# Present and Future Applications of Robotics and Automations in Agriculture

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**Abstract** – The significance of agriculture lies in its role in ensuring the sustenance of the human population through the production of essential resources such as food, feed, and fiber. Precision agriculture is employed to effectively administer appropriate treatments at the correct location and time in order to attain agricultural output that is characterized by low input, high efficiency, and long-term sustainability. The primary objective of precision agriculture is to enhance agricultural productivity while minimizing adverse environmental impacts. Precision agriculture, an agricultural approach that leverages advanced technologies such as robotics and automation, is predominantly employed to enhance the efficiency and precision of farm management practices. The utilization of mobile robots in agricultural activities, such as harvesting, spraying, inspection, and planting, has been extensively investigated and researched in the past few decades. This study investigates the rapid increase in the utilization of automation and robots in the agricultural sector over the past five years. In this study, we categorize the latest applications into four distinct groups, each representing a specific range of activities conducted during the entire process of planting management, starting from the initial sowing stage and concluding with the final harvest. In the final section of the paper, an analysis of various challenges and suggestions is provided to underscore potential opportunities and enhancements in the advancement of an effective robotic and autonomous system for agricultural purposes.

**Keywords –** Precision Agriculture, Precision Farming, Robotic and Autonomous Systems, Planting Management, Farming Management Practices.

## I. INTRODUCTION

Precision agriculture has become a pivotal instrument in contemporary society, enabling farmers to enhance environmental stewardship and ensure long-term food production with minimal human intervention. Precision agriculture encompasses the meticulous management of planting, fertilization, and harvesting procedures, characterized by a notable level of precision and accuracy. Agricultural operations are conducted using diverse methods that are contingent upon the specific soil type. There are four distinct groups of agricultural lands, namely orchards and vineyards, cropland and pasture, confined feeding activities. The land utilized in restricted feeding operations comprises ecosystems that have been modified by human activities to facilitate intensive livestock farming. In contrast, agricultural crops such as soybeans, maize, and wheat are frequently cultivated on both farmland and pasture land, which serves the dual purpose of supporting livestock grazing.

The land designated for cultivation in orchards and vineyards is primarily utilized for the growth and maintenance of fruit-bearing trees and plants, such as grapevines, apple trees, and pear trees. Lastly, the second category of agricultural land encompasses ecosystems that are being effectively utilized for the production of food and fiber, yet do not align with the classifications of the preceding two categories. Specialized agricultural areas encompass various examples such as farms, small ponds, and corrals. Currently, precision agriculture is being implemented across diverse landscapes. Precision agricultural development has focused on a range of topics, including technology, digitization, societal impact, skills, environment, and productivity.

Precision Farming (PF) [1] has effectively utilized various technological advancements like Global Navigation Satellite System (GNSS), geo-referencing, autonomous navigation, and advisory systems. The advent of the information and communication technology revolution has led to a significant digital transformation within the agricultural sector. The utilization of digitalization initiatives such as Internet of Things (IoT) and cloud computing has facilitated the ability of farmers to efficiently collect and analyze substantial volumes of data. In addition to streamlining farmers' tasks and reducing their workload, precision agriculture endeavors to instigate transformative societal changes within rural communities, akin to the impact of computers on urban populations, by introducing novel social paradigms and business ventures. The current scarcity of labor in the agricultural sector has resulted in an increase in the adoption of automated farming systems, which are capable of performing various tasks such as planting, inspecting, spraying, trimming, and harvesting.

The term "automated agriculture" encompasses various tools or machines designed to supplant human labor within agricultural settings. The focus of agricultural automation revolves primarily around the implementation of autonomous vehicle technologies, such as robots and tractors. These technologies aim to mitigate the challenging, hazardous, time-consuming, and physically demanding working conditions faced by farmers, while also offering a more accurate and efficient control system. Maintaining a consistent level of quality and quantity in the output is crucial to ensure its safe consumption by humans. Consequently, there is a growing interest in the agricultural research community to develop an efficient automation system in the field of agriculture, with the aim of ensuring the sustainable maintenance of food security in the long run.

This article examines the utilization of automation and robots by farmers over a retrospective period of five years. The classification of the current application is informed by four significant agricultural processes, namely planting, inspecting, spraying, and harvesting. Different agricultural operations will have diverse requirements, thus the implementation of automation and robots will differ in terms of structure, planning, and execution. The subsequent assessment will proceed to examine the challenges and potential advantages associated with the potential expansion of automation and robotics in the agricultural industry. The rest of the article has been organized as follows: Section II focusses on the present applications of robotic and automation systems in the agricultural sector. Section III reviews the challenges and future scope of the technological initiatives in the agricultural sector. Section IV is the final section, which provides final remarks regarding the article.

## II. PRESENT APPLICATIONS

The initial focus of this analysis will involve an examination of advancements in automation technology that have broad applicability across various industries. Subsequently, we will delve into an exploration of the projected adoption of automation and robotics within the realm of agricultural production. In [2] discusses three fundamental forms of automation technology, namely physical robotics, robotic process automation, and cognitive automation. In forthcoming times, automated machines will be employed to execute labor-intensive tasks within the industrial sector. Robotic process automation (RPA) entails the utilization of software to supplant human involvement in previously manual procedures. Cognitive automation leverages sophisticated software to either achieve complete process automation or enhance process accuracy. Cognitive automation encompasses the utilization of machine learning, visual data processing, and extensive data collections in order to augment the process of decision making.

According to [3], the widespread implementation of automation technologies does not necessarily imply the complete elimination of entire professions. Nevertheless, it is anticipated that a considerable portion of tasks across various professions will undergo automation. The classification of jobs into three distinct categories is undertaken by the [4], with the categorization being determined by the degree of susceptibility to automation. These categories are as follows: 1) jobs that are highly vulnerable to automation, 2) jobs that are moderately susceptible to automation, and 3) jobs that are least susceptible to automation. Personnel management, along with planning, creativity, and decision-making, is considered to be one of the least susceptible occupations. Examples of activities that are less susceptible to vulnerability include engagements with stakeholders and spontaneous physical labor. The [5] provided illustrations of physically demanding occupations that encompass construction, forestry, and animal rearing, highlighting their potential hazards. Tasks involving data processing and other mundane bodily functions are particularly susceptible to vulnerability. Tuncel and Topaloglu [6] provided instances of physically predictable activity, such as assembly-line welding and soldering, food preparation, and packing.

It is noteworthy to mention that a significant portion of businesses can potentially derive advantages from automation, primarily owing to the widespread utilization of data processing and the presence of predictable physical job tasks. Based on the findings of Kreuzfeld, Felsing, and Seibt [7], it has been determined that a significant proportion, specifically more than 20%, of the total working hours in Germany are allocated towards engaging in physically strenuous activities, such as the operation of machinery or the manipulation of materials. The researchers have identified three sectors that are particularly vulnerable to automation: the service industry, manufacturing, and retail. Financial and insurance services, building and construction, and farming are examples of activities and industries that occupy a position within the automation spectrum. Automating operations that entail the unpredictable manual labor frequently observed in agriculture and construction presents a greater level of complexity, albeit not an insurmountable challenge.

Automating the tasks of managing and directing individuals, as well as utilizing knowledge for decision-making, planning, and creative endeavors, presents significant challenges. Computers demonstrate exceptional performance when provided with explicit instructions. According to Deng, Ji, Rainey, Zhang, and Lu [8], there exists a difficulty in codifying and enhancing machine learning methods to replicate human attributes such as leadership, creativity, intuition, judgment, tacit knowledge, social interaction, peer evaluation, motivation, and various other tasks. Automation faces a significant challenge in dealing with tacit knowledge, which refers to the knowledge that individuals possess but are unable to fully articulate. The existence of tacit knowledge introduces complexity to the machine learning programming process.

### *Planting*

The act of planting involves the deliberate placement of seeds or seedlings in the soil with the intention of facilitating their growth and eventual maturation into fully developed plants. Due to the diverse spacing requirements of different plant species, achieving optimal development and maximum production necessitates a higher level of precision in this procedure. In the conventional method of planting, manual labor is employed to individually plant each seed. The successful implementation of this method necessitates a significant investment of time and effort, as it encompasses a vast agricultural region with a focus on achieving uniformity and accuracy. Consequently, an agricultural implement known as a planter machine has been devised, enabling farmers to sow seeds into the soil by directing its trajectory.

Hence, the implementation of a dependable autonomous system becomes imperative, wherein the system ensures the attainment of a flawlessly aligned plant row and eliminates any possibility of seed omission. Various crops like vegetables, sugarcane, wheat, and maize, have implemented autonomous models as a substitute for the labor-intensive manual planting method. A number of factors have been identified as key objectives in the design phase, with the intention of developing an efficient autonomous system for the planting procedure. The primary requirement is that the robot or vehicle possesses the capability to navigate accurately along a straight trajectory, even when confronted with the irregular terrain found in agricultural fields. The straightness of the seeding process is a critical factor as it directly impacts the efficacy of subsequent automated planting steps, including inspection and harvesting. Another important consideration is the impact of soil moisture on the excavation process. Various varieties of seeds require varying depths for soil excavation.

Consequently, in order to ensure the appropriate depth of excavation, it is necessary to modify the cultivation's digging force by taking into account the levels of soil moisture and compaction. Lastly, it is imperative to have a seeding detection device in place. This particular apparatus serves the purpose of identifying the moment when seeds are about to be sown by the vehicle. The implementation of this approach is of utmost importance in order to ensure that the planter does not overlook any areas designated for planting. The primary focus of current research in the field of planting is the refinement of autonomous seeding systems, which aim to ensure that seeds are planted at consistent distances and depths. The development of an autonomous seeding robot was achieved utilizing the Agribot platform, as documented by Terada, Ando, and Mizukawa [9].

In [10], an Infrared (IR) sensor was employed to assess the condition of the seed tank and to determine the arrangement of the rows. The findings demonstrated promising outcomes in terms of the accuracy of seed spacing. A technique was devised to regulate the seed metering units in order to achieve consistency in planting. A seed metering device is frequently employed during the planting procedure to dispense precise quantities of seeds into the soil. Prior to being dispersed at consistent intervals, the seeds are frequently classified into multiple categories. The evaluation of planting quality involves assessing variance among rows, plant spacing uniformity, negative slippage, and fuel consumption. To evaluate the operation of the seed metering device, it is necessary to consider varied speeds and seed spacing. The enhanced planting quality and approximately 22% rise in fuel efficiency have been ascribed to the effective design of the seed metering unit.

*Inspection*

As an integral component of the agricultural inspection process, plants undergo thorough examination to detect infections and other quality deficiencies. The primary cause of diminished productivity and subsequent economic losses in the agricultural sector can be largely attributed to the prevalence of plant diseases. The agricultural environment is characterized by its dynamic nature, leading to numerous unforeseen and abnormal stress scenarios that have had adverse effects on plants and their products. If these anomalies are not promptly addressed, there is a possibility of experiencing severe and irreversible harm. Throughout history, farmers have traditionally depended solely on their own visual faculties to detect any irregularities in plants during the inspection procedure. The efficiency of inspection operations has been compromised due to the increasing average age of American farmers and the natural degradation of the human visual system over time. In order to achieve full automation in agricultural inspection, it is imperative to substitute the visual inspection capabilities of human eyes with appropriate technological alternatives. Consequently, computer vision has predominantly supplanted human visual perception in the realm of agricultural plant inspection. Computer vision is an advanced image processing technology that exhibits promising potential and possesses the capability to supplant human vision in certain inspection tasks that require meticulous attention to detail.

Several other industries, such as the agricultural sector, have adopted computer vision systems. The expansion of image processing and computer vision applications in agriculture can be attributed to several factors, including minimized costs of equipment, increased computing power, and an increasing interest in non-perishable food evaluation techniques. Most agricultural vision system applications primarily focus on disease diagnosis, with a smaller portion dedicated to product quality assurance. Various methodologies have been devised to enhance the efficiency and precision of image processing. These methodologies encompass Support Vector Machine (SVM), Neural Network based algorithms, K-Nearest Neighbors, Machine Learning Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Over the past five years, there has been extensive utilization of neural network-based algorithms such as Convolutional Neural Network, Deep Convolutional Neural Network, Deep Neural Network, Back Propagation Neural Network, and Regions with Convolutional Neural Network (R-CNN) in the domain of agricultural inspection image processing.

Munikoti, Agarwal, Das, Halappanavar, and Natarajan [11] indicate that the Neural Networks algorithm exhibits strong performance in the field of agricultural monitoring, attained a peak precision of 99%. In addition to an approach to image processing approach commonly employed in agricultural monitoring, Mandal, Pedersen, George, Deborah, and Boust [12] utilize hyperspectral imaging for the purpose of plant disease diagnosis. Alexander [13] employ a novel Normalized Different Spectral Index (NDSI) for the purpose of detecting lesions on peanut leaves. The utilization of hyperspectral vegetation index deviation measurements is advantageous due to their distinctiveness in detecting variations in leaf characteristics. Other detection methods, such as immunochromatography, have also been employed to identify the presence of fumonisin, a chemical constituent that has the potential to contaminate agricultural products. The approach employed in this technique utilizes a quantitative immunochromatography detection method that relies on ultrasensitive gray imaging for the purpose of monitoring the presence of chemical molecules in food.

The emergence of cyber physical systems, characterized by the interconnection of devices and sensors through cloud technology, has become a prominent area of interest in the IR 4.0 (Industrial Revolution 4.0) concept. The direction of agricultural inspection technology is aligned with the concept of IR 4.0. Farmers are now able to remotely monitor their agricultural management systems through the utilization of computer technology and mobile applications. The predominant utilization of Internet of Things (IoT) applications in the agricultural sector involves the real-time monitoring of plant diseases through the capture of images and collection of sensory data pertaining to moisture levels, temperature, and humidity from the agricultural site. This data is subsequently presented on a website or mobile application for easy access and analysis. This enables the farmer to detect illnesses such as powdery mildew, late blight, and early blight at an early stage, thereby preventing their further dissemination.

In their study, Pietroń, Żurek, and Śnieżyński [14] observed a significant performance advantage of deep learning (DL) neural approaches over traditional machine learning (ML) methods in the context of plant categorization in mages. The research of deep neural network in an agricultural context is hindered by a lack of transparency resulting from unresolved issues with dense sceneries. In their scholarly publication, Yeboah, Department of Electrical and Computer Engineering, South China University of Technology, Zhuliang, Wei, and School of Automation Technology [15] conducted a comprehensive review examining the practical applications of machine vision technology within the agricultural industry. Based on their research findings, it is suggested that the application of computer vision has the potential to contribute to the progress of agricultural automation in the context of small-scale fields. This could result in notable benefits such as reduced costs, enhanced productivity, and heightened precision. Nevertheless, the focus was on the digital process instead of machine vision.

In their study, Hayashi [16] proposed the utilization of a convolutional neural network as an effective approach for the detection and quantification of maize kernels in photographic images. The researchers developed numerous models to facilitate efficient object identification across diverse environmental and illumination conditions. Yin, Li, Laghari, Karim, and Jumani [17] employed the established sliding window strategy for kernel detection in their study. The precision of their results, as depicted in **Fig 1**, can be attributed to the thorough dataset annotations.

(a) (b)

**Fig 1.** The Process of Counting Corn Kernels using Images That Have Been Processed Using a CNN

Gibson, Dirks, Medlin, and Johnston [18] achieved successful weed detection in photographs by employing various architectures, namely Mask R-CNN, YOLOv3, and SVM The respective F1 scores obtained were 94%, 94%, and 88%. The F1 metric can be defined as the harmonic mean of a model's accuracy and recall. Dunn's test was designed to receive statistical measures comparing evaluations conducted by humans and those conducted by automated systems. The researchers illustrated that deep learning models have the potential to enhance accuracy in estimating weed coverage and mitigate the influence of human error. Guo, Wei, and Yu [19] employed multiple distinct DCNN models in their study to classify Bermuda plants. The VGGNet model outperformed the GoogLeNet model in the task of weed detection, exhibiting superior F1 scores that exceeded 0.95. The scholars proposed several approaches to enhance the detection of anomalies for each deep learning model.

Mohammed Abdelkader [20] employed deep learning meta-infrastructures such as UNET and SegNet, alongside encoder blocks such as ResNet-50 and VGG16, to identify the presence of weed plants in canola lands. The ResNet-50-oriented SegNet system demonstrated the most significant outcomes, attaining a 0.8288 mean crossover value, and a 0.9869 frequency-oriented crossover value. In their study, the scholars employed DCNNs to evaluate various models aimed at the identification of prevalent weed species such as Taraxacum officinale Web (dandelion), Euphorbia maculata L (euphorbia), and Glechoma hederacea L. (ground ivy). The inclusion of GoogleNet, AlexNet, and DetectNet was considered. DetectNet achieved the greatest F-score (0.9843) in weed identification when compared to other models on the test datasets.

*Spraying*

In the field of agriculture, it is customary to apply a fine mist containing pesticides, fertilizer, or other growth-promoting substances to plants as a means of mitigating plant diseases and controlling plant growth. In order to mitigate the transmission of diseases, it is common practice to apply pest-control substances uniformly across entire agricultural fields. Despite the fact that numerous pests and diseases exhibit non-typical geographical distributions, especially during their initial stages of development, this approach continues to be employed. Hence, over the past twenty years, there has been significant progress in the development and examination of selective spraying techniques aimed at minimizing the expenses associated with pest-control chemicals employed in agricultural practices. Automated selective spraying systems, frequently operated by advanced machinery or mobile robots, enable the precise application of pesticides at specific locations and times as desirable. This targeted intervention is aimed at minimizing the reliance on pesticides for maintaining a disease-free environment within the greenhouse.

The utilization of herbicides and pesticides has been employed with the aim of augmenting agricultural productivity. However, the excessive application of these substances has resulted in the emergence of herbicide-resistant weeds and a significant decline in both flora and fauna biodiversity. Due to their diminutive dimensions, the visibility of weeds during the initial phases of crop growth, when herbicides are commonly employed, may be challenging. Farmers allocate financial resources towards the acquisition of herbicides and pesticides, which are subsequently applied to crops using conventional spraying methods such as Knapsack and Boom sprayers. This process is often characterized by inefficiencies in the distribution of the sprayed substances, as depicted in **Fig 2** (a) and (b). The excessive utilization of pesticides and herbicides has a deleterious impact on agricultural practitioners.

Traditional sprayers are inefficient in their application of pesticides, resulting in a significant amount of wastage. This wastage leads to a substantial financial burden on farmers, as the pesticides fail to effectively reach the targeted weeds and pests. The insufficient implementation of route planning and the absence of a GPS survey of the field resulted in suboptimal application of the maximum quantity of spray to the intended target. Consequently, spray loss was observed in the form of both spray drift and field turns. The inefficiency of broadcast sprayers can be attributed to the lack of precision, resulting in a significant amount of wasted effort. Throughout history, farmers have faced a significant challenge in the form of the adverse effects that weeds have on agricultural productivity. The occurrence of spray loss, manifested as spray drift and environmental contamination, can be attributed to the inadequacy of technologies in promptly identifying the precise weed and insect targets. In recent times, the market has witnessed the emergence of sensor and AI-driven spraying technology, such as variable sprayers and drone sprayers.

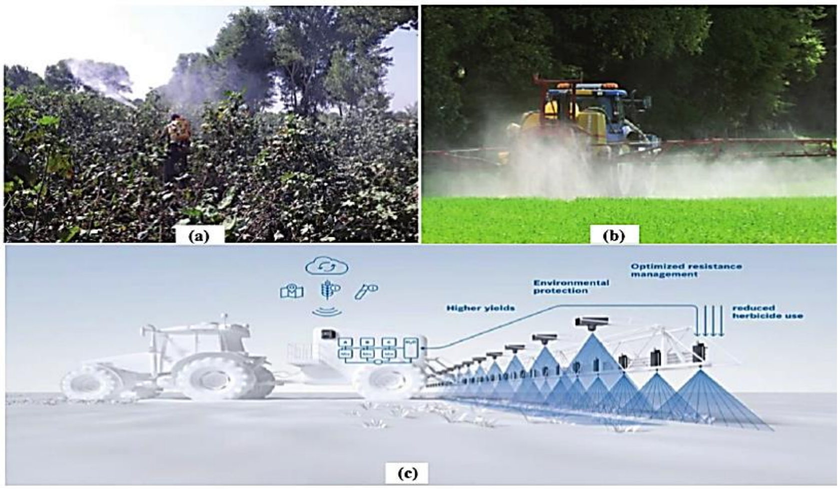


**Fig 2.** The application of a Knapsack sprayer on cotton (a), a boom sprayer on wheat (b), and the utilization of a schematic representation of a smart sprayer (c) are employed in agricultural practices.

Technology offers numerous advantages, such as its capability to identify and distinguish plants, weeds, and pests, followed by the precise administration of pesticides. Initially, an image or plant detection sensor captures visual data, which is subsequently processed by deep learning algorithms to differentiate between different plant species and identify instances of diseases. This enables the decision support system to accurately identify the specific plant variety or ailment under consideration. The selection of plants and herbicides will be determined by algorithms. **Fig. 2** (c) depicts a simplified schematic representation of a smart sprayer. The development of advanced sprayer technology is influenced by sustainable agricultural goals, which encompass environmental preservation, economic benefits for farmers, and enhanced food security. The recent advancements in cellular technologies, specifically 4G LTE and 5G, have brought about significant changes in conventional methods of crop monitoring and the precise application of insecticides and herbicides. Weeds and pests exhibit robust growth and proliferation in extensively cultivated field crops, encompassing a variety of plant species such as vegetables, wheat, rice, and cotton.

Prior research has primarily focused on the development of an effective spraying system that is cost-efficient in the context of autonomous selective spraying techniques. The aforementioned objective can be accomplished by employing a variable rate spraying technique, which permits farmers to dynamically transform herbicide or pesticide quantity employed to the target according to the sizes of the canopy and the necessary treatment. The implementation of this strategy has the potential to significantly reduce pesticide usage by precisely targeting application, thereby minimizing farmers' direct exposure to the adverse effects of chemicals. This is made possible by the availability of automation and robotics technologies that are currently prevalent in the market. Several studies have been conducted to investigate navigation management strategies aimed at reducing pesticide usage and optimizing the operational costs of robots, particularly in terms of time and energy, through the implementation of precise location monitoring.

The field of study under consideration is of paramount importance in ensuring the precise and efficient spraying capabilities of the robot, achieved through the minimization of travel distances. According to Wang, Tu, and Qiu [21], a multi-objective approach known as the Non-dominated Sorting Genetic method with Reference Point has been proposed as a means to reduce operational expenses. With the objective of reducing expenses in relation to time, distance, and deviation from the intended route. Truc, Van Quyen, and Quang [22] conducted a study to investigate the impact of various robot velocity on the mass discharge rate of flow of pineapple leaf fibers during composite spray operation. In [23], a route planning method using Simulated Annealing is proposed, which considers various objectives like input cost, herbicide volume, fuel efficiency, travel duration, and cost per mile.

Researchers focus on achieving high levels of location accuracy for agricultural robots, while simultaneously reducing the costs associated with developing navigation systems for spraying operations. The development of wheeled robot tractors designed for the purposes of weeding and spraying is documented in [24]. The navigation system utilizes an inertial measurement unit (IMU) and Real-Time Kinematic GPS (RTK-GPS) as attitude and position sensors, respectively. This integration aims to enhance the stability of the auto steering system, achieving a precision of 0.05 m. The high cost associated with RTK-GPS has led the scholars in [25] to propose a data fusion technique employing MSPI for the purpose of filtering noisy raw data obtained from affordable sensors like Differential GPS, inertial measurement units, and cameras. This technique is intended to enhance the performance of vineyard pesticide spraying robots.

However, this particular method exhibits lower accuracy compared to an implementation based on RTK-GPS, with a minimum variation of 0.11 m. Although the majority of autonomous spraying operations in the field of agriculture predominantly utilize ground-based vehicles, there is a growing interest in the potential application of unmanned aerial vehicles (UAVs). The mitigation of overspraying is achieved through the utilization of a fleet of unmanned aerial vehicles (UAVs) in [26]. These UAVs employ the Heat Equation Driven Area Coverage (HEDAC) approach, which is a multi-agent technique for achieving comprehensive coverage of a given area.

*Harvesting*

The exponential growth of the population has placed an overwhelming strain on the agricultural industry. In recent years, there has been a notable shift towards the adoption of smart agricultural systems, characterized by the integration of sensor technologies, diverse equipment, and robotics. This transition has resulted in enhanced precision and productivity within the agricultural sector. Significant progress has been made in various domains, including but not limited to planting, weeding, harvesting, detecting plant diseases, evaluating damage and defects in fruits and vegetables, categorizing their quality, and identifying pests and insects. The act of harvesting is an essential component of the process of collecting crops from agricultural fields, and the utilization of harvesting robots serves as a prominent factor in enhancing precision, effectiveness, and output.

Consequently, agricultural researchers encounter numerous challenges throughout the different phases of the autonomous robotic harvesting process, necessitating their resolution for the development of a proficient harvesting robot. In recent years, extensive research has been conducted to identify the optimal location for agricultural cultivation. The vision system is commonly employed to accurately determine the exact location of the fruit in the majority of instances. The designed vision system aims to tackle two complex challenges: the considerable natural variability present in the detected object and the absence of a consistent lighting or occlusion arrangement within the working environment. To effectively detect targets during the harvesting process, it is imperative to employ a diverse range of vision techniques. **Table 1** provides a summary of four different vision techniques that are employed for target recognition in the context of agricultural harvesting. The efficacy of utilizing agricultural robots in dense crop environments relies heavily on the implementation of strong motion management and accurate end-effectors placement at the required vegetable or fruit target.

The fruit-picking process was facilitated by the utilization of a robot, which was equipped with a stereo camera placed about half a meter beneath the robot arm base. This camera arrangement enabled us to obtain an upward perspective of the fruit tree. In instances where the fruit is situated at a distance beyond the access of the robotic arm, the lift table supporting the machinery can be adjusted vertically to facilitate access to the desired target. The robotic manipulator employed in our study is commonly referred to as the UR3 (UNIVERSAL ROBOTS). Based on the data presented in **Table 1**, the robot exhibits a 0.1 millimeters repeatability. The palm of the robot hand had a diameter of 5 centimeters, thereby effectively dampening any inadvertent motions. The stereo camera utilized in this study was ZED, developed by Stereo Labs. The specifications of ZED are presented in **Table 2**.

**Table 1.** UR3 Specifications

| **Capacity of weights** | **3 kilograms** |
|---|---|
| **Repeatability** | +/- 0.1 millimeters |
| **Weight** | 11 kilograms |
| **Freedom degree** | 6 |
| **Reach** | 500 millimeters |

**Table 2:** ZED specification

| **Resolution of output** | **3840 by 1080** |
|---|---|
| **Baseline** | 120 millimeters |
| **Range of depth** | 0.5 to 20 meters |
| **Frames/second** | 30 |

In this section, we elucidate the methodology for apple harvesting employing robotic technology. The experiment on an apple tree was conducted by the Horticultural Research Center and Miyagi Prefectural Agriculture, as depicted in **Fig 3**. The trees observed in this study exhibited a similar characteristic to those found at the Horticultural Research Center, and Miyagi Prefectural Agricultural, namely a shared V-shaped growth pattern. Given the challenges associated with undertaking the experimentation during the harvesting season of apples, a tree model was employed as a substitute.

**Fig 3.** Apple tree framework

**Fig 4.** Recognition of 2D position

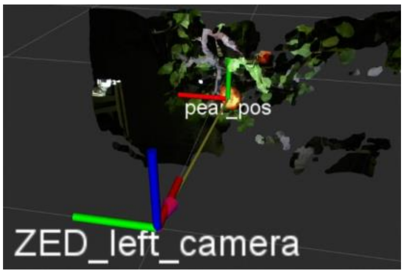


**Fig 5.** Recognition of 3D position

**Fig 6.** Reaching targeted apple

**Fig 7.** Harvesting targeted apple

**Fig 8.** Grasping targeted apple

This article presents the results of our experimental investigations involving an automated fruit harvesting system, along with an analysis of the robot's detection unit. The initial step involved the identification of the fruit within a two-dimensional framework. The outcome of the fruit detection performed by the SSD is illustrated in **Fig 4**. In the section pertaining to fruit position identification, a learning model was utilized, which demonstrated a success rate of over 90% in accurately identifying the fruits that were subjected to testing. A red border was applied to demarcate the area in which the probability of fruit occurrence exceeded or equaled 60%. The robot demonstrated a level of apple identification proficiency that was deemed comparable to that of a human, thus satisfying the requirements of the experiment. Furthermore, the depth of the fruit was quantified. **Fig 5** present the 3D optical center coordinates of the frame, as recognized by SSD. The 3-dimensional reconstructions of all objects, with the exception of the apples, exhibited subpar quality. However, for the purpose of this exercise, it is only necessary to focus on the underside of the apples. The apple's core was successfully captured, resulting in satisfactory outcomes.

The robot was positioned 10 centimeters beneath the targeted fruit in order to facilitate the insertion of the hand from beneath for the purpose of picking, as depicted in **Fig 6**. Subsequently, the appendage ascended above the edible produce (**Fig 7**). The fruit was subsequently collected by the robotic appendage through a twisting motion, specifically by detaching it from its peduncle, as illustrated in **Fig 8**. Each fruit was harvested at approximately 16 seconds. The process of determining the joint angle based on the detected fruit location typically requires approximately 2 seconds. The process of collecting all the fruit required approximately 14 seconds. The harvesting process was time-consuming due to the need for multiple rotations of the hand. Acceleration can be achieved through a reconsideration of these factors.

## III. CHALLENGES AND FUTURE SCOPE

**Fig 9** illustrates the global agricultural robotics market from 2020 to 2025, with specific emphasis on the valuation in United States dollars. During the specified projection period spanning from 2023 to 2028, it is anticipated that the Agricultural Robots Market will experience a notable growth trajectory. The marketplace is projected to increase from an earlier projected value of $13 billion in 2023 to a final projected value of $24 billion. Agribots, also known as agricultural robots, represent a recent advancement that holds considerable promise for revolutionizing the agricultural industry. Self-operating machines are utilized to enhance productivity and efficiency, thereby diminishing the reliance on human labor. The global population is experiencing a notable growth trajectory, which is contributing to the escalation of food prices. Consequently, farmers are progressively allocating resources towards the adoption of advanced technological solutions, such as agricultural robots, with the aim of augmenting agricultural productivity and enhancing financial gains.

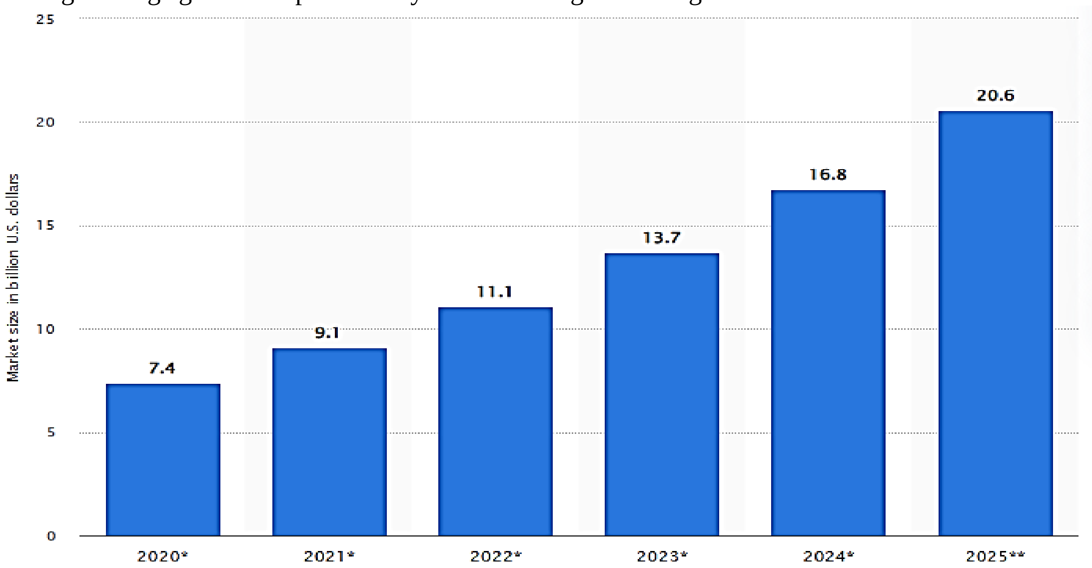


**Fig 9.** Global Agricultural Robotics Market from 2020 to 2025

Governments worldwide are implementing financial incentives and initiating educational campaigns to enhance farmers' comprehension of automated technology. This encompasses a wide range of technologies and practices in the agricultural sector, ranging from regulatory measures and intelligent tools to fully automated farming systems. Notably, the European Union has recently introduced initiatives like Robs4Crops, which aim to develop and implement autonomous farming systems. The issue of labor shortage in the agricultural sector is being tackled through the implementation of the recently introduced initiative known as Robs4Crops. The projected growth of the agricultural robotics industry is expected to be augmented as a consequence of this development. Furthermore, several prominent agribusiness corporations as well as emerging entities are allocating resources towards research and development endeavors aimed at creating a novel cohort of agricultural robots. In 2021, AGCO Corporation's Precision Ag Line (PAL) program conducted a trial to introduce a platform aimed at standardizing support services for farmers who utilize AGCO solutions and manage a mixed-fleet operation.

Agricultural robots, tailored for the purpose of farming, have the potential to enable a wide range of tasks, enabling farmers to decrease their reliance on manual labor while concurrently enhancing their productivity, product quality, and operational effectiveness. They are capable of performing various tasks, such as analysis, reflection, and action. The classification of the agricultural robots' market takes into account various factors, including the types of robots used such as drones, driverless tractors, automated harvesting models, and milking robots. Moreover, applications of these robots encompass dairy farm control, broad acre applications, aerial data collection, forecasting, weather tracking and inventory control. The market classification also considers the offerings available, which include hardware, software, and services. Furthermore, the geographical parts of Europe, North America, Asia-Pacific, Africa, and South America are taken into consideration when categorizing the agricultural robots market. The study offers an assessment of the market size and future projections for the aforementioned categories, expressed in US dollars.

Based on the assessment, a key objective of the act of planting is to establish consistency and identify any anomalous seeds. Greater emphasis, however, must be placed on the implementation of course correction strategies to maintain the integrity of the linear arrangement. The current state of research has reached a level of complexity that presents challenges in effectively monitoring and managing the structural integrity of robots during the execution of planting tasks. This difficulty arises from various factors, such as the non-uniformity of soil surfaces and the varying stiffness of different soil types (e.g., sand, loam, clay) under both dry and muddy conditions. Consequently, these factors can contribute to inconsistencies in the arrangement of rows during the planting process. The majority of the proposed inspection algorithms demonstrated efficacy in identifying the presence of illness or defects in both virtual and physical experimental settings. The majority of practical experiments typically entail the isolation of a genuine plant ailment or quality defect, which is subsequently superimposed onto a white background to facilitate its detection. Capturing an image of the plant within its natural environment, against a dynamic backdrop, will significantly augment this procedure.

Hence, forthcoming advancements in robot design will enable more precise implementation of plant disease and quality defect detection, rendering the robot a faithful emulation of the plant inspection process as conducted by humans. Upon reviewing the present status of robotics and automation in the context of spraying tasks, it becomes evident that the predominant focus of ongoing research lies in the development of a spraying system that is economically viable. In order to effectively implement a fully autonomous system in real-world spraying applications, it is crucial to place significant emphasis on spraying management. This entails developing an autonomous system that can identify an optimized route for executing selective spraying operations, taking into account various spraying characteristics such as spraying capacity and refill mechanism.

Most of the research conducted on harvesting has primarily focused on target identification as a strategy to precisely determine the location of the commodity to be gathered. While the identification of targets remains a crucial focus within the field of harvesting operations, there exists an opportunity for further enhancement in the realm of harvesting management. This is attributed to the existence of potential for enhancement in the ability of an autonomous system to devise a strategic plan for maximizing agricultural product yield within a minimal timeframe, while considering constraints related to travel timeframe to the depots and the storage capacity.

Therefore, the harvesting process can be conducted efficiently and with minimal operational costs. Farmers express concerns regarding the financial burden associated with the adoption of agricultural robots and automation, despite encountering numerous challenges in various agricultural activities. Certain farmers exhibit reluctance in allocating funds towards the acquisition of novel technological advancements, as they harbor apprehensions regarding the potential ineffectiveness of said innovations in the future. Hence, it is imperative for agricultural specialists to devise strategies for the creation of an affordable and adaptable agricultural robotic system. One potential avenue to explore during the development of an agricultural robot is the incorporation of a modular and highly resilient robotic architecture.

## IV. CONCLUSION

The significance of agriculture lies in its provision of the necessary sustenance for human survival, encompassing the production of food, feed, and fiber. Precision agriculture is employed to effectively administer appropriate treatments at the correct location and time in order to attain agricultural output that is characterized by low input, high efficiency, and long-term sustainability. The achievement of future food security is contingent upon the substantial utilization of robotics and automation within the agricultural sector. The advent of robotics machinery has facilitated the timely completion of agricultural tasks, thereby enabling farmers to leverage advanced technology in their operations. The primary objective of agricultural robotic system development is to replicate human labor in the execution of various agricultural activities like inspecting, spraying, planting, and harvesting. This approach aims to achieve efficient task completion while minimizing operating costs and reliance on human labor. Several ongoing studies are focused on enhancing the efficiency and reducing the errors of the existing autonomous system. This is crucial because different agricultural operations require specific features and specifications that are dependent on the unique environment and type of plants involved. The agricultural sector continues to face several unresolved challenges, prompting scholars to diligently investigate and address these issues. In the future, it is conceivable that a comprehensive autonomous agricultural robotic system could be devised by integrating various technologies developed for each specific operation. The ultimate goal would be to establish a resilient and effective agricultural robotic system that can be widely adopted by farmers worldwide, with the primary objective of generating substantial agricultural output to ensure food security.

### Data Availability
No data was used to support this study.

### Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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### Ethics Approval and Consent to Participate
The research has consent for Ethical Approval and Consent to participate.

### Competing Interests
There are no competing interests.

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