Robotics and Agriculture

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The world's population is steadily increasing, necessitating an increased food supply. According to Sylvestere, agricultural production, particularly field agriculture, must increase by 70% by 2050, when the global population is predicted to exceed 9 billion people. Simultaneously, increased agricultural activity leads to the waste and exploitation of irrigation water, fertiliser, and other phytosanitary products, compromising environmental sustainability and farmers' profits. The employment of robots in agriculture appears to be a potential option in the context of precision agriculture since it enables repetitive labour to be accomplished without losing precision throughout the working day. This sort of application is growing in popularity in robotics research, and a variety of robots are now available for purchase.

precision agriculture | mobile robotics | smart farming

1. Robotics and Agriculture

As a consequence of intensification, mechanisation, and automation, agricultural production has increased significantly over time [1][2]. Agricultural equipment has become more efficient, reliable, and precise thanks to automation, which has reduced the need for human involvement [3]. Despite this, agriculture, particularly the horticulture industry, continues to be plagued by a severe shortage of people. Trends such as increasing farm size, declining farmer numbers, and increasing environmental consequences of food production all exacerbate the challenges posed by a lack of workers, necessitating even more efficient agricultural techniques [4], and the productivity of traditional farming, which involves farmers manually cultivating and managing crops, can be greatly improved by using intelligent machines [5]. Furthermore, it is necessary to develop a new agricultural system that leverages advanced automated techniques to eliminate human involvement, in addition to going beyond the extremely productive levels of conventional crop farming.

The employment of robots in agriculture appears to be a potential option in the context of precision agriculture [6][7] since it enables repetitive labour to be accomplished without losing precision throughout the working day. This sort of application is growing in popularity in robotics research, and a variety of robots are now available for purchase [8]. Agricultural robotics, in fact, intends to do more than just apply robotic technology to farming. Currently, the majority of agricultural vehicles used for weed identification, pesticide distribution, terrain levelling, irrigation, and other operations are operated manually. Due to the fact that information about the environment may be obtained autonomously and the robot can then conduct its job accordingly, the autonomous performance of such robots would enable continuous field management as well as better productivity and efficiency [9]. For robots to function adequately in agricultural settings and perform agricultural tasks, research must focus on the integration of numerous complementary sensors to achieve acceptable localisation and monitoring abilities, the design of simple manipulators to accomplish the required agricultural activity, the development of path planning, navigation, and guidance algorithms adapted to situations other than open fields, and the integration with workers and operators in this complex and highly dynamic scenario. This is a primary goal for the use of a variety of technologies targeted at enhancing crop yield and quality while cutting agricultural costs. Indeed, the primary long-term aim of food security in the face of climate change necessitates a shift in the existing agricultural paradigm, which focuses on lowering natural resource usage while increasing crop productivity. For example, Tremblay et al. [10][11] demonstrated that precision seeding and planting, combined with precise treatment application (which means only adding water and plant nutrients required by the crop at the optimal place and time), result in not only an increase in average plant size and uniformity of plant maturity, but also a reduction in the ratio of phytosanitary products and water to crop production and, thus, environmental impact. Furthermore, deploying robots or autonomous tractors to perform various agricultural tasks saves fuel consumption and pollution, according to recent studies [12][13].

Agricultural research on autonomous vehicles began in the early 1960s, with a focus on the development of automated steering systems [14]. In the 1990s, the great majority of mechanical activities in field crop farming used large, powerful, and high-capacity machinery that required a lot of energy and had high handling and operating costs. However, in the last decade, research at many universities and research institutes around the world has undergone a paradigm shift: agricultural robot automation is now regarded as critical for increasing overall productivity and should include the potential for improving fresh produce quality, lowering production costs, and eliminating the repetitive tasks of manual labour [15]. Cultivation and production processes, on the other hand, are sophisticated, diversified, labour-intensive, and typically specific to each crop. Crop characteristics and demands, geographical surroundings, and climatic and meteorological settings are all factors that determine the type of method and its components. This means that the technology, equipment, and procedures required to execute an agricultural operation involving a certain crop and environment may not be suitable for another crop or environment.

Nonetheless, a large body of recent research has demonstrated the technological viability of agricultural robots for a variety of crops, agricultural tasks, and robotic features [16]. However, only a few recent breakthroughs have been tested, adopted, and put into service, and automation solutions for field operations have yet to be commercially applied efficiently and widely [17][18]. From an industrial viewpoint, the bulk of the processes was changed [19]. In the previous three decades, many agricultural robots and intelligent automation research projects never made it to the implementation stage. The excessive cost of the intended systems, their inability to conduct vital agricultural labour, low system durability, and difficulty to efficiently repeat the same activity in slightly varied circumstances or meet mechanical, economic, and/or industrial criteria were the primary causes for these failures.

Bechar and Vigneault [20][21] outlined certain criteria that, in most cases, can guarantee that robot technology may be deployed in agriculture.

- The cost of employing robots is lower than the cost of employing any other method.

- Using robots in agriculture improves agricultural production capacities, yields, profits, and survival while also boosting product quality and uniformity.
- The use of robots in growth and production processes minimises uncertainty and volatility.
- In comparison to the conventional method, the introduction of robots allows the farmer to make higher-resolution judgements and/or increase the quality of the output, allowing for growth and production phase optimisation.
- The robot is capable of doing tasks that are either dangerous or impossible to execute manually.

There are two key trends in robotics for agriculture that can be identified in the literature: (1) flying drones for remote sensing and certain small crop management duties and (2) ground rovers for all-around local monitoring and multi-task specialisation.

2. Flying Drones

As previously said, remote sensing using aerial images is a frequently used method for monitoring large areas. Satellite pictures are too expensive for the common farmer, and their resolution and quality are sometimes poor and impracticable because of weather conditions. As a result, human-piloted aircraft aerial footage is of greater quality than satellite images, but it is still prohibitively expensive for most farmers [22]. Unmanned Aerial Vehicles (UAVs) have just entered the market and have found several applications in a variety of disciplines, with the majority of research confirming UAVs' enormous potential in PA [22][23][24]. UAVs can deliver centimetre-level resolution, integrate 3D canopy height and orthophoto data, deliver multiangular data, deliver high-quality hyperspectral data, and include a variety of auxiliary sensors. UAVs have the potential to become the standard platform for remote sensing applications that need very high-resolution, thermal, or hyperspectral data, such as weed identification and early crop disease detection [23].

Several publications have attempted to categorise the most typical UAV use in PA [22][23][24]. The most prevalent use is remote sensing for soil and crop monitoring, followed by patch spraying [22]. Remote sensing is based on the collection of several aerial pictures in various spectral ranges. Drought-stress detection, for example, is mostly based on thermal photography, but pathogen diagnosis based on the combination of thermal and hyperspectral data yields excellent results. Weed identification, on the other hand, is based on RGB cameras and machine learning object-based image analysis. UAVs are interesting for nutrient status monitoring and yield prediction, but integration with models can increase their application [23]. Combining electrical conductivity data with elevation and slope maps, as well as crop indices that characterise crop vigour, can improve the definition and quality of MZs in vineyards or fields with significant slopes, according to a recent study [25]. Except for irrigation management, where thermal and/or multispectral sensors monitor the crop's water demands [24], it appears that there is a complete absence of standardisation, because various methodologies are used for the same application [23][24][26].

Although UAVs can monitor individual plants, the MZ’s typical spatial resolution is roughly 10 metres (e.g., sprayers with independent nozzles). As a result, UAVs can support technical improvement in order to enhance the resolution of management zones [23].

3. Land-Based Robots

Because they may be deployed locally and operate in the needed place, unmanned ground vehicles (UGV) can fill the UAV monitoring resolution gap. UGVs are also capable of proximal sensing and are frequently built to execute one or more specialised agricultural operation such as seeding, planting, weeding, treating, pruning, picking, handling, and harvesting. Many supporting tasks, including localisation and navigation with obstacle avoidance, detection of the object to treat, treatment or action to undertake, and so on, must be performed by the robot in order for its core functions to be completed. For example, the primary task in developing a disease-monitoring robot [27] is disease monitoring, but the robot must also be capable of self-localisation, trajectory planning, steering, navigating in the field, collaborating with workers and operators, and interacting with other robots or unexpected objects. Ceres et al. [28] developed and implemented a framework for a human-integrated citrus-harvesting robot, whereas Nguyen et al. [29] developed and implemented a framework for apple-harvesting robot motion and hierarchical job planning. A framework for agricultural and forestry robots was developed by Hellstrom and Ringdahl [30].

Many examples of the re-adaptation of agricultural devices with various degrees of automation are available in the market and academic literature. Although tractors and agricultural machinery in general (autonomous or not) are large and powerful, they tend to degrade soil and make it more difficult to traverse [31]. As a result, customised robotic UGVs have recently been designed to be tailored to select specific jobs to decrease bulkiness, weight, and soil deterioration owing to unwanted compaction while still being able to fit into the PA approach’s criteria. Unlike UAVs, where the mobile robotic platform makes little difference and the focus is mostly on the used remote sensing, agriculture UGVs produce more distinctive solutions that are heavily focused on and connected to the work environment and the capabilities required by the activities [32][33].

The following is the current state of the art in commercial and academic agricultural UGVs. In addition, many classifications of agricultural robots are given depending on the most prominent trends.

3.1. Agricultural Robot Main Functions Taxonomy

Due to the fact that comparable technologies can be readily implemented in UAVs, the great majority of agricultural robots are entirely dedicated to remote or proximal soil or crop monitoring (also known as phenotyping, i.e., evaluating plant attributes to determine their state and potential helpful treatments). Due to the fact that the sensors are the primary emphasis of this type of robot, the designs are often simple. For almond orchards, Underwood et al. [34] presented a mobile robot with a scanning system that can map flower and fruit distributions, as well as estimate and anticipate outputs for individual trees. Mueller-Sim et al. [35] showcased a robot that can go beneath the canopy of row crops such as sorghum or maize and deploy a manipulator to collect plant phenotypic data using a modular array of non-contact sensors. Virlet et al. [36] created a massive robot based on an overhead gantry design that uses RGB, chlorophyll fluorescence, hyper-spectral, and thermal cameras to generate high throughput and extensive monitoring data. Cubero et al. [37] and Rey et al. [38] presented two separate robotic systems for detecting pests and disease on carrot fields and olive trees, respectively. Barbosa et al. [39] successfully tested an autonomous robot for monitoring cotton and soy crops; Menendez-Aponte et al. [40] suggest a robot for strawberry field scouting, and ByeLab [41][42][43][44] is a robot designed to check plant volume and health in orchards. Commercially accessible robotic platforms have lately been available [45][46].

Mechanical and chemical weed eradication is the second-most popular use for mobile robots in agriculture. Researchers are primarily interested in systems that use a vision system to detect and classify weeds before removing them using a precision mechanical actuator or a localised chemical application. Bakker et al. [47] suggested a multipurpose research vehicle with a diesel engine, hydraulic transmission, four-wheel drive, and four-wheel steering to test one of the first autonomous weeding robots a decade ago. Bawden et al. [48] used a vision-based online algorithm to develop a robot that eliminates weeds chemically or mechanically depending on the species with a 92.3% accuracy of correct weed detection. Utstumo et al. [49] developed a three-wheeled robotic platform for chemical weeding in indoor carrot fields that reduced herbicide consumption significantly while avoiding overloading chemicals that might otherwise impact and destroy the crops. Furthermore, autonomous weeding robots appear to be of special relevance to the industrial sector. Oz [50], DINO [51], and TED [52] are three distinct weeding robot models made by Naio Technologies. Carré built Anatis [53] to mechanically eliminate weeds without the need for a detecting system, a self-contained solution that is more akin to traditional agricultural gear with a three-point hitch for mounting weeding equipment. AVO by Ecobotix [54], on the other hand, is an autonomous robot with a big solar panel that sprays herbicide accurately to eradicate weeds using vision-based detection.

Seeding, planting, and transplanting are three more important areas where agricultural robots may be used. For instance, Haibo et al. [55] conducted a study and an experimental campaign on a robot for wheat precision planting with a 90% accuracy. Ruangurai et al. [56] used an unusual three-wheel rice-seeding robot to attain comparable seeding accuracy. Hassan et al. [57] presented a low-cost modular robot with a custom-designed seeding mechanism, whereas Srinivasan et al. [58] created a modular tracked robot for the same task. Several researchers used extremely basic and low-cost autonomous robotic platforms to construct and test their precision seeding methods [59][60][61][62][63][64]. Mohammed and Jassim [65] developed and tested a robot that can seed, fertilise, and irrigate. Li et al. [66] created a unique solar and wind-powered tumbleweed-inspired robotic seeder for desert locations. Iqbal et al. [67] created a robotic pepper transplanter that moves on rails for greenhouse production, while Liu et al. [68] created a sweet potato transplanting robot that crawls. Rowbot [69], an autonomous seeding robot for row crops, is one of the few commercial alternatives available.

Robotic harvesters are another popular issue, with vision-based crop-recognition systems, specialised manipulators, and appropriate mobile platforms being strongly emphasised. Foglia and Reina [70] created and tested a pneumatic robotic arm for harvesting red radicchio, which was directed by one of the first vision-based systems to accurately detect the plants, in 2006. Tomato-harvesting robots have lately been proposed by several researchers [71][72], but there are many other harvesters for strawberries [73][74][75], sweet peppers [76][77][78], carrots and cantaloupes [79], lettuce [80], asparagus [81], apples [82], and fruits in general [83].

Spraying agrochemicals is another activity that largely relies on vision-based systems to accurately apply just the right amount of chemical goods in order to avoid dangerous spread. Chemical weeding robots fit under this category; however, spraying can also be used for other treatments, particularly in orchards. Cantelli et al. [84] provided numerous insights into designing a re-configurable robot for plant protection product distribution in greenhouses and the associated spraying management system. Danton et al. [85] followed the development of a robot for vineyards and orchards that can execute autonomous spraying operations to treat vegetation while minimising the spread of contaminants substances by using an array of independent sprayers. Terra et al. [86] took an alternative approach, developing an autonomous sprayer that can apply just the needed quantity of pesticides and is towed by a regular tractor. Some agricultural robots are not focused on a particular duty but can complete a variety of them owing to modular tools. Amrita et al. [87] built a robot that can plough, sow, pick crops, and spray pesticides automatically. Thorvald II, a modular robot that can be customised dependent on the environment and type of crop, was introduced by Grimstad and From [88]. Some robotic solutions based on traditional tractors that may be equipped with standard agricultural tools have also been developed by industrial producers, particularly agricultural machinery brands [89][90][91].

Robotic platforms' great adaptability has resulted in more one-of-a-kind solutions for unusual tasks. Bug Vacuum [92], a pest control robot that eliminates insects by aspiring them, was commercialised by Agrobot. Williams et al. [93] tested a unique kiwifruit pollination robot, while Galati et al. [94] built a tracked robot to compress flax fibres, and Loukatos et al. [95] constructed a robot that works alongside farmers during harvesting as an autonomous carrier of fruits and vegetables.

3.2. Agricultural Robots and Vineyards

Among all the crops that may be grown, the ones with the highest market values appear to be the ones where robotics is used the most. Vineyards, in particular, appear to be attracting a lot of agricultural robot concepts. A selective pesticide sprayer built by Oberti et al. [96], a semi-autonomous sprayer designed by Adamides et al. [97], and even the European project Rovitis4.0 [98] are all examples of specialised agricultural robots. There are definitely some prototypes dedicated to phenotyping [99] and others meant for mechanical weeding tasks [100], but there are also other robots built for pruning [101] and shoot thinning [102], as well as multi-purpose robots [103].

3.3. Agricultural Robots Classified by Size

When agricultural robots are classified by their size, numerous patterns emerge in terms of capability, design, and characteristics. The vast majority of precision agriculture UGVs are small electrically driven robots that are primarily used for crop and/or soil monitoring. They are rarely utilised for activities other than remote and proximal sensing because of their tiny size and limited power. Despite this, they need less investment, are more agile, do not have particular energy supply issues, and can be adapted to a wide range of crops.

There are robots with the size and power of traditional agricultural machinery and tractors on the opposite end of the robot size spectrum. In this instance, the more commonly recognised design trend, especially among major agricultural equipment manufacturers, is to incorporate autonomous features into current agricultural vehicle architectures (e.g., tractors, combine harvesters) rather than developing wholly new designs [3][104]. Apart from farmers' experience with similar machinery and the adaptability of tractor implements (i.e., an autonomous tractor with a typical three-point hitch, or a similar interface, can easily employ traditional agricultural machinery usually towed and powered by traditional tractors), these systems are expensive and work conveniently mostly in wide-open fields.

Medium-sized robots offer the best of both worlds, as well as the widest range of designs. This group of robots can generally monitor the field using remote and proximal sensing, but they can also perform tasks in the field. As previously said, many robots are highly specialised for a very small range of tasks; as a result, the demands of the job drive their design. Other robots, on the other hand, are versatile platforms that can complete a lot of tasks, resulting in designs that are more adaptable and modular.

Small-to-medium-sized systems that can perform several tasks (multipurpose systems) are seen as a viable alternative to all of them. Indeed, they have the potential to lower the required economic investment [105] and to promote a new production paradigm (especially in developing countries), one that employs lucrative technology that has significant environmental and social advantages [106].

3.4. Agricultural Robots by Mobility Layout Configurations

Fue et al. and Oliveira et al. [107][108] published reports on agricultural robots that provided a measure of the most often used mobility layout variants. According to Oliveira et al. [108], 63% of agricultural robots are four-wheel drive or four-steering-wheel robots, with the latter being favoured where tight manoeuvrability is required. All other layouts (such as tracked, legged, rolling, etc.) have far lower adoption rates. Fue et al. [107] also mentioned the widespread usage of robots running on tracks in greenhouses or, more generally, in highly organised environments. Both evaluations included some discussion of legged robots, which suggested similar ideas: despite the fact that they are very light and thrive in extremely impervious terrain, their feet must be constructed adequately to minimise soil damage from penetration and the robot sinking due to the great pressure present in the small contact areas.

Vidoni et al. [109] used an ad hoc simulator to compare mobile robotic platform configurations in order to determine which mobility architecture configuration is best for agricultural activities on steep slopes, embankments, or hills. A tracked vehicle, according to the researchers, can handle the steepest inclines while maintaining high manoeuvrability, enhancing traction and decreasing soil compaction. Nonetheless, track slippage is unavoidable, and it causes substantial soil degradation that can lead to erosion, landslips, and water exposure [110][111][112][113][114][115][116]. Wheeled layouts offer a number of benefits, including increased efficiency and maximum speed. However, when the wheeled platform encounters especially loose or rough terrain, its efficiency plummets, and the vehicle may become stuck. Vidoni et al. [109] examined all wheeled alternatives and found that a three-wheel arrangement was the most nimble and basic, although it was readily overturned when used on steep inclines. Four-wheel platforms, on the other hand, preserve wheeled mobility benefits while providing substantially superior stability over severe inclines. Furthermore, due to their greater steering capability, agility, and stability, articulated wheeled vehicles were shown to be the best suited for uneven and side-slope terrains.

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