic tractors for precision agriculture. Biosystems Engineering, 143, 79-94.
[56] Zahedi, A., Shafei, A. M., & Shamsi, M. (2023). Application of hybrid robotic systems in crop harvesting: kinematic and dynamic analysis. Computers and Electronics in Agriculture, 209, 107724.
[57] Farooq, M. U., Eizad, A., & Bae, H. K. (2023). Power solutions for autonomous mobile robots: A survey. Robotics and Autonomous Systems, 159, 104285.
[58] Ünal, İ., Kabaş, Ö., Eceoğlu, O., & Moiceanu, G. (2023). Adaptive Multi-Robot Communication System and Collision Avoidance Algorithm for Precision Agriculture. Applied Sciences, 13(15), 8602.
[59] Xie, B., Jin, Y., Faheem, M., Gao, W., Liu, J., Jiang, H., ... & Li, Y. (2023). Research progress of autonomous navigation technology for multi-agricultural scenes. Computers and Electronics in Agriculture, 211, 107963.
[60] Shalal, N., Low, T., McCarthy, C., & Hancock, N. (2013). A review of autonomous navigation systems in agricultural environments. SEAg 2013: Innovative agricultural technologies for a sustainable future.
[61] Hameed, I. A. (2014). Intelligent coverage path planning for agricultural robots and autonomous machines on three-dimensional terrain. Journal of Intelligent & Robotic Systems, 74(3), 965-983.
[62] Pingzeng, L., Shusheng, B., Guansheng, Z., Wenshan, W., Yushu, G., & Zhenmin, D. (2011, December). Obstacle avoidance system for agricultural robots based on multi-sensor information fusion. In Proceedings of 2011 International Conference on Computer Science and Network Technology (Vol. 2, pp. 1181-1185). IEEE.
[63] Tsiakas, K., Papadimitriou, A., Pechlivani, E. M., Giakoumis, D., Frangakis, N., Gasteratos, A., & Tzovaras, D. (2023). An Autonomous Navigation Framework for Holonomic Mobile Robots in Confined Agricultural Environments. Robotics, 12(6), 146.
[64] Stronzek-Pfeifer, D., Chemmadan, F. M., Patel, S., & Büskens, C. (2023). LiDAR-based object detection for agricultural robots. PAMM, 23(3), e202300128.
[65] Heidari, A., & Parian, J. A. (2021). Greenhouse Mobile robot navigation using wheel revolution encoding and learning algorithm. Journal of Agricultural Machinery, 11(1), 1-15.
[66] Han, C., Wu, W., Luo, X., & Li, J. (2023). Visual Navigation and Obstacle Avoidance Control for Agricultural Robots via LiDAR and Camera. Remote Sensing, 15(22), 5402.
[67] Ding, H., Zhang, B., Zhou, J., Yan, Y., Tian, G., & Gu, B. (2022). Recent developments and applications of simultaneous localization and mapping in agriculture. Journal of Field Robotics, 39(6), 956-983.
[68] Bini, D., Pamela, D., & Prince, S. (2020, March). Machine vision and machine learning for intelligent agrobots: A review. In 2020 5th International conference on devices, circuits and systems (ICDCS) (pp. 12-16). IEEE.

[69] Gonzalez-de-Santos, P., Fernández, R., Sepúlveda, D., Navas, E., Emmi, L., & Armada, M. (2020). Field robots for intelligent farms—Inhering features from industry. Agronomy, 10(11), 1638.
[70] Nikander, J., Manninen, O., & Laajalahti, M. (2020). Requirements for cybersecurity in agricultural communication networks. Computers and electronics in agriculture, 179, 105776.
[71] Adamides, G., & Edan, Y. (2023). Human–robot collaboration systems in agricultural tasks: A review and roadmap. Computers and Electronics in Agriculture, 204, 107541
[72] Redhead, F., Snow, S., Vyas, D., Bawden, O., Russell, R., Perez, T., & Brereton, M. (2015, April). Bringing the farmer perspective to agricultural robots. In Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems (pp. 1067-1072).
[73] Mahadhir, K. A., Tan, S. C., Low, C. Y., Dumitrescu, R., Amin, A. T. M., & Jaffar, A. (2014). Terrain classification for track-driven agricultural robots. Procedia Technology, 15, 775-782
[74] Xu, G., Khan, A. S., Moshayedi, A. J., Zhang, X., & Shuxin, Y. (2022). The object detection, perspective and obstacles in robotic: a review. EAI Endorsed Transactions on AI and Robotics, 1(1).
[75] Botta, A., Cavallone, P., Baglieri, L., Colucci, G., Tagliavini, L., & Quaglia, G. (2022). A review of robots, perception, and tasks in precision agriculture. Applied Mechanics, 3(3), 830-854.
[76] Chang, C. L., Chen, H. W., & Ke, J. Y. (2023). Robust Guidance and Selective Spraying Based on Deep Learning for an Advanced Four-Wheeled Farming Robot. Agriculture, 14(1), 57.
[77] Gravalos, I., Avgousti, A., Gialamas, T., Alfieris, N., & Paschalidis, G. (2019). A robotic irrigation system for urban gardening and agriculture. Journal of agricultural engineering, 50(4), 198-207.
[78] Krishna, K. L., Silver, O., Malende, W. F., & Anuradha, K. (2017, February). Internet of Things application for implementation of smart agriculture system. In 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 54-59). IEEE.
[79] Marinoudi, V., Lampridi, M., Kateris, D., Pearson, S., Sørensen, C. G., & Bochtis, D. (2021). The future of agricultural jobs in view of robotization. Sustainability, 13(21), 12109.
[80] 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.
[81] Meshram, A. T., Vanalkar, A. V., Kalambe, K. B., & Badar, A. M. (2022). Pesticide spraying robot for precision agriculture: A categorical literature review and future trends. Journal of Field Robotics, 39(2), 153-171.
[82] Halachmi, I., Guarino, M., Bewley, J., & Pastell, M. (2019). Smart animal agriculture: application of real-time sensors to improve animal well-being and production. Annual review of animal biosciences, 7, 403-425.
[83] Łukowska, A., Tomaszuk, P., Dzierżek, K., & Magnuszewski, Ł. (2019, May). Soil sampling mobile platform for Agriculture 4.0. In 2019 20th International Carpathian Control Conference (ICCC) (pp. 1-4). IEEE.
[84] Wang, C., Ding, F., Ling, L., & Li, S. (2023). Design of a teat cup attachment robot for automatic milking systems. Agriculture, 13(6), 1273.
[85] Dewi, T., Risma, P., & Oktarina, Y. (2020). Fruit sorting robot based on color and size for an agricultural product packaging system. Bulletin of Electrical Engineering and Informatics, 9(4), 1438-1445.
[86] Santos, A. S. D., Dalzot, J. C. T., Pereira, G. A., Cunha, J. G. D., Evangelista, T. Y. L., Fonseca, W. L., ... & AbdElgawad, H. (2023). Pruning and fruit thinning of Psidium guajava cv. Paluma under a seasonal tropical climate. Agriculture, 13(8), 1537.
[87] Roldán, J. J., del Cerro, J., Garzón-Ramos, D., Garcia-Aunon, P., Garzón, M., De León, J., & Barrientos, A. (2018). Robots in agriculture: State of art and practical experiences. Service robots, 67-90.
[88] McAllister, W., Osipychev, D., Davis, A., & Chowdhary, G. (2019). Agbots: Weeding a field with a team of autonomous robots. Computers and Electronics in Agriculture, 163, 104827.
[89] Bilal, M., Rubab, F., Hussain, M., & Shah, S. A. R. (2023, November). Agriculture Revolutionized by Artificial Intelligence: Harvesting the Future. In Biology and Life Sciences Forum (Vol. 30, No. 1, p. 11). MDPI.
[90] Aravindaguru, I., Mathan, C., Sharmila, B., Nagarajapandian, M., & Veeramani, P. (2023). Environmental Drones for Autonomous Air Pollution Investigation, Detection, and Remediation. In Drone Data Analytics in Aerial Computing (pp. 107-118). Singapore: Springer Nature Singapore.
[91] Bale, A. S., Varsha, S. N., Naidu, A. S., Vinay, N., & Tiwari, S. (2024). Autonomous Aerial Robots Application for Crop Survey and Mapping. In Precision Agriculture for Sustainability (pp. 123-145). Apple Academic Press.
[92] Tomar, P., & Krishnan, S. (2022, August). Development of a Drone with Spraying Mechanism for Agricultural Work. In Biennial International Conference on Future Learning Aspects of Mechanical Engineering (pp. 295-308). Singapore: Springer Nature Singapore.
[93] Malo, M. (2020). Artificial intelligence in agriculture: strengthening the future of farming. *AGRICULTURE & FOOD e-NEWSLETTER*, 71.
[94] Panwar, K., Prasad, S., & Semwal, A. (2022). Different Approaches of Robotic Spraying Drones for Agricultural Activities. *resmilitaris*, 12(5), 1377-1384.
[95] Escandón-Panchana, P., Herrera-Franco, G., Martínez Cuevas, S., & Morante-Carballo, F. (2023, October). Prospects of UAVs in Agricultural Mapping. In *International Conference on Applied Informatics* (pp. 309-322). Cham: Springer Nature Switzerland.
[96] Chinnasamy, S., Ramachandran, M., & Sriram, S. (2022). An Detailed Study on Unmanned Aerial Vehicle and Its Surveillance‖. *Environmental Science and Engineering*, 1(1), 41-47.
[97] Shvets, Y., Morkovkin, D., Basova, M., Yashchenko, A., & Petrusevich, T. (2024). Robotics in agriculture: Advanced technologies in livestock farming and crop cultivation. In *E3S Web of Conferences* (Vol. 480, p. 03024). EDP Sciences.

[98] Basri, R., Islam, F., Shorif, S. B., & Uddin, M. S. (2021). Robots and drones in agriculture—a survey. *Computer vision and machine learning in agriculture*, 9-29.

[99] Hutsol, T., Kutyrev, A., Kiktev, N., & Biliuk, M. (2023). Robotic technologies in horticulture: analysis and implementation prospects. *Agricultural Engineering*, 27(1), 113-133.

[100] Waked, J., Sara, G., Todde, G., Pinna, D., Hassoun, G., & Caria, M. (2023, October). Analysis of Factors Affecting Farmers' Intention to Use Autonomous Ground Vehicles. In *International Congress on Agricultural Mechanization and Energy in Agriculture* (pp. 423-440). Cham: Springer Nature Switzerland.

[101] Han, J. H., Park, C. H., Kwon, J. H., Lee, J., Kim, T. S., & Jang, Y. Y. (2020). Performance evaluation of autonomous driving control algorithm for a crawler-type agricultural vehicle based on low-cost multi-sensor fusion positioning. *Applied Sciences*, 10(13), 4667.

[102] Moshayedi, A. J., Li, J., & Liao, L. (2021, June). Simulation study and PID tune of automated guided vehicles (AGV). In 2021 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA) (pp. 1-7). IEEE.

[103] Bonadies, S., Lefcourt, A., & Gadsden, S. A. (2016, May). A survey of unmanned ground vehicles with applications to agricultural and environmental sensing. In *Autonomous air and ground sensing systems for agricultural optimization and phenotyping* (Vol. 9866, pp. 142-155). SPIE.

[104] Jensen, K., Larsen, M., Nielsen, S. H., Larsen, L. B., Olsen, K. S., & Jørgensen, R. N. (2014). Towards an open software platform for field robots in precision agriculture. *Robotics*, 3(2), 207-234.

[105] Albiero, D., Garcia, A. P., Umezu, C. K., & de Paulo, R. L. (2022). Swarm robots in mechanized agricultural operations: A review about challenges for research. *Computers and Electronics in Agriculture*, 193, 106608.

[106] Xu, R., & Li, C. (2022). A modular agricultural robotic system (MARS) for precision farming: Concept and implementation. *Journal of Field Robotics*, 39(4), 387-409.

[107] Tangarife, H. I., & Díaz, A. E. (2017, October). Robotic applications in the automation of agricultural production under greenhouse: A review. In *2017 IEEE 3rd Colombian Conference on Automatic Control (CCAC)* (pp. 1-6). IEEE.

[108] Tzachor, A., Devare, M., King, B., Avin, S., & Ó hÉigeartaigh, S. (2022). Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. *Nature Machine Intelligence*, 4(2), 104-109.

[109] Küçüktopcu, E., & Cemek, B. (2021). Comparison of neuro-fuzzy and neural networks techniques for estimating ammonia concentration in poultry farms. *Journal of Environmental Chemical Engineering*, 9(4), 105699.

[110] Achmad, A., & Syarif, S. (2021, July). Prediction of Ammonia Contamination Levels in Wastewater Management Plant Using the SVM Method. In *2021 International Seminar on Intelligent Technology and Its Applications (ISITIA)* (pp. 250-255). IEEE.

[111] Geng, K., Ata, J. M., Chen, J., Hu, J., & Zhang, H. (2023, March). ENOSE Performance in Transient Time and Steady State Area of Gas Sensor Response for Ammonia Gas: Comparison and Study. In Proceedings of the 2023 2nd Asia Conference on Algorithms, Computing and Machine Learning (pp. 247-252).

[112] Gil, G., Casagrande, D. E., Cortés, L. P., & Verschae, R. (2023). Why the low adoption of robotics in the farms? Challenges for the establishment of commercial agricultural robots. *Smart Agricultural Technology*, 3, 100069.

[113] Yang, Q., Du, X., Wang, Z., Meng, Z., Ma, Z., & Zhang, Q. (2023). A review of core agricultural robot technologies for crop productions. *Computers and Electronics in Agriculture*, 206, 107701.

[114] Mohan, S. S., Venkat, R., Rahaman, S., Vinayak, M., & Babu, B. H. (2023). Role of AI in agriculture: applications, limitations and challenges: A review. *Agricultural Reviews*, 44(2), 231-237.

[115] Bazargani, K., & Deemyad, T. (2024). Automation's Impact on Agriculture: Opportunities, Challenges, and Economic Effects. *Robotics*, 13(2), 33.