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The Evolution of Agricultural Robotics: A Comprehensive Review and Future Challenges

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Abstract: Agricultural robotics is constantly evolving in an effort to address the problems caused by urbanisation, population increase, high cost of high-quality goods, environmental preservation, and shortage of skilled workers. The primary current applications of agricultural robotic systems are reviewed in this study, which include their use in land preparation prior to planting, sowing, planting, plant treatment, harvesting, yield calculation, and phenotyping. The criteria used to evaluate all robots include their locomotion system, intended use, whether they had sensors, robotic arm, or computer vision algorithm, level of development and the nation or continent to which they belong. Four key areas that require further research to advance the state of the art in smart agriculture were identified after evaluating all similar characteristics, exposing research trends, common pitfalls, and characteristics that impede commercial development. The findings of this review indicate that investment in agricultural robotic systems enables the achievement of short-term goals (harvest monitoring) and long-term goals (yield estimation).
Keywords: Agricultural robots, Automation, Internet of Things, phenotyping, algorithms

I. INTRODUCTION

Although each of the 193 countries that have formally joined the United Nations faces its own unique challenges, the UN emphasizes that all these nations must prioritize addressing a common concern that is global population growth. Earth's current population is approximately 7.6 billion and it is predicted that by 2050, that number will rise to 9.8 billion (Cazzola *et al.*, 2020), a 28.94% increase, with half of that growth is concentrated in just nine countries that is India, Nigeria, the Democratic Republic of the Congo, Pakistan, Ethiopia, the United Republic of Tanzania, the United States of America, Uganda, and Indonesia. As people are searching for healthier foods, free of pesticides and herbicides (Ayaz *et al.,* 2019), farmers are being forced to make adjustments to the way they control, monitor, and manage their farms in order to meet the growing demand for high-quality food, which is expected to double the current capacity for food production by 2050 (Zhang *et al.,* 2018). However, by 2050, 68% of people will live in urban areas due to the global urbanisation trend that is changing rural landscapes into urban ones (United nations 2018). Since the percentage of world arable land was approximately 9.6 % in 1991 and 10.7% in 2022, which represents a slight increase in the amount of arable land available, rural producers are therefore searching for innovative methods to produce their food in progressively smaller habitats (Zhang *et al.,* 2018).

A. Global Socioeconomic Issues

Human labour is still a major component of agricultural activities, and is prone to health issues like the global public health crisis caused by the coronavirus pandemic (COVID-19), which has not only resulted in a significant number of deaths worldwide (2,527,891 deaths have been confirmed as of January 3, 2021) (WHO, 2020), but has also imposed various forms of social and economic activity restrictions (Buheji *et al.,* 2020).

Similarly, the pandemic will have the greatest effect on developing nations that rely mostly on food supplied by small farmers, livestock producers and artisanal fishermen (Delardas *et al.,* 2022). The Food and Agriculture Organisation (FAO) claimed that recent COVID-19's social isolation policies increase post-harvest losses, which hinder farmers' access to markets for products and inputs (FAO, 2020). However, in wealthy nations like the US, where farming is viewed as "hard work" and low-profitability, young people are searching for work in cities, while farmers are searching for innovative ways to automate their farms and minimize losses (CFBF 2019).

B. Precision Agriculture

Fortunately, scientific advancements in various fields of human knowledge are changing the way agricultural activities are managed, reducing the need for human intervention in order to overcome the challenges posed by population growth, accelerated urbanisation, high competition for high-quality products, shortage of skilled labourers and the vulnerability of human labour to health risks (Shafi *et al.*, 2019). According to Mc Bratney *et al.*, 2005, we need to adopt Precision Agriculture (PA) which is defined as "*That kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits*". This definition is more inclusive, allowing both humans and artificial equipment to make decisions (Singh *et al.*, 2024). However, the PA is defined as "a management strategy that uses electronic information and other technologies to gather, process, and analyse spatial and temporal data for the purpose of guiding targeted actions that improve efficiency, productivity, and sustainability of agricultural operations" (Lowenberg-DeBoer *et al.*, 2019). This concept makes it very evident how technologies can be used to enhance agricultural operations. These technologies are divided into three primary categories in this assessment work: robotics, artificial intelligence (AI), and the Internet of Things (IoT) (Sanyaolu *et al.*, 2024). As shown in **Fig 1**, these technologies can be utilised separately or in combination. The employment of robotic equipment and electrical gadgets in agricultural chores like planting, sowing, harvesting, pest management, and land preparation has made PA more well-known (Tarannum *et al.*, 2015). According to estimates, the precision agriculture industry was worth \$3.67 billion in 2016 and is expected to expand at a rate of 14.7% to reach \$7.29 billion by 2025 (Santesteban *et al.*, 2019).

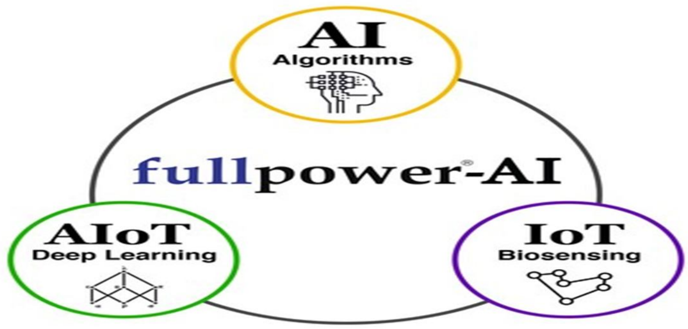

Fig 1. Graphic Abstract

Although this analysis will focus on the use of robots in agriculture, as illustrated in Figure 1, the technological domains of artificial intelligence (AI) and the Internet of Things (IoT) are frequently included in the subsystems of an application that uses robots to carry out agricultural tasks. Zha, who reviewed AI's application in agriculture, claims that AI may be used to control weeds, manage soil, and work with IoT technology (Carpio *et al.*, 2020; Zha *et al.*, 2020). He explains that in complex environments that is, with changing ambient lighting, background complexity, capturing angle, variations in shapes and colours of fruits and weeds, computer vision algorithms like Deep Belief Networks (DBN) and Convolution Neural Networks (CNN) show promise in fruit classification and weed detection. A review of the advantages of IoT and data analytics in agriculture was conducted by (Elijah *et al.*, 2018). They claim that IoT technologies enable farm monitoring using a variety of sensors, including optical, mechanical, electrochemical, dielectric, soil moisture, and location sensors. These sensors function as a data source for prediction, storage management, decision-making, farm management, and precise application algorithms because of the availability of short- and long-range communication technologies (Rajak *et al.*, 2023). Safety and fraud protection, competitive advantages, wealth creation and distribution, cost reduction and waste, operational efficiency, awareness and asset management are some of the benefits of using IoT in agriculture (Paul *et al.*, 2022). The authors list several unresolved issues, including the necessity for technological advancements, implementation of applications in actual large-scale settings (pilot project), and standardisation, regulation, and cost reduction of IoT technologies that make their use in agriculture easier. An additional review of IoT-based smart agriculture is provided by Ayaz *et al.*, 2019, who also discussed how various electronic sensors might be used to enhance agricultural control and monitoring activities. One similarity among the aforementioned survey papers is that they all discussed the use of robots as instruments for agricultural technological advancement. The kind of task that the robot is designed to accomplish determines its success in agriculture, in addition to the kind of crop. The employment of robots in agriculture to carry out general tasks, including harvesting high-value crops (Bac *et al.*, 2014) and resolving navigation issues for wheeled mobile robots (Gao *et al.*, 2018), or to enhance the performance of specialised jobs, like these, covered in review works (Fountas *et al.*, 2020; Oliveira *et al.*, 2020).

II. APPLICATION OF ROBOTICS IN AGRICULTURE

Many agricultural processes are divided into the following subsections: phenotyping, yield estimation, plant treatment, sowing/planting, harvesting, and land preparation prior to planting. Thus, the many kinds of robotic systems applications in distinct agricultural situations will be covered in the ensuing subsections.

A. *Utilizing Robots in Agriculture to Prepare Land for Planting*

One of the first agricultural job is preparing the field before planting, which includes fertiliser application and ploughing. Although ploughing the field (inverting the soil layers) provides higher entry of oxygen and an expulsion of carbon dioxide, it can also negatively impact future crops by significantly lowering the carbon stocks in the soil, depending on the local climate (Mahmud *et al.,* 2020). The construction of a finely controlled robotic system is one of the primary obstacles in the development of robots that operate in rough terrain, such as a ploughed field (Sistler *et al.,* 1987 & Oliveira *et al.,* 2021). A robot called Casar, **Fig 2a**, was developed in 2014 by the German company Raussendorf to help rural workers with soil fertilisation, pest control, soil management, harvesting, and transportation. The commercially available Cäsar robot can fertilise the soil independently or with a remote control. With a location accuracy of up to 3 cm, it uses Real-Time Kinematic (RTK) technology for the Global Navigation Satellite System (GNSS) to carry out tasks automatically. The GNSS is the navigation device, but it can use various services, such as Global Positioning Systems (GPS) (North American), GLONASS (Russian) or GALILEO (European) (Siciliana *et al.*, 2016; Khan *et al.*, 2018). The Casar robot, was made to operate alongside humans on the farm, features a collision detection system that uses ultrasonic sensors to ensure that it stops instantly. Its maximum detection distance is five meters (Oliveira *et al.*, 2021).

Greenbot robot, **Fig2b**, which is also commercially available, can perform duties including seeding, ploughing, and fertilising. It can carry up to 750 kg in its front compartment and 1500 kg in its back compartment due to its 100 HP diesel engine and four-wheel Steering (4WS) technology. The Greenbot contains collision detection sensors, just like the Cäsar robot, to identify things in front of it and stop in an emergency. The Chinese company DJI created an Unmanned Aerial Vehicle (UAV) to perform agricultural tasks, in contrast to the terrestrial robots, Cäsar and Greenbot. Since UAVs are terrestrial, obstacles such as rocks, holes, altitudes, and branches do not interfere with their ability to fly over farms (Bergerman *et al.*, 2016). However, UAVs have a limited flying period due to battery power, are susceptible to collisions with high-vegetation branches or power lines and have trajectories that are significantly impacted by wind and rain. In this way, the UAV's increased efficiency in doing agricultural duties without coming into touch with the soil which was made possible by improvements in its energy consumption and consequently, its flight duration (Shamshiri *et al.*, 2018). A UAV's load and control capacity increase with the number of rotors. As a result, DJI created the AGRAS MG-1P octocopter in 2016 to precisely apply liquid pesticides, herbicides, and fertilisers. It has a 6 ha/h spraying capacity, can carry up to 10 l of payload over a maximum distance of 3 km, and can control up to 5 UAVs with a single remote control. It contains an anti-collision system that uses omni-directional radar with a maximum detection distance of up to 15 m to prevent collisions with high vegetation or high voltage cables. It demonstrates how to integrate an Inertial Measurement Unit (IMU) (gyroscope, accelerometer, and compass) with the RTK GPS to perform spraying precisely, ensuring an accuracy of 1 cm + 1 ppm. UAV incorporates propeller rotor redundancy, which can continue to fly steadily even if one of its rotors malfunctions (Nonami *et al.*, 2010).

a) Casar robot b) Green bot c) AgBot

Fig 2. Examples of robots used in agriculture for land preparation before planting

AgBot robot, **Fig 2c**, is still in the research stage, in contrast to the robots previously discussed. The robot was created to apply herbicide and fertiliser on a corn farm using a Two-Wheel Drive (2WD) system. AgBot robot's contain four separate reservoirs for fertiliser or herbicide.

Its navigation and control system is made up of platforms and parts for creating inexpensive embedded systems (Raspberry Pi and Arduino). The robot can identify three typical weeds in corn fields: giant ragweed, redroot pigweed and cocklebur. It does this by employing a cheap Red Green Blue (RGB) camera and the machine learning algorithm known as Haar feature-based cascade classifiers (Kim *et al.*, 2022). Despite weed recognition, the inexpensive RGB camera that was employed was not suitable for outdoor application, necessitating further research (Khan *et al.,* 2018).The comparison of discussed robots is described in **Table 1.**

Table 1: A comparison of the updated land preparation robotic applications

Robots	Locomotion system	Final Application	Navigation sensors	Obstacle Detection sensors	Development stage	Year
Casar	4WD	Orchard or vineyard	RTK GNSS	Ultrasonic sensor	Commercial	2014
Greenbot	4WD	Horticulture, fruit and arable farming	RTK GPS	Bump sensor	Commercial	2015
AGRAS MG-1P	UAV Octocopter	Rice, soy and corn	RTK GPS, RGB CAMERA,, gyroscope,accelerometer and compass	Omnidirectional radar	Commercial	2016
AgBot	2WD	Corn	RTK GPS,RGB camera, campass and accelerometer	-	Research	2017

Since the farm is regarded as semi-structured environment, all of the robots that were previously described demonstrate the integration of the RTK system and the GNSS in order to travel the entire farm with precision in its location data. Therefore, since RTK technology first appeared in the mid-1990s, it was observed that, when it comes to the control of robots in actual agricultural environments, the use of RTK/GNSS technologies has greatly improved (Sistler *et al.,* 1987 & Valente *et al.,* 2020).

B. Robotic Applications in Agriculture for Sowing and Planting

Conventionally, sowing and planting tasks are carried out using specialized planting equipment, which is typically attached to the rear of a tractor. Tractors are heavy equipment, though, and as a result, their continuous movement around the farm exacerbates soil compaction (Mahmud *et al.,* 2020). In addition to affecting the chemical properties and biogeochemical cycles, soil compaction activity has a number of detrimental effects on agricultural environments, including increasing apparent density, soil resistance, decreasing porosity, accelerating water infiltration and aeration, influencing plant growth and soil biodiversity (Nawaz *et al.,* 2012 & Oliveira *et al.*, 2021). To overcome this problem, Sakaue *et al.*, in 1996 created robotic systems to automate the planting and sowing process in Japan. Its simple design, can plant 2200 plants of celery, cauliflower, broccoli, lettuce, or cabbage each hour. *Ladybird*, an autonomous field robot designed at the Australian Centre for Field Robotics and data set contains weekly scans of cauliflower and broccoli (*Brassica oleracea*) covering a 10 week growth cycle from transplant to harvest (Bender *et al.,* 2020).

a) Lumai 5 b) Di- Wheel c) Sowing Robot 1

Fig 3. Examples of Robots used in Agriculture for sowing and planting

The Lumai-5 robot, depicted in **Fig 3a**, was created with the goal of creating a compact, highly precise robot that could move quickly and effortlessly through Chinese wheat fields (Bale *et al.*, 2024) and must ensure that the sowing procedure stays same for this kind of operation, regardless of the detachment pace. The Lumai-5 robot can precisely plant wheat due to its 4WS, closed-loop control system, and speed, angle, and pressure sensors (Lin *et al.*, 2016). The primary variables that directly impacted the seeding quality were the planting tray size, vacuum chamber pressure, and planting speed (Haibo *et al.*, 2015). The Di-Wheel robot, **Fig 3b,** was developed by Australian academics with the goal of creating a robotic system using the idea of *off-the-shelf components*, both digital and physical (Koleosho *et al.*, 2019). A 2WD robot that only supports and moves on two wheels makes up the Di-Wheel concept, which reduces the robot's size, weight, mechanical complexity and also making assembly and transportation easier (about 15 minutes). With all electronic components housed in its centre, the robot was made to carry out the duties of precision sowing, spraying, and weeding (Samantaray *et al.*, 2022). The distance between the wheels can be changed to accommodate different crop varieties. The Di-Wheel has the ability to mount smartphones at a height which permits use of the device's internal sensors, including RGB cameras, gyroscopes, accelerometers, GNSS devices, and sensors for temperature, light, and humidity (Pulgarin *et al.*, 2024). Thus, Di-Wheel robot is the only robot featuring a modular physical and digital framework, despite its reliance on inexpensive gadgets. By utilizing off-the-shelf technology, it eliminates the need for additional sensors, as it leverages the embedded sensors in cellphones (Sarkar *et al.*, 2023). Despite such advantages, the primary obstacle preventing small producers from using robotic systems is the cost (Sukkarieh *et al.*, 2017; Onwude *et al.*, 2016).

A 4WD seeding robot, **Fig 3c,** developed in Pakistan was utilized to plant corn using a separate seed selector that could distribute the quantity of seeds in appropriate manner for planting (Chang *et al.*, 2023). The prototype can sow 90 seeds every minute, or 0.66 acres per hour, which is five times faster than the traditional method (Hassan *et al.*, 2016). Using a locomotion system with tracked drives to carry heavy loads on uneven soils, Indian researchers demonstrated a prototype of a small seed drill robot in 2016 that could transport a reservoir with up to 17 kg of payload, maximizing the robot's weight versus soil compaction ratio (Raikwar *et al.*, 2022; Srinivasan *et al.*, 2016). The comparison of robots for planting and sowing are discussed in **Table 2.**

Table 2. A comparison of the updated robotic planting and sowing applications

Robots	Locomotion system	Final Application	Guidance sensors	Seeding mechanism	Development stage	year
Lumai-5	4WS	Wheat	Angle and speed	Seeding motor and vacuum fan	Research	2010
Di-Wheel	2WD	Horticultural in general	Smartphone embedded sensors	Roll type seeder	Research	2015
Sowing robot 1	4WD	Corm	Ultrasonic	Linear actuator and vacuum motor	Research	2016
Sowing robot 2	Track	Seeds in general	Ultrasonic and magnetometer	Solenoid actuator	Research	2016

C. Robotic Applications in Agriculture for Plant Treatment

After the seeding stage, the farmer must continuously monitor plant growth to ensure it remains healthy and free from diseases and pests. According to FAO data, pests and diseases account for the loss of 20 to 40 percent of global crop production. Weed infestation severely impairs crop growth and can even lead to crop destruction (Mahmud *et al.*, 2020). In addition to attracting pests, weeds can harbor small creatures such as mice and snakes. Therefore, the sooner weeds are removed, the greater the reduction in financial losses. For example, the cost of weed control in Australia amounts to approximately $4 billion annually (Sindin *et al.*, 2004). Herbicides and pesticides (fungicides and insecticides) are frequently used to treat plants. Automation of the plant disease identification and weed detection processes is not a new endeavor; research in this field dates back to 1998 (Meshram *et al.*, 2022). A robotic tomato weed control system based on the Bayesian classifier algorithm was presented by Lee *et al.*, in 1999. In the validation set of field photos, the system accurately detected 73.1% of tomatoes and 68.8% of weeds. Instead of using the Bayesian classifier to increase plant identification, researchers Lee and Slaughter decided to create a hardware-based neural network (Lee *et al.*, 1998). The robotic system successfully recognized 85.7% of weeds and 38.9% of tomato cotyledons using this novel classification technique (Anand *et al.*, 2024). Out all the robots that have been created over the years, these were just the first to be used for weed management.

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Thus, with an emphasis on recent advancements, a robotic system was created to detect tomato spotted wilt virus and powdery mildew in greenhouses using a 6 Degrees of Freedom (DoF) manipulator arm, an RGB camera, and a laser distance sensor (DT35, SICK) that is fixed on a platform (Schor *et al.* 2016). To capture photos from various perspectives and prevent collisions with the plant, the RGB camera and laser sensor were mounted on the manipulator's last actuator, **Fig 4a**, (Schor *et al.* 2015). The pictures were utilized in the Principal Component Analysis (PCA) and Coefficient of Variation (CV) methods for illness identification. The method achieved an accuracy rate of up to 90% in case of tomato spotted wilt virus and 64% for the categorization of plants with powdery mildew disease in an early stage of evolution, allowing for precise disease diagnosis in its early stages (Schor *et al.*, 2016 and Hemming *et al.*, 2024). The mobile robot eAGROBOT, **Fig 4b**, was employed for the same objective, identifying pests in groundnut and cotton crops (Solanke *et al.*, 2018). The robot achieved a precision of 83–96% for disease identification in normal images and 89% for wide images by applying artificial intelligence algorithms, such as artificial neural networks and K-means, to images captured by an RGB camera of crops during the initial sowing stage (when diseases like leaf spot and anthracnose are beginning to emerge) (Pilli *et al.*, 2015; Al-Mashhadani *et al.*, 2020).

a) Robotic disease detection system b) e-AGROBOT c) Weeding robot

d) AgBot II e) Oz f) Dino

g) Ted h) Vitirover i) Tertill

j) K-Weedbot k) Aigamo-Robot l) Weeding robot 2


m) Weeding robot 3


n) Agrirobot


o) Savsar


p) Robotic sprayer


q) Rippa


r) Lady bird


s) Boni-Rob


t) Swag-bot


u) Bly-c-agri


v) Pollinator robot


w) Pruning robot


x) Thorvald II

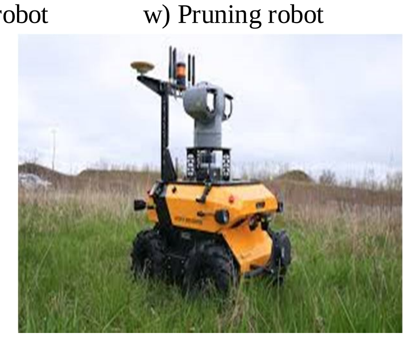
y) Avora robots

Fig 4. Examples of robots used in agriculture for plant treatment

Concerning weed control, the robots can perform the detection and its subsequent removal, through the application of herbicides in the weeds and/or through mechanical tools. Robotic system with RGB-Depth (RGB-D) Kinect v2 camera, **Fig 4c,** was developed for weed detection in lettuce and broccoli crops (Fu *et al.,* 2020; Kusumam *et al.,* 2017). The Random Sample Consensus (RANSAC) approach, plant extraction (two-dimensional connected-component method), resource extraction (leaf length, width, and height, rib arrangement, and area), and plant categorization (based on attributes) were the four phases of image processing (Moreno et al., 2020). This robotic system obtained a detection rate of 90.8% for lettuce and 91.7% for broccoli when evaluated in a real time (Gai *et al.,* 2020).

According to Jorgensen *et al.* (2006), 90% of Denmark's total outdoor gardening area can be managed using mechanical weed control in conjunction with herbicides. Additionally, 10% of the area can be managed entirely through mechanical weed control. This idea was expanded upon in this review, which separated weed control into two categories: mechanical equipment and chemicals (herbicides).

According to this idea, the Australian AgBot II robot, **Fig 4d,** uses three different kinds of tools—an arrow-shaped hoe, a toothed tool, and a cutting tool—to mechanically remove weeds from crops in addition to detecting them. In order to identify weeds, the AgBot II employs image processing methods including Local Binary Pattern (LBP) and Covariance Feature, which are gathered by the RGB camera (Mccool, 2018). The French robots Oz, **Fig 4e**, Dino, **Fig 4f**, and Ted **Fig 4g** are examples of autonomous robots being used in commercial weed control. They are all made for the markets (vegetables, nurseries, and horticulture), large-scale vegetable farms (vegetables in a row and on beds), and wine growers (vines–row width > 150 cm/60 inches), respectively (Robert *et al.,* 2020).

Depending on the kind of tool and the soil, these robots can operate independently for up to eight hours while using mechanical tools to remove weeds. They are all powered solely by lithium batteries (Saint-Aimé *et al.,* 2011). 70 Oz robots were sold in 2018 alone, with 80% of those sales going to the French domestic market, 15% to European nations, and 5% to the rest of the world (Abbas *et al.,* 2020).

Since they are advanced robots with RTK/GPS sensors, RGB cameras, and Light Detection and Ranging (LiDAR) that can work independently in large crops without human supervision, they are all monitored and equipped with a communication protocol that allows them to send SMS messages in the event of theft (Engwall *et al.,* 2022 & Clabaugh *et al.,* 2019). The VITIROVER and Tertill robots, **Fig 4h** and **4i,** respectively, are lightweight, compact robots with photovoltaic panels built into their mechanical constructions. These use mechanical cutting tools and can work in both rainy and sunny environments, and pull weeds (Oliveira *et al.,* 2021).

It enables both robot information monitoring and control via a mobile application examining IoT ideas (Sarkar *et al.,* 2023). Tertill, the first robot made to clear weeds from residential gardens, includes wheels made to help with weed removal in addition to a cutting tool (Farooq *et al.* 2023). In paddy fields, small robots with automated weeding were also employed. Both the rice seed and the weed seed grow underwater when rice is planted in a field that has been inundated with arable land. In order to prevent collisions with the plants, the 4WS K-Weedbot robot, **Fig4j,** was designed to remove weeds while moving under the guidance of a high precision image processing system that employs grayscale images, median filters, the Otsu method, noise elimination, image segmentation, and K-means clustering (Oliveira *et al.,* 2021). K-Wheedbot has gears rather than wheels to enhance weed extraction. The robot navigates the rice field with a maximum deviation of 1° in its course using a common RGB camera and a row identification algorithm (Chaoi *et al.,* 2015 & Bale *et al.,* 2024). The AIGAMO-ROBOT, **Fig 4k**, was designed simple to be small, battery-operated (to stop oil leaks and the release of harmful gasses into the atmosphere)(Nakamura *et al.,* 2019). It pulls weeds with its tracked movement technology.

As a result, the robot lessens the emergence of weeds within and across ranks (Mitsui *et al.,* 2008). Japanese researchers, examined how weeds developed in rice fields and how to eradicate them using a robot and herbicide application, **Fig 4l**. Larger roots, stems, leaves, height, and weight of the rice are just a few of the enhancements for crop productivity and growth that can be achieved by combining the robotic system with more widely spread rice fields, as shown in **Fig 5** (Sori *et al.,* 2018). In contrast to the K-Weedbot (4WS) and AIGAMO-ROBOT (track) robots, a robotic device, **Fig 4m**, was utilized to float on the surface of paddy fields to disturb water, making it murky in order to lower the incidence of sunlight and decrease weed photosynthesis, (Takayanagi *et al.,* 2017). The researchers employed uniformly spaced chains that were fastened to the back of the robot to create the water disturbances. The weed species separate from the soil surface and move toward the water surface as these chains are dragged across the drenched soil's surface. The robot was also successful in reducing the emergence of weeds,
despite the fact that it is not autonomous (Uchida *et al*., 2019).

Fig 5. Crop yield effect of each area

Pesticides are not only expensive, but they are also bad for people's health. A rural worker needs wear multiple pieces of personal protective equipment in order to apply the pesticide to the plants. Researchers created two robots, AgriRobot and SAVSAR, **Fig 4n, 4o**, to remotely spray pesticides on vineyards using a Human Machine Interface (HMI) in order to move the rural worker who applies the pesticides to a safe environment through human–machine interaction (Gonzalez, 2017; Adamides *et al.*, 2017). A 45% reduction in pesticide material was achieved by using a different mobile robot, **Fig 4p**, which uses an RGB camera and distance sensors to automatically open the pesticide spray valve based on the machine vision Foliage Detection Algorithm (FDA) and Grape Clusters Detection Algorithms (GDA) (Berenstein *et al.*, 2018; Mallas *et al.*, 2020). Herbicides are an additional method of controlling weeds. **Fig 4q** and **4r** illustrate how the RIPPA (Bogue *et al.*, 2016) and Ladybird (Underwood *et al.*, 2015) robots were created to eradicate weeds, respectively. RIPPA uses some of Ladybird's technology, but it is smaller. In contrast to the AgBot II, the RIPPA and Ladybird robots capture Hyperspectral photos and eliminate weeds by spraying pesticide where it is needed, in addition to having a photovoltaic panel built into their mechanical components (Sarkar *et al.*, 2023). Plant health can be inferred from spectral data (using machine learning methods). That means same system will apply the proper amount of fertilizer to a plant that has been identified as having a poor health rating (Oliveira *et al.*, 2021). Therefore, it should be mentioned that robotic systems with a liquid spraying system can be utilized to boost crops by applying fertilizer in addition to pulling weeds (Hammou *et al.*, 2023). The BoniRob robot, **Fig 4s**, is more comprehensive since it can detect weeds using cameras, ultrasonic sensors and remove them by applying herbicide in addition to mechanical tools (Wu *et al.*, 2020). The Swagbot robot, **Fig 4t,** was created by Australian researchers at ACFR, just like the RIPPA and Ladybird robots. The robot was designed to do a variety of tasks, including autonomous weed detection, spraying, examination of soil and pasture, assessment of biomass and livestock monitoring (Wallace *et al.*, 2019). Establishing a method of standardization and modularization of robotic systems is the aim of creating robots with a broad range of uses. A UAV was utilized to travel the farm and evaluate the soil and irrigation system management effectiveness utilizing an IMU and GPS service (Turner *et al.*, 2011). The UAV's multispectral camera calculates the wine-growing vegetation indices using the Normalized Difference Vegetation Index (NDVI) to assess when the irrigation system needs to be turned on (Eiffert *et al.*, 2021). In addition to avoiding the use of satellites and airplanes, UAVs monitor crops at low altitudes free from cloud disturbance. It can help maximize crop management efficiency and minimize usage of pesticides (Ayaz *et al.*, 2019; Kin *et al.*, 2019). A model was proposed to assist with weed identification, planting, and monitoring. In this, a behavioral analysis of plants was conducted in wheat fields both before and after herbicide treatment, for which variety of indexes were used, including CIVE, ExG, ExGR, Woebbecke Index, NGRDI, and VEG, to perform multi-temporal mapping of a portion of the vegetation at the start of the season (Sanchez *et al.*,2014; Xiang *et al.*,2011).

For steep slopes, Italian researchers created the UAV Bly-c-agri, **Fig 4u,** to perform the controlled administration of pesticides in crops. It can carry up to 10 liters of pesticide in its tank, removing any issues with land locomotion (Badeka *et al.*, 2020; Sarri *et al.*, 2019). Urea, an organic chemical, was sprayed inside predetermined areas using a different UAV. This kind of application, which has a maximum load capacity of 5 L, also enables cost savings through the widespread use of herbicides (Meivel *et al.*, 2016). For pollination, a CNN-based machine vision system, **Fig 4v,** was developed to carry kiwifruit pollination and regulate the spray duration of a mechanical system made up of 20 nozzles. At a speed of 3.5 km/h, the robot successfully pollinated almost 79.5% of the kiwi blossoms (Barnett *et al.*, 2017; Williams *et al.*, 2020; Abutalipov *et al.*, 2016). Verbiest *et al.*, (2020) and H L, Schupp, (2018), conducted research in pome orchards and stated that pruning of plants is an essential activity, despite the fact that it is difficult for a robot to complete. The primary difficulties for robots are measuring and scanning the plant structures to determine the precise location for pruning. Therefore, adjusting the crop's geometric properties to the technical specifications of robotic systems is one method of enhancing pruning performance (Bloch *et al.*, 2018; Karkee *et al.*, 2014).

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A mobile platform, **Fig 4w,** with a 6-DoF manipulator, Light-Emitting Diode (LED), and three RGB cameras are installed in order to prevent the interference of changes in natural lighting and the background landscape (Bolterill *et al.*, 2017) which describes a robot system for the automatic pruning of grape vines. A saw attached to the robotic arm's end is used for pruning, and the Rapidly Exploring Random Tree (RRT), RRT-Connect, and Support Vector Machine (SVM) learning algorithms are used to classify the branches that need to be trimmed (Majeed *et al.*, 2021). Automatic green shoot thinning in vineyards was carried out using a platform made up of a 3-DoF prismatic manipulator fitted with inexpensive RGB-D cameras. In this instance, the system design consists of a control system (6th order polynomial-based) to run the thin end-effector and a Faster R-CNN-based method to extract the cordon trajectories. At a forward speed of 6.6 cm/s, the robotic platform achieved a thinning end-effector position with a Root Mean Square Error (RMSE) of 1.47cm. The Thorvald II modular robotic system, **Fig 4x,** was created by SAGA Robotics in order to standardize the parts frequently seen in agricultural robotic systems. It also possesses a number of general-purpose robotic systems and models with two options for a differential motor drive with caster wheels for support, models with varying track widths, with or without suspension modules, varying heights and models with three to six wheels (Grimsted *et al.*, 2017). Last but not least, Avrora Robotics, a Russian business, created the AgroBot universal control system, which can be mounted on any tractor or special equipment. Comparison between the analyzed robotic applications for plant treatment are illustrated in Table 3.

Table 3. Comparison between the analyzed robotic applications for plant treatment.

Task	Robots	Locomotion system	Final application	Location sensors	Sensors used to perform the task	Computer vision Algorithm
Disease identification	Disease robot	Not included	Bell pepper	-	RGB camera and laser	PCA and CV
	eAGROBOT	4WD	Cotton and groundnut	-	RGB camera	k-means and neutral networks
	Weeding robot 1	4WD	Broccoli and lettuce		RGB-D camers	RANSAC
	AgBot II	4WS	Cotton, sow,thistle, feather top Rhodes grass and wild oats	-	RGB- camera	LBP
	0Z	4WS	Vegetables, nurseries and horticulture	LIDAR	RGB- camera	-
	Dino	4WS	Vegetables in row and on beds	TK/GPS	RGB camera	-
Mechanical Weeding	Ted	4WS	Grape	RTK/GPS	RGB camera	-
	VITIROVER	4WD	Soil grass	RTK/GNSS	-	-
	Tertill	4WD	Residential gardens	-	Capactive sensors	-
	K-Weedbot	4WS	Paddy feild	RGB camera	-	Hough transform
	AIGAMO-ROBOT	Track	Paddy feild	-	-	-
	Weeding robot 2	4WD	Paddy feild	Capactive and azimuth sensors	-	-
	Weeding robot 3	Boat	Paddy feild	GPS and IMU	-	-
Chemical weeding	Agribot	4WD	Grape	RGB camera and LIDAR	-	FDA and GDA

	SAVSAR	4WD	Grape	RGB camera and LIDAR		FDA and GDA
	Robotic sprayer	4WD	Grape	RGB camera and LIDAR		FDA and GDA
	RIPPA	4WS	Lettuce, cauliflower and broccoli	RTK/GPS/INS AND LiDAR	Hyperspectral and thermal cameras	ExG-ExR
	Lady Bird	3WS	Lettuce, cauliflower and broccoli	RTK/GPS/INS AND LiDAR	Hyperspectral and thermal cameras	ExG-ExR
	BoniRob	4WS	Sugar beet	-	RGB NIR cameras and ultrasonic sensor	CNN
	Arial robot	UAV (octocopter)	Grape	GPS ani IMU	Multispectral cameras	NDVI
	Bly-c-agri	UAV (Hexacopter)	Grape	GNSS	-	-
Pollination	Pollinator robot	4WD	Kiwi	Odometry	RGB camera	CNN
Pruning	Pruning robot 1	Mobile plataform	Grape	-	RGB camera	SVM
	Pruning robot 2	Mobile plataform	Grape	-	RGB-D camera	Faster R-CNN
General purpose	Swagbot	4WS	General farms	GPS and LIDAR	RGB-D, IR and hiperspectral cameras	NDVI
	Thorvaid II	Many forms	General farms	Depends on the application	Depends on the application	Depends on the application
	Clearpath robots	Many forms	General farms	Depends on application	Depends on the application	Depends on the application
	Agrobot	4wd	Genral farms	-	-	-

The following topics covered in Table 3 include:

- Disease identification: Researchers (Schor *et al.*, 2016) and (Pilli *et al.*, 2015) were identified plant diseases with hit rates ranging from 64 to 96% using traditional RGB cameras.
- Mechanical weeding: A number of projects, both in the research stage and commercially available, employ mechanical instruments to get rid of weeds, removing the need to apply expensive herbicidal treatments and enabling the production of organic products. As previously mentioned, researchers (Sori *et al.*, 2018) report the several advantages produced by the mechanical removal of weeds using a low-cost robot.
- Chemical weeding: To cut costs associated with excessive spraying, the majority of robots that carry out this activity use a particular computer vision technique or algorithm. Crop features were extracted and further classified using vegetation indices like NDVI and ExG-ExR. The herbicide is applied to the weed by the particular spray system once it has been properly classified. As a result, plants deemed to have low health value can get precise fertilizer applications using the same spraying technique utilized for herbicidal agents (Bogue *et al.*, 2016; Underwood *et al.*, 2015).
- General tasks: The robots utilized have terrestrial (4WD, 4WS, track), aerial (hexacopter, octocopter), and marine (boat) locomotion systems, as shown in Table 3's "Locomotion Systems" column. SwagBot platforms, Thorvald II, Clearpath, and AgroBot were created to do various jobs in various agricultural situations in order to prevent the replication of current systems and expedite the process of moving from research to the commercial stage.

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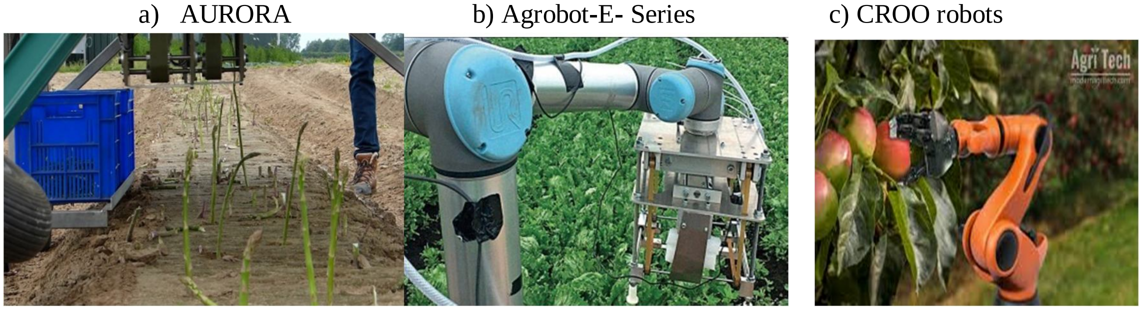
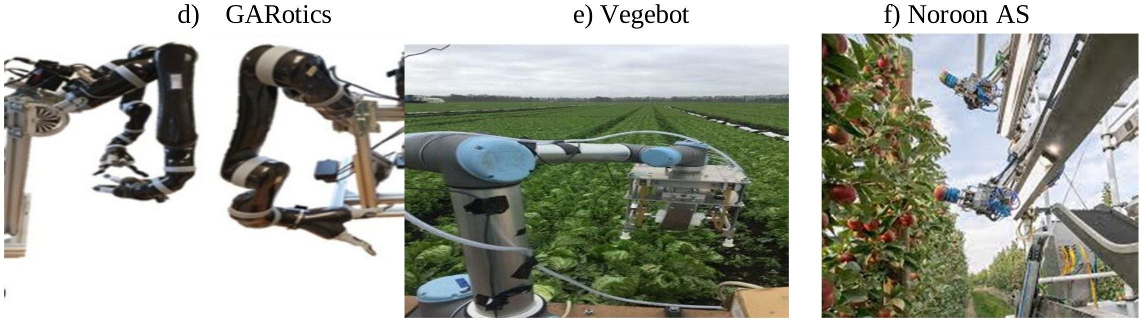
D. Robotic Applications in Agriculture for Harvesting

Harvesting is not only a repetitious task that needs to be done with agility, but it also takes a lot of work on the part of the harvester. In Japan, harvesting activities account for around 25% of total agricultural work hours (Hayashi *et al.*, 2014). In terms of financial expenses, which are a significant determinant in farmers' decision-making, labor rent account for 20% to 75% of total production costs and is rising yearly (Abares, 2014; Jie *et al.*, 2019). Due to this reason number of studies, as shown in **Fig 6**, are being conducted that suggest using robotic systems to carry out agricultural harvesting tasks. Numerous scholarly publications discuss various image processing methods used in various cultural contexts. Fruit-harvesting robot was designed and implemented by Cere *et al.*, (1998). They discovered that the primary challenges in the development of such systems were guiding the robot from tree to tree and row to row in the field; identifying and locating fruits; and grasping and releasing specific targets. The autonomous mobile robot AURORA, **Fig 6a,** for greenhouse operation, which was developed in the 1990s, was another pertinent study. It was able to navigate the greenhouse corridors on its own with the use of ultrasonic sensors (Mandow *et al.*, 1996). The robot was designed to be a multipurpose platform that could carry out activities including fruit transportation, harvesting, and inspection planning. The project criteria in this instance were cheap cost, adaptability, multifunctionality, supervisable autonomous operation, user-friendly interface, and navigation in intact greenhouses. Bac *et al.* (2014) examined approximately 50 robotic applications used for agricultural harvesting tasks across various regions. Their study, along with the findings of Emmi *et al.* (2021), highlighted that despite widespread recommendations for using robots in harvesting, significant improvements were observed only in the task of fruit capture. When compared to advancements made between 1984 and 2014, other harvesting tasks did not show a similar trend of improvement. Moreover, as of yet, the evaluated robotic systems have not surpassed human harvesters in overall performance. To endure various weather conditions seen in the field, the Agrobot E-Series robot, **Fig 6b,** is constructed entirely of military-grade aluminum and stainless steel. To pick up strawberries, it uses 24 autonomous Cartesian robotic arms that move around the robot's body. With three wheels in total (the electric motor is in the middle), the robot's mechanical construction can be adjusted to fit the size of the crop. It uses information from the LiDAR sensor to prevent collisions with any farm workers due to its huge size.

a) AURORA b) Agrobot-E- Series c) CROO robots



d) GARotics e) Vegebot f) Noroon AS



g) Aubergine robotics h) Strawberry harvester i) apple harvester

j) Harvester robot 4

k) Harvey platform

l) Sweeper

m) Amaran

Fig 6. Examples of robot s used in agriculture for harvesting

With a picking speed of 8 seconds per fruit and a speed of 1.6 km/h, the Berry 5 robot can harvest up to eight acres of strawberries every day, which is equivalent to the produce of 25 to 30 human harvesters. Created by the American company Harvest CROO Robotics, **Fig 6c,** this automatic harvester is making progress towards commercialization (Robert *et al.*, 2020). Similar to the Agrobot E-Series, the Berry 5 robot's numerous mechanisms are patent-protected, making scientific research challenging. A green asparagus harvesting robot called GARotics, **Fig 6d,** was created by researchers (Crocetti *et al.,* 2023; Leu *et al.,* 2017), for the market to accept asparagus, as it must be harvested when it reaches a height of 15.24 to 20.32 cm. Automating the harvest of asparagus is challenging because the stalks are delicate and need to gather together before marketing. Therefore, two robotic arms with specially designed grippers were created in this instance to capture the asparagus without causing any harm to it. A single pneumatic cylinder in the robotic arms converts linear action into a circular motion. The robot's RGB-D camera provides the planting data for its vision module, which includes the following functions: point cloud generation, camera calibration (using Template Point Cloud (TPC) and Model Point Cloud (MPC)), and online asparagus tracking (using RANSAC and Euclidean clustering methods) in order to identify asparagus that is ready for harvesting in real-time. Due to the effort, the German robot was able to move at an average pace. 90% of harvests were successful using a harvest cycle of 2 seconds per robotic arm at a speed of 0.2 m/s (Leu *et al.*, 2017). Vegebot, a robotic lettuce harvesting device, **Fig 6e,** was developed by English researchers in 2018 (Birellel *et al.,* 2020). Since lettuce is a very delicate produce, the task's obstacles are correctly identifying it and removing it without causing any damage. The Region-based Convolutional Neural Network (R-CNN) was used to identify the lettuce head using two RGB cameras that were positioned above and 45° from the vegetation. Vegebot uses a 6-DoF robotic arm and a gripper device with closed-loop force monitoring to locate the lettuce and then extract it. The algorithm achieved an 82% accuracy rate in correctly classifying vegetables and 91% success rate in locating lettuces (Hu, N *et al.,* 2022; Birellel *et al.*,2020). Ge *et al.,* (2019) created an algorithm to find and gather strawberries using a robot (made by Noronn AS) that has an RGB-D camera, as shown in **Fig 6f**. The collision-free path-planning technique was based on 2D pictures and the 3D point cloud, and R-CNN was used to recognize strawberries. After several tests in real environments, 74.1% of the identified ripe strawberries were successfully harvested (Ge *et al.,* 2019; Badwal and Bhardwaj, 2020). Dual-arm manipulation for robotic aubergine harvesting was studied by Sepúlveda *et al.,* (2020) & Korostynska *et al.,* (2018). The robotic system was utilized to examine the advantages produced by the cooperative action of the manipulators using two 6-DoF robotic arms, under actuated grippers with a set of three flexible fingers (off-the-shelf), and two cameras, **Fig 6g.** The robotic system identified potential aubergines that were partially obscured by leaves and lifted the leaves so that the camera could catch the fruit, just how a human picker would typically use one hand to clear the path to reach the fruit and collect it with the other. The image was divided into four classes—aubergines, leaves, branches, and background—using an algorithm based on the SVM classifier.

The suggested occlusion method generates a vector, indicating the direction in which the leaf must be raised in order to unblock the aubergine by comparing the distances between the centroids of the aubergines and the leaves that were recognized in the picture. Following a number of experimental testing, the harvesting robot's success rate was 80% for an occluded part and 95% for two isolated pieces, both of which used two arms. Fruit processing time (image processing, inverse kinematics, and action) was reduced by the system from 42.90 seconds with one arm to 26.54 seconds with two arms. The primary difficulties faced by the strawberry picker robot in **Fig 6h,** uses the Thorvalds II robots' locomotion system, which is made by the Saga Robotics group, and is based on the modularization concept. It has a 3-DoF Cartesian-type dual-arm mechanism to extend its harvest time. The two Cartesian robotic arms were utilized to maximize harvesting efficiency and prevent collisions by using simplified inverse kinematics to compute. For cluster choosing, a novel active obstacle-separation path planning technique was developed (Xiong *et al.*, 2020). A common issue in many harvesting robot applications is the occlusion of fruits (by leaves, branches, or other immature fruits). Thus, the picker robot recognizes strawberries using an RGB-D camera and an algorithm based on Hue Saturation Value (HSV) color-thresholding. Less sensitivity to variations in ambient lighting is possible using the HSV color-thresholding technique. The mechanism tries again if the robotic arm fails to pluck the fruit on the first try. The strawberry picker robot's success rate on the first try was 97.1% for isolated strawberries and 5% for strawberries that were entirely encircled by unripe strawberries. On the second try, the robot's success rate was 100% and 20% for the same scenarios as previously mentioned. By using a twin arm system, the robot can handle fruit in 4.6 seconds instead of 6.1 seconds when using just one robotic arm (Xiong *et al.,* 2020). Improvements in visual perception are becoming more widespread. In order to accomplish the following tasks: vision perception, motion planning, fruit verification, and fruit detachment, created a prototype of an apple harvesting robot that includes a 6-DoF robotic arm, a soft-finger-based gripper (so as not to damage the apples' surface), and an RGB-D camera, **Fig 6i** (Kang *et al.,* 2020; De Jong *et al.*, 2022). The Dasnet deep convolution neural network was used for fruit recognition, and the 3D Sphere Hough Transform (3D-SHT) was used to calculate the fruit's pose. The authors used the distance-based denoising approach on points to address the issue of ambient light significantly interfering with the RGB-D camera's distance estimations. Therefore, all fruits with a significant length imbalance on the X, Y, and Z axes or insufficient points are eliminated from the list of fruits found. The environment where the apples are located was modeled using the RGB-D camera's point cloud; in this instance, the authors employed an octree-based description of occupied space in work contexts. The authors recommend identifying ripe and damaged fruits as enhancements after the system's fruit detection accuracy achieved an F1 score of 0.871 (Kang *et al.,* 2020). Rotate-YOLO (R-YOLO) approach, a variant of the original YOLO deep learning algorithm, was suggested to carry out real-time visual localization of the picking sites for a strawberry harvesting robot that plants strawberries on ridges (Xiong *et al.,* 2020; Yu *et al.,* 2020). The pick point can be more precisely located by rotating the bounding box by an angle α to follow the orientation of the strawberry. The robot **Fig 6j,** is specially designed to work on a strawberry ridge-planting and incorporates fiber sensors on its end-effector to speed up control without requiring real-time distance measurement (Yu *et al.,* 2020). For 640 x 480 photos taken with a standard RGB camera, the robot's strawberry detection accuracy rate was 94.43% at a speed of 0.056 s utilizing R-YOLO recognition method. The Harvey platform and SWEEPER, depicted in **Fig 6k** and **l**, respectively, are two examples of harvesting robots that employ artificial intelligence algorithms as well. These robots are installed on a mobile platform and are utilized to harvest sweet pepper in protected cropping areas. While the SWEEPER robot employed deep learning, a shape and color-based detection algorithm, and Hough Transform (HT), the Harvey platform chose to use Deep Convolutional Neural Networks (DCNN) (Lehnert *et al.,* 2020; Arad *et al.,* 2020; Lehnert *et al.,* 2017). Both have 6-DoF robotic arms, but their cutting systems and capturing techniques differ. For example, SWEEPER uses flexible fingers to grip the sweet pepper, whereas Harvey uses a vacuum pump to suction it. Consequently, the Harvey platform required roughly 3.7 seconds and 2.2 seconds to do the same tasks as the SWEEPER robot, which took an average of 4.3 seconds to detect sweet pepper and 14.5 seconds for detachment.

In developing nations, harvesting coconuts is sometimes carried out without any safety gear. A coconut tree can fall and cause fatalities in addition to severe injuries (Wibowo *et al.,* 2016). Amaran, **Fig 6m**, is an autonomous robotic coconut tree climber and harvester that was created in this regard by Indian researchers (Megalingam *et al.,* 2020). The Amaran robot climbs the coconut trees using a lightweight mechanical framework consisting of eight wheels, four at the top and four at the bottom. A certain activation sequence allows Amaran to move left, right, up, or down. It uses a 4-DoF robotic arm and a cutting tool as an end-effector to separate the coconuts. Both components are lightweight and designed to maintain the robot's mobility around the coconut tree. The robot's RGB camera helps the human operator, who is situated in a secure area of the ground, with remote control and robot monitoring without the need of any kind of computer vision system. Using the Bluetooth communication protocol and an application for smartphones, the Amaran robot may be operated, leveraging the Internet of Things concept. Following multiple testing, Amaran demonstrated the ability to successfully scale trees up to 15.2 m in height, with diameters ranging from 0.66 m to 0.92 m and slopes of 30° (Megaligam *et al.*, 2020). Even though the Amaran's entire harvest time (21.9 minutes) is longer than that of a professional climber (11.8 minutes), the robot can climb as many coconut trees as needed without putting the human operator in danger of illness or even death. **Table 4** illustrates the comparison of harvesting robots.

Table 4. Comparison of the examined harvesting robotic applications

Robot	Robotic Arm	Final Application	Location Sensors	Sensors Used to Perform the Task	Computer Vision Algorithm	Success Rate (Cycle Time)
Agrobot E-Series	24 Cartesians arms	Strawberry	LiDAR	RGB camera, ultrasonic and inductive sensors	–	–
Berry 5	Multiple robotic components	Strawberry	GPS and LiDAR	RGB camera	–	–
GARotics	Pneumatic cylinder with two blades	Green asparagus	–	RGB-D camera	RANSAC and euclidean clustering	90% (2 s)
Vegebot	6-DoF and a custom end effector	Lettuce	–	RGB camera	R-CNN	88.2% (31.7 s)
Noronn AS	5-DoF	Strawberry	–	RGB-D camera	R-CNN	74.1%
Harvester robot 1	6-DoF dual-arm	Aubergines	–	RGB-D and ToF cameras	SVM	91.67% (26 s)
Harvester robot 2	3-DoF cartesian dual-arm	Strawberry	LiDAR and encoder	RGB-D camera	HSV color-thresholding	50–97.1% (4.6 s)
Harvester robot 3	6-DoF soft-finger based gripper	Apple	–	RGB-D camera	Dasnet, 3D-SHT and Octree	*F*1F1: 0.81 (7 s)
Harvester robot 4	6-DoF	Strawberry	–	RGB and laser sensors	R-YOLO	84.35%
Harvey plataform	6-DoF	Sweet pepper	–	RGB-D camera, pressure and separation sensors	DCNN	76.5% (36.9 s)
SWEEPER	6-DoF with custom designed end effector	Sweet pepper	–	RGB-D camera	Deep learning, shape, color-based detection and HT	61% (24 s)
Amaran	4-DoF	Coconut	–	RGB camera	–	80–100% (21.9 min)

On interpreting the data in Table 4, the following is recorded:

- Challenges: Even with ongoing technology advancements, issues like fruit occlusions and variations in ambient lighting still need to be investigated scientifically in order to make it possible to utilize robots in agricultural settings.
- Simplicity and efficiency: The ease of construction and effectiveness of the robotic system, in addition to the difficulties of occlusion and variations in ambient lighting, enable the commercialization process to go more quickly. The effectiveness of the robotic system as a whole will rise with the advancement of computer vision algorithms, which are directly linked to the system's efficiency. Only Agrobot E-Series and Berry 5 robots are in the commercialization phase.

- Evolution between 2014–2023: As previously mentioned, Bac *et al.*, (2014) conducted a thorough analysis of harvesting robot evolution over the last 30 years (1984–2014). The values (average; minimum–maximum) of his work are thus contrasted with the analyses of the current work (which range from 2013–2023). He reached the following values: percent of harvest success (66%; 40–86%), cycle time (33 s; 1–227 s), and the results of this study were as follows: success rate of harvest (81.17%; 50–100%) and cycle time (2–36.9 s; 18.88 s). Since the Amaran robot's cycle time depends on the operator's skill level, it was ignored. Therefore, overall, the average harvest success rate has increased by 22.98%, and the average cycle time value has decreased by 42.78%, suggesting that the harvesting robots' performance has improved.

E. Robotic Applications in Agriculture for Yield Estimation and Phenotyping

Farmers can better manage their crops by using more advanced equipment that provide precise data on the growth of fruits in terms of number and quality. Monitoring the entire crop and estimating the amount of fruit produced is all that yield estimation entails. On the other side, a number of factors, including soil quality and climate change, might impede plant growth. Therefore, it is feasible to determine the ideal growing conditions by connecting the plants' phenotype to their corresponding genotype. However, it should be highlighted that a robot needs both effective computer vision algorithms and trustworthy sensory inputs in order to estimate phenotyping or yield. Researchers were already suggesting the use of sensors and machine vision algorithms to identify crop rows and collect field data (Noguchi *et al.*,1998; Noguchi *et al.*, 2001). In this instance, an RTK/GPS device and a camera were mounted on a tractor to produce spatial maps that connected the crop's width and height. 84% success rate was achieved by the robotic system using ANN, suggesting that a machine vision system might be employed as a crop prediction sensor. Dong *et al.*, (2020) used RGB-D cameras to create a semantic map of an orchard. These maps contain more information than just coordinates which could be used for phenotyping, yield estimation and to build a 3D reconstruction of the canopy. Apple orchard yield was estimated using the Shrimp robotic system, Fig 7a, which has six RGB cameras, in natural illumination. The Shrimp platform uses the integration of a GPS and an Inertial Navigation System (INS) to pinpoint each sampled image. Watershed (WS) segmentation and the Circular Hough Transform (CHT) were used to detect the apples in the image processing, which is based on Multiscale Multilayer Perceptron (MLP) and CNN. Using CNN and WS, the Shrimp platform achieved an apple identification rate of 82.5%, an F1 of 0.791, and a coefficient of determination r2 of 0.826 (Bargoti *et al.*, 2017). Silwal *et al.* (2017) used ToF to identify apples for their proof-of-concept robotic harvester. Onishi *et al.* (2019) used a three-fingered gripper that encases the apple. Cramer *et al.* (2018) investigated hybrid grippers containing magnetorheological fluids that could be used as a solution between soft, forceless grippers and rigid, damaging grippers, with picking apples as potential application.

a) Shrimp

b)Vinbot

c) VineRobot

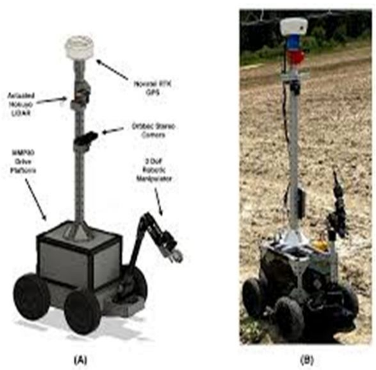
d) Agri-BOT


e) Agrob V14


f) Agrob V16

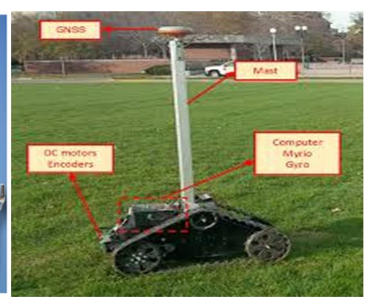

g) Hexapod


h) TerraSentia


i) Vinobot


j) Vinoculer

k) Pheno-copter



l) Ara ecRobotix

Fig 7. Examples of robots used in agriculture for yeild estimation and phenotyping

Due to soil, climate, variety, and the methods used by individual farmers, the output of vines might differ from one area to another in a highly competitive market. In this way, the quality of the harvested grapes may be measured by keeping an eye on the grapes throughout the crop (Vrochidou *et al.*, 2021). In this field, VINBOT and VineRobot, two projects supported by the European Union's Seventh Framework Program, are displayed in **Fig 7b** and **7c**, respectively. After detecting grapes using CNN, VINBOT calculates the area occupied by the grapes in the pictures and calculates each one's weight in kilos (Lopes *et al.*, 2016). VineRobot uses the following methods to track variables such as grape yield, vegetative growth, vineyard water status, grape composition, RGB machine vision, thermography, and fluorescence based on chlorophyll (Botterill *et al.*, 2017). Likewise, we know that Brazil is one of world's biggest exporters of food.

In order to provide a modular robotic platform for data collection and yield estimation in orange and sugar cane crops, the Brazilian Agricultural Research Corporation (EMBRAPA) funded the development of the AgriBOT agricultural robot, **Fig 7d** (Sutera *et al.*, 2020). The navigation efficiency of algorithms D* and Focused D*, which AgriBOT uses with 4WS, was compared by Abráhão *et al.* in (2011). In situations where maps were erroneous or lacking, the Focused D* method outperformed D* in terms of efficiency. Based on the extraction of objects from actual natural scenes, Lulio and Lugli *et al.*, (2016) implemented a J Segmentation (JSEG) algorithm, statistical Artificial Neural Networks (ANN) image segmentation techniques, and sensory fusion in the AgriBOT robot. This allowed them to identify objects like fruits, grasses, stems, branches, and leaves (Lulio *et al.*, 2016; Lugli *et al.*, 2011; Farooq *et al.*, 2023).The 4WD Agrob V14 robot, **Fig 7e**, was created to keep an eye on the vineyards in Portugal's Douro area, which has steep slopes. The robot is equipped with RGB cameras, LiDAR, IR sensors, and encoders. It was made to function independently even when the GNSS signal is unavailable (Santos *et al.,* 2016). The odometer and IMU statistics are affected by the high concentration of stones in the soil. In order to address these issues, the information produced by Radio Frequency IDentification tags (RFID) at the start and finish of each vineyard line was combined with Simultaneous Localization and Mapping (SLAM) techniques (Santos *et al.,* 2015; Kalampokas *et al.,* 2020). Agrob V14 can traverse slopes with an inclination of up to 30%, rocks, and ditches (Santos *et al.,* 2015). Based on a wireless sensor network, the robot Agrob V16, **Fig 7f**, designed for yield estimate and trimming operations, took a different strategy to enhance the robot's location and positioning. Combining the ideas of SLAM and the Internet of Things, the Agrob V16 reads the Received Signal Strength Indication (RSSI) signals produced by a Bluetooth Low Energy (BLE) transmission module and estimates the position of the signal source based on the received signal strength (Verbiest *et al.*, 2020). An Extended Kalman Filter (EKF) was used to fuse encoder data with distance signals based on RSSI. The standard deviation of the robot's trajectory might be reduced by 25% with the usage of RSSI following the deployment of the EKF filter (Reis *et al.*, 2018). A hexapod robot with biological inspiration was created to track the wholesome development of agricultural fields, including agronomic data on soil nutrients. However, because of the hexapod's size and power supply limitations, using high-precision navigation systems (RTK/GNSS) is not practical (Iida *et al.*, 2008). The researchers demonstrated a novel method of controlling the robot without the use of RTK/GNSS by utilizing the insect's sense of smell, much like the locomotion mechanism was biologically inspired by insects. The hexapod follows the wind direction and CO_2 sources as it moves independently around the crop using an anemoscope and CO_2 gas sensors. The tripod gait was employed by the hexapod robot in **Fig 7g**, which changed step length and/or speed in response to update control time. The hexapod can be guided by air currents on its own while also tracking the amount of CO2 gas released from soil and crops (Iida *et al.*,2008).Similar to the hexapod robot, the TerraSentia robot is compact, keeps an eye on the crops, and lacks an RTK/GNSS system. With only one LiDAR for light detection beneath the canopy and ranging-based autonomous navigation, the TerraSentia robot, shown in **Fig 7h**, was utilized in this instance to navigate between the high-height vegetation of maize and sorghum crops (Higuti *et al.*,2019). TerraSentia uses a navigation system based on LiDAR and reads the LiDAR input data, filters it by eliminating outlier points, and then uses least squares and a series of heuristics to predict its trajectory. Over 6 km of straight rows were traversed by the robot on its own during a number of testing. In order to create a globally recorded ray cloud, researchers used AgScan3D, a mobile vehicle-mounted 3D spinning LiDAR system, to estimate the canopy density at four different locations in South Australia (Lowe *et al.,* 2021). The AgScan3D is a 3D spinning LiDAR, 3DM-Gx3 IMU, and GPS unit that is mounted on the back of a Kubota farm truck. In order to estimate the canopy density, the AgScan3D system uses the variable resolution approach, extracts and segments the ground and vine rows, and applies a Continuous-Time SLAM algorithm to a globally registered 3D ray cloud (He L, Schupp, 2018). Approximately 93,000 vines were scanned across a 160 km traverse in experimental tests, yielding repeatability with a root mean square error of 3.8% for the vehicle moving at an average speed of 5 to 6 km/h.

Plant height, weight, biomass, form, color, volume, light absorption, and temperature are just a few of the ways that plant phenotyping can be derived (Shafiekhani *et al.*, 2017). As seen in **Fig 7i** and **7j**, respectively, two robotic platforms; Vinobot and Vinoculer, were combined to extract the phenotypic traits of maize plants. Vinobot moves across the entire crop to extract the unique phenotypic traits of each plant, while as Vinoculer is a stationary platform that continuously measures height and gathers 3D data from the crop (reconstructed using Visual Structure From Motion, or Visual SFM, as shown in **Fig 8**). Correlation between the overall data from Vinoculer and the individual data from Vinobot is thus feasible. These robots use a variety of sensors to evaluate air temperature and light intensity, as well as to compute the Leaf Area Index (LAI) and track plant height. Unwanted vegetation, including weeds, can be less of interference by filtering the point cloud according to vegetation height. Consequently, the phenotyping process is significantly accelerated by gathering such data from the farm (Cui, 2020).

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Two robotic platforms make up the architecture: a mobile observation tower (Vinoculer) and an autonomous ground vehicle (Vinobot). The observation tower monitors a whole field and identifies particular plants for the Vinobot to examine further, the ground vehicle gathers data from individual plants. This architecture has three benefits:

- It enables the system to examine vast swaths of a field at any time of day or night while pinpointing particular areas impacted by biotic and/or abiotic stresses;
- It offers high-throughput plant phenotyping in the field by acquiring precise and detailed data from groups or individual plants in a comprehensive or selective manner;
- It does away with the need for costly and unwieldy aerial vehicles or similarly costly and constrained field platforms.

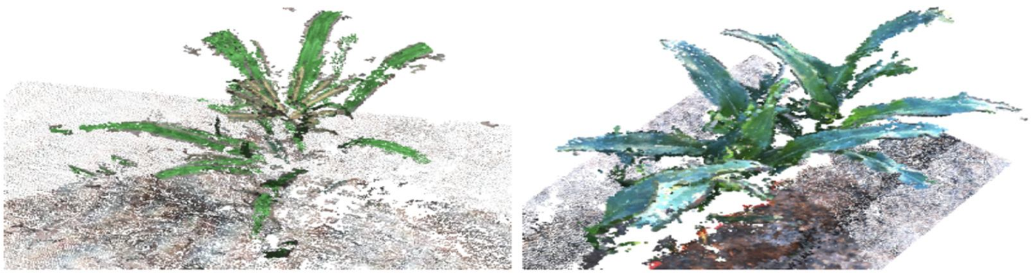

Fig 8. Comparison between the 3D reconstruction of a corn plant by Visual SFM generated using different ways of collecting data (shafiekhani *et al.*, 2018).

Using concepts from RANSAC and Digital Elevation Models (DEM), a customized helicopter, Pheno-Copter, shown in **Fig 7k,** was used to estimate variations in the land cover of sorghum (early season), the temperature of cover in sugar cane (mid-season), and three-dimensional measures of crop lodging in wheat (late season). This demonstrated the ability to meet various levels of needs and image coverage (Chapman *et al.*, 2014). The Ara robot from ecoRoboticx, **Fig 7l,** which is intended for scouting and phenotyping applications, can correct RTK/GPS via GSM/3G communication; however, it lacks algorithms and sensor solutions because it is made to be integrated with multiple sensors from various manufacturers. The robot, which weighs about 130 kg, can be controlled by a smartphone over WiFi or 3G/4G. A summary of the previously described works is presented in **Table 5**.

Table 5: Comparison of the robotic applications for phenotyping and yield estimation that were studied.

Task	Robot	Final Application	Location Sensors	Sensors Used to Perform the Task	Computer Vision Algorithm
Yield Estimation	Shrimp	Apple	–	RGB camera	MLP and CNN
	VINBOT	Grape	RTK, DGPS and LiDAR	RGB and NIR cameras	NDVI
	VineRobot	Grape	–	FA-Sense LEAF, FA-Sense ANTH, ultrasonic and RGB camera	Chlorophyll-based fluorescence and RGB machine vision
	AgriBOT	Orange and sugar cane	GPS/INS and LiDAR	RGB camera	–
	Agrob V14	Grape	LiDAR	RGB camera	SVM
	Agrob V16	Grape	RTK/GPS/INS and LiDAR	Stereo, RGB-D and RGB cameras	hLBP and SVM
	Hexapod	General farms	–	$CO2$CO2 gas module, anemoscope and infrared distance sensor	–
	Kubota farm vehicle	Grape	GPS and IMU	LiDAR	Continuous-Time SLAM

Phenotyping	TerraSentia	Corn	RTK/GPS and LiDAR	RGB camera	LiDAR-based navigation
	Vinobot	Corn	DGPS and LiDAR	Stereo camera and environmental sensors	VisualSFM
	Vinoculer	Corn	–	Stereo RGB and IR cameras and air temperature sensors	VisualSFM
	Pheno-Copter	Sorghum, sugarcane and wheat	–	RGB and thermal cameras and LiDAR	RANSAC and DEM
	Ara ecoRobotix	General farms	RTK/GPS and compass	RGB camera	–

- Sensors: Whether for phenotyping or yield estimate, the micro observation of each plant's biological phenomena necessitates specialized and extremely dependable sensors, such as RGB cameras, multispectral, Near-Infrared (NIR), IR, environmental, and fluorescence level detection sensors.
- SLAM: The lack of GNSS-based systems, whether as a result of physical limitations, power supply restrictions, or vegetation height, drives advancements in SLAM approaches. Robots thus employ both natural (such as the creation of trajectories based on the average distance between rows and the direction of the airflow) and artificial (such as the use of RFID tags and wireless sensors) features to enhance navigation under these situations. Santos *et al.,* (2020); Aguiar *et al.,* (2020); Iqbal *et al., (*2020) provided detailed descriptions of a number of SLAM algorithms and path planning strategies for agricultural and forestry robots.
- Artificial Intelligence: Vegetation indices (such NDVI and chlorophyll-based fluorescence) and artificial intelligence algorithms (like MLP, CNN, and SVM) can be applied based on the unique traits of each crop. As a result, it is necessary to try to strike a balance between the anticipated efficiency or outcome and the computational complexity level of the suggested strategy.

III. DISCUSSION

Following the identification and discussion of the primary robotic systems now in use or under investigation, a number of data were gathered for analysis. Thus, the research trends, typical challenges, indicators impeding commercial development, which nations are funding the development of these kinds of solutions, and, lastly, the ideal specifications for robotic agricultural systems will all be covered in this section.

A. Agricultural Robots

The majority of robotic systems applications in agricultural settings are focused on creating 4WD robots without robotic arms that are used to pull weeds and make use of RGB cameras, respectively. According to the research, even if 32.23% of the works employ RGB cameras, the majority of them lack or do not disclose the use of computer vision algorithms (Otsu method, HT, and CV). 86 % of the 62 initiatives that were examined are still in the research phase.

Although Australia does not currently dominate the global market for agricultural output, its agricultural sector has been expanding every decade, according to FAO (2019). Notably, a significant portion of the research reviewed was conducted by Australian academics and businesses. Another intriguing finding is the distribution of research output by continent, highlighting the contributions of corporations and researchers worldwide. It is noteworthy that no research was conducted by researchers or businesses from Africa, a continent known for having the greatest rates of famine, poverty, and a shortage of skilled workers worldwide.

B. *Unsolved Issues*

A number of suggestions are made to help future researchers to enhance the agricultural robotic systems that are now in use. The majority of agricultural robots, are 4WD; nevertheless, since the agricultural environment is categorized as semi-structured, as previously indicated by Santos *et al.* (2015), 4WD robots are significantly impacted by soil properties in this situation. According to Khan *et al.*, (2018), there is still a significant trade-off between the price and quality of agricultural cameras. In contrast to the work done in the previous century, a variety of computer vision algorithms can now be used in high-performance embedded systems; nonetheless, there is still room for improvement in selecting the best algorithms for each kind of scenario. The IoT devices must be utilized in tandem with the robots since they are electronic systems that function in the same environment as the robots. Thus, the proposals can generally be categorized into four areas: communication technologies, sensors, computer vision techniques, and locomotion systems.

C. *Locomotion Systems*

The majority of agricultural robot mobility systems are 4WD.

However, the features of the local terrain, including rocks and branches which have a significant impact on wheeled systems. Additionally, the continuous movement of these robots across the farm causes a high rate of soil compaction. Improvements in UAV flight duration may lead to a rise in their application in agricultural settings (Kim *et al.,* 2019). Legged robots provide an additional option for moving around in unstructured areas (Oliveira *et al.*, 2020; Bac *et al.*, 2014). These robots have the advantage of being able to navigate in challenging areas since they don't require continuous touch with the ground to move about and may modify their posture in accordance with the terrain's slope (Oliveira *et al.*, 2018; Selva *et al.*, 2012). These robots are small, autonomous, relatively light, and have environment-adaptive movement patterns. The robots' feet have a tiny contact area, which puts a lot of pressure on the foot placement location even while it permits less damage to the ground. In this regard, legged robots must have specially designed foot-ground contact areas (based on the principles of soil mechanics) to decrease pressure (increasing the foot-ground contact area) under the soil during locomotion in order to keep their feet from penetrating soft soils and becoming trapped. They are therefore less likely to be rejected by the agricultural market because they are widely used robotic platforms.

Fig 9. Commercially accessible quadruped off-the-shelf legged robots

D. *Sensors*

The RGB camera was the most often utilized sensor in the examined works. Despite offering more information (depth, temperature, and more spectrum data), the RGB-D, thermal, hyperspectral, and multispectral cameras are more expensive, which prevents their widespread use. Temperature, humidity, and dust incidence can all directly affect how well sensors work in an agricultural setting. The trade-off between quality and financial cost must be determined based on the minimal system which is needed to be constructed. In this regard, the creation of sensors with high Ingress Protection (IP) (IP65, IP66, or IP67), which function in a wide range of temperatures and humidity levels and are primarily inexpensive, may help in building agricultural robotic systems that are more resilient to changes in weather (rain and sun), thus prolonging their useful lives.

E. *Computer Vision Algorithms*

By using artificial intelligence algorithms (like MLP, CNN, R-CNN, R-YOLO, and SVM) and crop characteristics (like ExG-ExR, NDVI, Chlorophyll-based fluorescence, and RGB/thermal/hyperspectral/multispectral images), diseases, weeds can be detected, herbicides and pesticides can be applied selectively, fruits and vegetables can be located, ripeness (ripe/unripe) can be classified and yield can also be estimated. Once more, the efficacy of the computer vision algorithm may be hampered by the crop's short-term (ambient lighting) and long-term (seasons) fluctuations. Therefore, it is suggested to develop new computer vision algorithms or enhance existing ones that can adjust to the short-term and long-term changes of the crops and are designed to run on low-cost and processing-power devices.

F. IoT-Based Smart Agriculture

The idea of smart agriculture must be closely related to the usage of IoT technology, just as the idea of smart cities (Oliveira *et al.*, 2020; Oliiveira *et al.*, 2019). A high degree of adaptation to the quick changes in natural illumination, seasons, and crop growth was shown by the application of several artificial intelligence systems, including CNN. Therefore, the many ways that IoT devices are integrated into agricultural activities along with the different kinds of AI algorithms and the many robotic systems that are reviewed and discussed in this article, may help to improve process control, monitoring, preservation, and standardization (Neumann *et al.*, 2018; Cui *et al.*, 2020). Accurate multipurpose systems that address both short-term (harvest monitoring) and long-term (yield estimation) issues may be developed. Furthermore, IoT sensors allow for the exchange of Machine-to-Machine (M2M) data, integrating them with mobile robots holds significant promise for advancing the ideas of parallelism and swarming of robots.

IV. CONCLUSIONS

In order to determine the actual needs for changes, it is necessary to first understand the major existing works in the field of smart agriculture, highlighting their benefits, drawbacks, and typical faults before proposing new technical and scientific advancements. 37% of agricultural robotic systems are 4WD, 64.52% lack a robotic arm, 22.06% are used for weeding tasks, 32.23% use RGB cameras, 35.48% do not include/report computer vision algorithms, 80.65% are in the research stage, 16.67% are designed by Australian companies/researchers, and 41.94% are developed by countries on the European continent, according to a systematic review of agricultural robotic systems used in the execution of land preparation before planting, sowing, planting, plant treatment, harvesting, yield estimation, and phenotyping. Simple and effective computer vision algorithms, parallelism, the swarm of robots, the limited use of the off-the-shelf concept, and multipurpose platforms that suitably adjust to the crop type under study were the primary features noted. Four primary areas have been suggested for further research in order to enhance the current agricultural robotic systems: sensors, computer vision algorithms, locomotion systems, and Internet of Things-based smart agriculture. This study examined numerous agricultural robotic systems. Given that the average harvest success rate increased by 22.98% and the average harvesting robot cycle decreased by 42.78% between 2014 and 2021. Thus, it is anticipated that as the aforementioned areas improve, agricultural robotic systems will continue to advance in terms of efficiency and robustness. Therefore, it is thought that this work was able to correlate the benefits of investing in technologies that serve as instruments for changing nature in addition to demonstrating the noteworthy advancements in the field of mobile robots.

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