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Robots for Harvesting of Horticultural Crop: A Review

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ABSTRACT

Robotics in horticulture is revolutionizing conventional agricultural methods, providing substantial enhancements in productivity, accuracy, and cost-efficiency. This analysis assesses the present status of robotic harvesting systems for horticulture crops, with a specific emphasis on progress, obstacles, and potential future developments. According to statistical data, the worldwide agricultural robot market was worth USD 4.6 billion in 2020. It is projected to see a compound annual growth rate (CAGR) of 20.8% and reach USD 20.3 billion by 2026. Special emphasis is placed on the implementation of robots in the fruit picking industry, which is expected to see significant advantages as a result of manpower shortages and the requirement for accuracy. Presently, robotic systems are able to pick fruits at an average pace of 10-12 seconds per fruit, while maintaining an accuracy rate of 85-90%. Nevertheless, there are still obstacles to overcome in the adoption of this technology, including the significant upfront expenses, the current technological constraints in handling fragile fruits, and the requirement for enhanced integration of sensory and artificial intelligence capabilities. Future developments are expected to prioritize the enhancement of machine learning algorithms, the improvement of robotic dexterity, and the reduction of prices. The ultimate goal is to boost the rate of adoption of robotic systems in horticultural harvesting to more than 50% by 2030. This review emphasizes the capability of robotic harvesting to transform horticulture, by tackling important problems and facilitating the adoption of sustainable farming methods.

Keywords: Robotics, Automation, Agriculture, Precision harvesting, Horticultural practices

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INTRODUCTION

India is second in horticulture crop production, following China. Horticulture is an important sub-sector of agriculture in the Indian economy. India's horticulture production has witnessed remarkable growth in recent years, mostly due to significant progress in expanding the cultivation area, resulting in higher output. According to Anonymous (2022), the horticulture sector has shown a consistent annual growth rate of 2.20% over the past decade, leading to a significant 2.30% rise in production. In the fiscal year 2020–21, the production of horticulture crops amounted to 334.60 million metric tons, cultivated on an area of 27.48 million hectares. In the fiscal year spanning from 2019-20 to 2020-21, vegetable production saw a significant increase from 189.46 million metric tons to 197.23 million metric tons. Similarly, fruit production also saw a notable rise from 100.45 million metric meters to 103.03 million metric tons, according to Anonymous, 2022. The significant progress highlights the horticulture sector's critical contribution to stimulating growth in the Indian agriculture sector. Currently, India has an incredible horticulture production of 342.33 million metric tons, grown on 28.08 million hectares of land (Anonymous, 2022). Precision agriculture optimizes agricultural practices based on spatially variable data, including tillage, planting, irrigation, fertilizer application, pesticide spraying, and harvesting. This transformation from traditional extensive production to intensive production is particularly beneficial for horticulture crops.

Implementing farm mechanization in Indian horticulture for activities such as transplanting, sowing, spraying, inter-cultural operations, fertilizer application, and harvesting can improve the overall production, productivity, and quality of horticultural products. Horticultural mechanization encompasses a range of methods and processes for cultivating plants, performing tasks, implementing technical procedures, employing suitable soil management systems, utilizing orchard tractors, employing soil-working machinery, employing machinery for mulching and mowing grass, using post hole diggers, spreaders, sprayers, front-fitted knife trimmers, harvesting machinery, transportation equipment,

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shakers, harvesters, and more. Khandetod (2018) calculates that the power density needed to guarantee prompt operations is 3.75 kW ha1

Precision farming techniques have proven to be highly effective in various aspects of horticultural cultivation, as demonstrated by Ehsani *et al.* (2004). Seed planters and transplanters with RTK-GPS are used to accurately place row-crop plants. Other technologies include wireless sensor networks (WSNs) for monitoring crop stress, site-specific variable rate irrigation, robotic systems for quickly finding and getting rid of weeds, microcontroller-driven variable rate herbicide and pesticide application systems, and automated harvesting and yield monitoring systems. These approaches provide both accuracy and cost-efficiency by minimizing the requirement for significant human intervention and preserving precious agricultural resources (Tiwari *et al.*, 2019).

Several mechanical methods are available for collecting fruit, including limb shakers, canopy shakers, trunk shaking, air blasting, and robotic harvesting. According to Torregrosa *et al.* (2009), the tractor-mounted shaker had a detachment rate of 72%, which was higher than the hand-held shakers' detachment rate of 57%. Intense vibrations led to significant leaf loss and harm to the tree's outer layer.

Researchers have conducted extensive research on the application of robots and automation across various domains, demonstrating their technical feasibility. Recent research and advancements have been made in the application of robots to horticulture, encompassing the associated concepts, principles, limitations, and areas that require further development. The adoption of intensive farming practices, mechanization, and automation has significantly contributed to the remarkable increase in horticultural output. Precision seeding and planting is a method that enhances plant growth by ensuring more accuracy and consistency (Tremblay *et al.* 2011).

RTK-GPS-enabled seed planters or transplanters, as demonstrated by Ehsani *et al.* (2004), can accurately map the geographic location of agricultural seeds or transplants as the planter releases them. Precision fertigation is a method that involves supplying water and necessary plant nutrients at the optimal time and place, resulting in decreased utilization of agricultural resources and reduced environmental consequences (Abioye *et al.*, 2022). Remote sensing and fuzzy inference algorithms improved nitrogen delivery throughout the growth period, resulting in similar crop yields with 31% less nitrogen (Tremblay *et al.* 2011). Tillett *et al.* (2008) tested a computer vision-based weeding device that can locate and remove weeds inside rows. Recent studies show that autonomous tractors or robots reduce fuel consumption and air pollution in agriculture. Automation has increased machinery efficiency, reliability, and accuracy while reducing human interaction. The agricultural industry still lacks skilled laborers, especially in horticulture. Larger farms, fewer farming experts, and a greater ecological impact on cultivation all contribute to labor shortages. These scenarios require more efficient agricultural practices and conventional farming productivity when farmers manually cultivate and manage crops. Adding smart machines can enhance these operations.

Robotics and automation require a greater upfront investment in professional staff and machinery, but they improve agricultural efficiency by reducing labor costs and relying largely on experienced machine operators. Jyoti *et al.* (2020) and Gatkal *et al.* (2023) found that agricultural robotics and automation reduce manual labor and boost yield. The aging of agricultural laborers and the decline in farms suggest that this field is not attracting newer workers. Despite the challenges of integrating automation and robotics into agricultural practices, we hope that farmers' quality of life and reduced workload will make farming more appealing. Unfortunately, agricultural robotics and automation require more complex technology than industrial ones. Complexity, lack of repetition, and unpredictability distinguish agricultural employment from industry's basic, repeatable, well-defined, and predictable duties. We must address complex and ever-changing problems to ensure productivity. Agriculture also produces perishable goods, including fruits, vegetables, cereals, and flowers, which are susceptible to temperature, moisture, gas, force, degradation, and velocity. These goods are fragile and require precise, complicated control techniques to maintain quality from manufacturing to end users.

This trait makes replacing human abilities with technology or automation difficult. Thus, we still need human labor to support plants with trellises, gather crops, organize them, and prepare them for sale. Manual labor accounts for up to 40% of field operations costs (Bechar & Eben-Chaime, 2014). Agricultural operations are characterized by dynamic, unpredictable situations with rapid time and spatial changes. These military, aquatic, and space environments have unstable and unpredictable air conditions, illumination, visibility, flora landscape, and topography. Four types of robotic systems exist based on their structural qualities in relation to their surroundings and objects (Bechar & Eben-Chaime, 2014): a) environments with a clear organization and defined objects; b) environments without a clear organization but with defined objects; c) environments without a clear organization but without defined objects; and d) environments without a clear organization and defined objects.

RESEARCH GAP

India is a major global player in horticulture crop production, ranking among the world's largest producers. It holds the second position in fruit and vegetable production, making a significant impact on the global agricultural industry. The horticulture sector in India makes up around 33% of the gross value-added (GVA) in agriculture, playing a key role in the country's economy (Anonymous, 2023). Although bulk commodities like maize, rice, and wheat are primarily mechanized, horticulture crops such as fruits, vegetables, and nursery crops, which are considered high-value crops, still rely heavily on manual labor (Silwal *et al.*, 2017). Because horticulture products are perishable, they must be handled with care during harvesting. Rough handling can cause harm to the product and decrease its commercial worth. In contrast to staple crops like wheat and rice, which reach maturity equally, fruits and vegetables frequently do not mature evenly. As a result, many operations are required to harvest the mature produce (Kootstra *et al*., 2021). This requirement necessitates a significant investment of time and manual work to complete the harvesting process. Moreover, the labor-intensive process of harvesting horticulture crops has additional difficulties, such as shortages of personnel, rising labor expenses, and the requirement for competent laborers who can accurately identify and selectively harvest mature crops. To address these issues, researchers are progressively investigating the utilization of robotics in diverse agricultural tasks, such as transplanting, weeding, spraying, and harvesting. Engineers specifically design agricultural robots to perform repetitive and targeted tasks, thereby reducing costs and saving time. Deploying these robots has the capacity to improve the productivity of horticulture fields and reduce produce shortages (Barbashov *et al*., 2022).

METHODS OF ROBOT HARVESTING IN HORTICULTURAL CROPS

The worldwide population growth is driving an increase in the demand for food, which in turn requires a higher level of agricultural productivity. Agricultural operations include rigorous physical exertion, and the scarcity of labor during high-demand periods, such as harvesting, presents substantial difficulties (Koostra *et al*., 2021). Harvesting is an essential stage in the crop production cycle. In India, the majority of farms are tiny or marginal, with an average size of approximately 1.08 hectares. Because of this, farmers in India generally rely on physical labor for harvesting, especially in horticulture crops. Urban migration and an aging population have exacerbated this dependence on physical labor. In light of these circumstances, there is an urgent requirement for enhanced automation and robotization in the agriculture sector to fulfill the growing food demand and tackle labor shortages.

We collected data on existing horticultural crop harvesters and harvesting techniques to examine the current patterns of mechanization and automation in horticultural crop harvesting. More precisely, we were looking for case studies that specifically examined the use of robots for harvesting, and we narrowed down our search to those that specifically focused on horticultural crops. Robotic harvesters prioritize selective harvesting, which means they focus on collecting only fully grown crops while leaving the underdeveloped ones for future harvests. Machine-vision systems facilitate this process. The search criteria used to find similar publications included machine vision, selective harvesting, and robotic harvesters.

In the last thirty years, there has been considerable focus on researching and developing agricultural robotic systems, specifically for orchard crops such as citrus, apple, cotton, tomato, melon, and watermelon (Bechar & Vigneault, 2017). Researchers have developed a range of specialized harvesters designed for specific crops. Examples of research and advancements in apple harvesters include the contributions of Onishi *et al.* (2019), Silwal *et al.* (2017), and De-An *et al.* (2011). Zhao *et al.* (2016), Lee *et al.* (2019), and Feng *et al.* (2018) have conducted studies on tomato harvesters.

Furthermore, Bac *et al.* (2017), Lehnert *et al.* (2020), Arad *et al.* (2020), and Lee *et al.* (2019) have made notable progress in the development of sweet pepper harvesters. Hayashi *et al.* (2010) and Xiong *et al.* (2020) have conducted studies on strawberry harvesters. Williams *et al.* (2019) and Barnett *et al.* (2020) achieved significant advancements in the field of kiwifruit. Almendral *et al.* (2018) have made significant contributions to the advancement of orange harvesters.

We thoroughly examined the methods and technology used in each instance, specifically focusing on the incorporation of machine vision systems to enable targeted harvesting. These improvements emphasize the growing trend towards improved automation and efficiency in horticulture crop harvesting.

Different methods for harvesting fruit, vegetables, and flowers

Different mechanism is used to harvest fruits, vegetables and flowers. Crop is picked up by end effecter with the help of robotic arm. The mechanism to be used is decided based on characteristics of the product such as type, attachment strength, structure of plant etc. to maximize the efficiency.

Plucking:

Plucking is a simple method of robotic harvesting in which an arm or grasper grabs the fruit and pulls the fruit away from the plant. The gripping mechanism may have soft or flexible fingers to minimize damage to the fruit or plant (Fig. 1).

Fig. 1: Robot for plucking kiwifruit (Williams et al. 2019)

Twisting: This method involves applying a twisting motion to detach the fruit from the plant. The fruit is held firmly in the robot's gripping mechanism while being gently rotated until the stem is removed (Fig. 2). Fruits like apples and pears, where the stem serves as a natural attachment point, are frequently twisted.

Fig. 2: Apple plucking and twisting with robotic arm (Silwal *et al*., 2017)

Suction:
The fruit is held against the robot's gripper by a vacuum system in suction-based picking techniques (Fig. 3). A pump or fan generates a vacuum, and the force of the suction holds the fruit to the gripper as the robot takes it away from the plant. Once the fruit is in a safe position, the vacuum is released, and the fruit is collected.

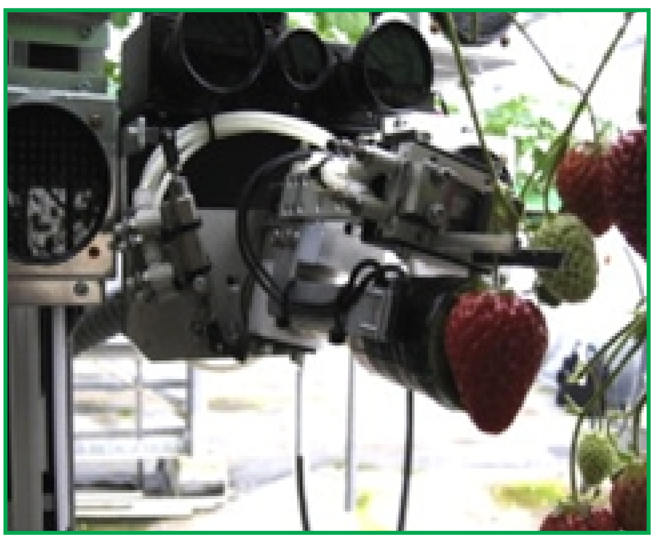


Fig. 3: Apple plucking and twisting with robotic arm (Silwal *et al*., 2017)

Cutting:
Fruits are clipped from the plant to be picked. Robotic harvesters can precisely cut off the fruit's stem or attachment point when outfitted with small cutting tools like blades or scissors (Fig. 4). To ensure a clean cut and prevent injuring the fruit or neighbouring plant tissues, care must be exercised.

Fig. 4: Robotic arm with cutting type end effecter (Masood *et al*., 2021)

Shaking:
For fruits like berries or cherries that are lightly bound to the plant, shaking is a frequent approach. The robot shakes or vibrates in a regulated manner to move the fruits, which then drop into trays for collection or onto conveyor belts. In order to avoid causing significant harm to the plant or young fruits, this procedure needs to be carefully managed.

Shaking:
A widely used harvesting technique for delicate fruits like berries or cherries is shaking the plant. This technique involves the robot delicately oscillating or vibrating the plant in a regulated manner. This exact shaking motion results in the separation and descent of the mature fruits onto collection trays or conveyor belts located underneath. It is imperative that this procedure is carefully controlled to avoid harm to the plant itself or to immature fruits that should stay connected. The controlled agitation guarantees the selective gathering of only fully developed fruits, so preserving the well-being and production of the plant for subsequent harvests. This method emphasizes the significance of accuracy in robotic harvesting to attain effectiveness without jeopardizing the quality of the product.

Raking:
For crops that grow near to the ground, like strawberries, raking is a common technique. The robot carefully combs over the plants with a unique instrument that resembles a rake and has soft bristles or tines, gathering the ripe fruits into a container.

AUTONOMOUS ROBOT SYSTEM

Autonomous robot systems (ARS) have been developed to carry out tasks, make decisions, and operate in real-time without the need for human involvement. Recently, there has been a growing emphasis on mobile autonomous robotic systems (ARS) study in unstructured situations, both indoors and outdoors. Perceiving and logical thinking are fundamental prerequisites for achieving a satisfactory level of independence. Therefore, Autonomous Robotic Systems (ARS) must exhibit a significant level of adaptability in order to effectively navigate through dynamic environmental circumstances and effectively analyze the data collected by its sensors (Bechar *et al.*, 2016). They are necessary in some fields that often require decreases in labor and effort, and are most appropriate for tasks that need consistent precision and high productivity in stable circumstances.

Components of ARS for horticulture crop harvesting

Horticultural crop harvesting necessitates the use of Automated Robotic Systems (ARS), which are composed of various interconnected components and tools that work together to perform their tasks (Fig.5). These elements include steering and control mechanisms, path planning, navigation, mobility, sensing capabilities, manipulators or robotic arms, and end effectors (devices that come into contact with the produce). Crucially, these systems also incorporate instructions for handling unforeseen events independently or simultaneously. Agribots are mainly designed to perform specific agricultural tasks, typically focusing on harvesting.

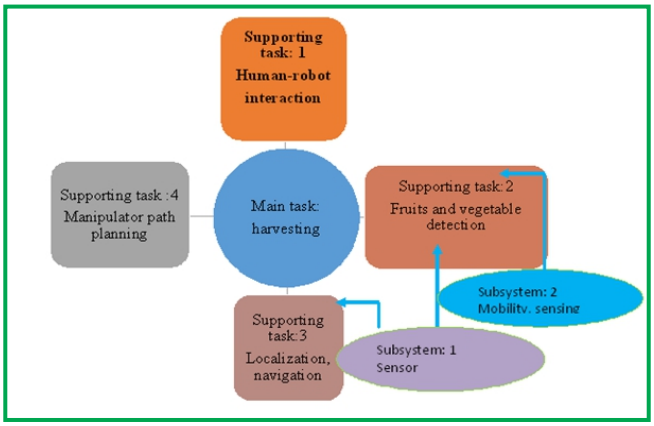


Fig. 5: Task sub-system structure of agricultural robot

Nguyen *et al.* (2013) developed and implemented a framework for arranging the movement and hierarchical task scheduling of a robot specifically designed for harvesting apples. To achieve modularity and reusability, the harvesting task has been divided into four sub-domains:

Target list:

Handles the target of the harvesting task, includes fruit detection (location, orientation, size, etc), detaching situation recognition. The detaching situation derived from sensing data of objects present in action radius will be used to decide which detaching strategies would be used.

Collision map:

The collision map includes the compressed 3D point cloud data with annotations of the current target, the future targets with pre-planning order and other obstacles.

Navigation:

Handles the arm navigation in the collision map. This provides the manipulator ability to approach target, perform the detaching movement based on the pre-defined strategies.

Task planner:

Handles the sequence and schedule of sub-tasks, chooses the predefined detaching movement and plans the order of the targets. It also includes the condition monitoring for each sub-task

Similarly, Ceres *et al.* (1998) designed and applied a structure for a robot that harvesting the citrus and was integrated with human assistance (Fig. 6). In addition, Hellstrom and Ringdahl (2013) developed a framework specifically tailored for agricultural and forestry robots.

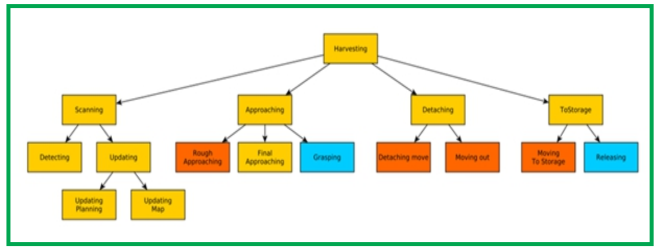


Fig. 6: Hierarchical planning and execution ree for apple harvesting robot

Sensing and navigation

The worldwide population growth is driving an increase in the demand for food, which in turn requires a higher level of agricultural productivity. Agricultural operations include rigorous physical exertion, and the scarcity of labor during high-demand periods, such as harvesting, presents substantial difficulties (Koostra *et al.*, 2021). Harvest

Independent navigation is a crucial component of automation in agriculture. Initially, agricultural navigation systems employed cameras as sensors, relying on computer vision techniques. Autonomy in navigation, guidance, and transportation can be classified into three levels: conventional steering, a system that is supported or automated by a human operator (under the supervision of a higher authority), and a fully autonomous system (Bechar *et al.*, 2016). The system can prioritize navigation and guidance as its main goal, such as when transporting crops from the farm to the packing site. Alternatively, it can use navigation and guidance as secondary tasks to assist its main function, such as supporting spraying or transporting a robot between trees during the harvesting process (Bechar *et al.*, 2016). Current navigation systems for agricultural vehicles use the geographic position system (GPS) as the primary sensor for steering control. However, in situations such as orchards where the tree canopy blocks the satellite signals received by the GPS, there is a requirement for an alternative method (Lipinski *et al.*, 2016).

Machine Vision

Visual fruit detection is an essential component in developing an autonomous robotic harvesting system. The fruit detection technique utilizes a machine vision algorithm developed by Silwal *et al.* (2017). This program combines two primary methodologies to precisely detect apples, even in intricate surroundings. Firstly, it utilizes the Circular Hough Transformation (CHT), which is highly skilled at identifying individual apples that are separate from each other in a group. The CHT methodology detects circles based on their geometric characteristics by converting the image into a parameter space. This method is especially efficient at detecting spherical fruits, such as apples, among greenery. Additionally, for apples that are only partially visible or hidden by foliage and branches, the method employs blob analysis (BA) in an iterative manner. The technique of blob analysis identifies areas in an image with distinct qualities, like variations in brightness or color, compared to the surrounding regions. The algorithm is capable of detecting and segmenting apples that are only partially visible through iterative application of BA, thereby increasing the overall detection rate. We evaluated the efficacy of this dual-technique approach in demanding settings characterized by dense clusters and complex canopy topologies. Surprisingly, the system has demonstrated fruit identification accuracy that is greater than 90% in these circumstances. The robotic system's manipulation components depend on accurate identification and precise location of the fruits in order to grip and collect them without inflicting any damage. Scientists and engineers have recently investigated various machine vision approaches to improve fruit identification. These improvements encompass the utilization of deep learning models, spectral imaging, and 3D vision systems. Each method possesses distinct advantages, including enhanced precision, the capability to accommodate various fruit shapes and sizes, and resilience under diverse lighting situations.

Fruit detection

The unpredictable and fluctuating lighting conditions in the outdoor environment, along with the intricate and diverse canopy structures, can influence the performance of machine vision systems in identifying and pinpointing fruit (Karkee & Zhang, 2012). People widely employ color to distinguish fruits and vegetables from their surroundings and backgrounds. Changing lighting conditions can greatly affect the initial step of image segmentation, crucial for fruit identification, by altering the physical properties (texture and color) necessary for fruit identification. As a result, segmentation has frequently led to significant errors in vision systems. Researchers have looked into more ways to identify fruits besides color. These include using global mixtures of Gaussians, geometric properties, BA, region growth, and CHT for texture-based segmentation. In recent years, the use of machine learning tools for fruit identification by pixel classification has gained attention. People widely recognize artificial neural networks (ANN) and support vector machines (SVM) as the leading options in the domain of robotic fruit harvesting.

Fruit localisation

Fruit localization, in the context of fruit harvesting, refers to the identification and tracking of fruit on a plant or tree to determine its exact position and ripeness with respect to a fixed or reference point of the machine (Gongal *et al.*, 2015). Fruit localization is a crucial step in modern fruit harvesting as it ensures the efficient and selective harvest of ripe fruit, leading to higher quality yields, reduced waste, and improved resource management. Laser range finders operate by utilizing the principle of time-of-flight (TOF) of light. A laser distance sensing device consists of a laser transmitter that releases pulsed laser rays, as well as a detector that captures the rays reflected from objects. The distance between the item and the detector directly influences how long it takes the laser beam to bounce back after making contact with it. Stereovision systems, on the other hand, employ two or more cameras positioned at a specific distance from each other. By contrasting numerous images captured by these cameras, the systems ascertain the spatial divergence (or disparity) of objects between the two images. The cameras' relative positions and orientations, along with their focal lengths, transform the image disparity into distance measurements. TOF cameras, alternatively referred to as 3D cameras, function based on a comparable concept as laser distance sensors yet deliver a comprehensive distance depiction of the entire environment simultaneously. The PMD CamCube 3.0, developed by PMD Technologies in Siegen, Germany, acts as an instance of such a camera. In addition to delineating distances, these cameras also provide information about the magnitude and three-dimensional positions of objects within the visual range. In contrast to alternative 3D sensing systems such as stereoscopic cameras, 3D cameras facilitate swifter data acquisition and processing for 3D localization of objects.

Manipulator path planning

The scheduling of trajectory points and path planning poses fundamental challenges for autonomous robotic systems. One of these challenges involves determining the quickest route to navigate a path within the reachable workspace of a robotic system. Time-optimal path parameterization (TOPP) is a widely researched issue in robotics with diverse real-world implementations. To address TOPP, there are two primary categories of methods: numerical integration (NI) and convex optimization (CO), which are characterized by their speed but pose challenges in implementation and are susceptible to robustness concerns. On the other hand, CO-based approaches offer greater robustness but are significantly slower. Pham *et al.* (2018) suggest an innovative method using reachability analysis to tackle TOPP.

We present a hierarchical optimal path planning (HOPP) algorithm from a broad robotic path planning perspective, which falls under the category of offline path planning. The apple harvesting robot possesses advanced knowledge of the 3D environment of the apples and their trees, enabling it to have complete information. However, the HOPP algorithm can also operate in real-time if additional data such as apple positioning and three-dimensional reconstruction become available during data collection. Moreover, the HOPP algorithm specifically belongs to the point-to-point path planning category. In other words, its aim is to ascertain an enhanced route from an initial location to a final location by taking into account important factors such as duration and distance. The algorithm (HOPP) shares similarities with the method of cell decomposition commonly employed in robotic trajectory planning. This method involves dividing the free space into small regions known as cells, which in this case correspond to apple harvesting zones. Subsequently, the algorithm searches for an optimal path within this cell structure using well-known algorithms like A*, Dijkstra, or TSP (Travelling Salesman Problem).

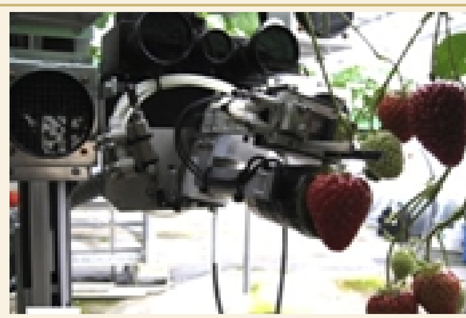
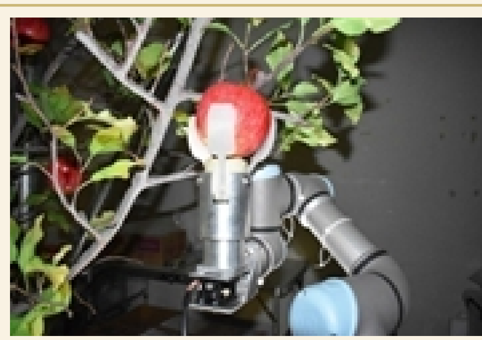
Additionally, the HOPP algorithm bears resemblances to the coverage path planning (CPP) algorithms. CPP focuses on determining a trajectory that covers all important points within a workspace volume while also keeping away from obstacles. In this study, CPP aims to identify a route that passes through all apple harvesting zones, all the while avoiding obstacles.

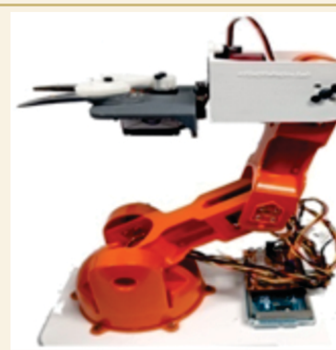
HARVESTING AND PICKING ROBOTS

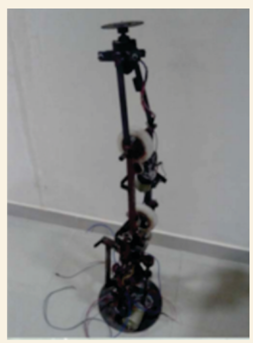
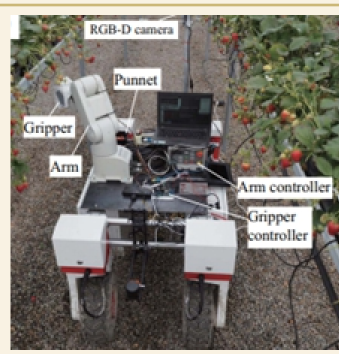
Farmers currently harvest most horticultural crops, including fruits and vegetables, manually. This process is time-consuming and labor-intensive, primarily due to the uneven ripening of these crops. Robotics and automation offer a promising solution to these challenges. Robotic harvesters utilize computer vision and sensors to detect and locate fruits on trees. A robotic arm with specialized end effectors picks the identified fruits. The detection process employs machine vision techniques and various sensors, such as thermal cameras or RGB cameras, to identify fruits based on color, temperature differences, texture, and other attributes. Table 1 presents several examples of robotic harvesters. Figure 7 depicts the robotic fruit harvester, a notable development by Onishi *et al.* (2019). This harvester uses a stereo camera and a robotic hand to detect and detach fruits. Within two seconds, the camera can identify the position of 90% or more of the fruits. The entire process of harvesting a single fruit takes approximately 16 seconds. Any variety of apples and fruits that resemble apples can use this versatile system.

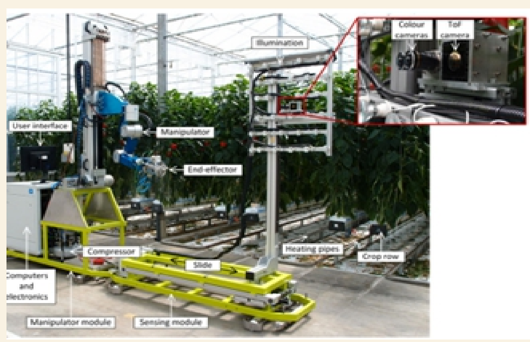
Fig. 7: Developed apple harvester

Table 1: Types of harvesting robots

Object	Mechanism	Appearance	Reference
Tomato	cutting		Zhao *et al.* (2016)
Strawberry	Suction and cutting		Hayashi *et al.* (2010)
Apple	Twisting		Onishi *et al.* (2019)

Object	Mechanism	Appearance	Reference
Kiwifruit	Plucking		Williams *et al.* (2019)
Iceberg lettuce	Cutting and picking		Birrell *et al.* (2020)
Chile pepper	Cutting		Masood *et al.* (2021)
Apple	Pulling and twisting		Silwal *et al.* (2017)
Apple	Cutting		De-An *et al.* (2011)

Object	Mechanism	Appearance	Reference
Cucumber	Cutting		Van Henten et al. (2003)
Sweet pepper	Cutting		Lee et al. (2019)
Coconut	Cutting		Parvathi, and Selvi (2017)
Kiwifruit	Plucking		Barnett et al. (2020)
Strawberry	Picking		Xiong et al. (2020)

Object	Mechanism	Appearance	Reference
Sweet pepper	Cutting		Arad *et al.* (2020)
Sweet pepper	Suction and cutting		Lehnert *et al.* (2020)
Cherry tomato	Cutting		Feng *et al.* (2018)
Sweet pepper	Cutting		Bac *et al.* (2017)
Orange	Cutting		Almendral *et al.* (2018)

Challenges in Robotic Harvesting of Horticultural Crops

Robotic harvesting of horticultural crops presents several significant challenges that must be overcome for successful implementation. These challenges include:

1. Differentiating between Ripe and Unripe Crops: One of the primary hurdles is the ability to distinguish between ripe and unripe fruits or vegetables. This requires sophisticated vision and sensing technologies capable of accurately identifying and classifying crops based on maturity. Advanced machine learning algorithms and multispectral imaging can be employed to enhance the precision of this task.

2. Handling Delicate Crops: Many horticultural crops are fragile and susceptible to damage during harvesting. Robotic systems must be designed to handle these crops with exceptional care to avoid bruising, scarring, or other forms of damage. This involves developing end effectors with soft, adaptive grips and precise control mechanisms to gently pick and place the produce.

3. Adapting to Crop Variability: Horticultural crops often exhibit significant variability in shape, size, and orientation. Robots need to be highly adaptable to these variations, employing flexible harvesting methods and dynamic adjustment capabilities. This might include using 3D vision systems and adaptive algorithms that can modify the robot's actions in real-time based on the specific characteristics of each fruit or vegetable.

4. Navigating Unstructured Environments: Agricultural fields are typically uneven and filled with obstacles such as rocks, weeds, and irrigation equipment. Developing robots that can navigate these unstructured environments without causing damage is a substantial challenge. Robust locomotion systems, obstacle detection, and avoidance technologies are essential for ensuring efficient and safe operation in such conditions.

5. Cost-Effectiveness: The development and deployment of robotic harvesting systems can be expensive. Growers must consider the cost-effectiveness of these systems compared to manual labor. Although robots can potentially reduce long-term labor costs and increase efficiency, the initial investment and maintenance costs must be justified by the benefits.

6. Ensuring Safe Human-Robot Cooperation: In scenarios where human workers are present alongside robots, ensuring safe and efficient human-robot interaction is crucial. This involves implementing safety protocols, designing robots with collision detection and avoidance capabilities, and creating interfaces that allow for seamless cooperation between human workers and robotic systems.

Addressing these challenges requires a multidisciplinary approach, integrating advancements in robotics, computer vision, artificial intelligence, and agricultural sciences. By tackling these issues, the potential for robotic harvesting to revolutionize horticulture becomes increasingly feasible, promising increased efficiency, reduced labor costs, and improved crop handling.

Way Forward

Presently, the robots are performing different tasks individually according to different agricultural operations like sowing, weeding, irrigation, and harvesting. Future redesigned and optimized machines will perform better in terms of speed and quality (Ven Henten *et al.,* 2016). The use of robotics in horticultural crop harvesting presents significant opportunities to increase productivity, reduce labor costs, and address labor shortages in the agricultural sector. Subsequent investigations in this domain should concentrate on improving harvesting robots' capacities to make them more adaptable, accurate, and economical.

The complexity of the crop environment, which is defined as the robot's working environment, is the primary bottleneck to better performance. There are numerous causes of variation in crop environments that are important for robotic harvesting. Robotic harvesting harvests objects with poorly defined placements, forms, sizes, and colors. Occluding branches and leaves make objects difficult to see and reach. By improving gripper technology, vision systems, and machine learning algorithms for fruit detection and handling, we can create robots that can harvest a variety of fruits, including those with delicate or unusual shapes. It is necessary to lessen the need for specialized machinery and investigate the viability of developing robots that may alternate between harvesting various crops (such as apples, berries, and tomatoes) within the same horticulture environment. The design of robots capable of prolonged autonomous operation can reduce the need for human intervention and increase the financial viability of large-scale harvesting operations. Examine ways to handle fragile fruits and vegetables more delicately, minimizing damage and waste during the harvesting process, by utilizing soft robotics, such as soft grippers and actuators.

Fruit is grown in a variety of production environments with varying lighting conditions. These systems affect the fruit's visibility and accessibility. For many crops, color serves as a ripeness indicator, and different crops have different ripeness requirements. Improve the vision systems of harvesting robots so they can more accurately detect, find, and classify ripe crops in cluttered, complex environments—even in different lighting conditions. Develop robotic systems equipped with tactile sensors, enabling precise and gentle harvesting of produce by utilizing touch to assess its quality and ripeness. Enhancing the robot's ability to manipulate and deftly handle various crop types and conditions, including those with thorns, spines, or irregular growth patterns, is crucial. Enhancing the localization and navigation capabilities of harvesting robots is crucial for their efficient operation in diverse environments like fields, greenhouses, and orchards, while also enabling them to avoid obstacles and elevation changes.

We are optimizing harvesting strategies by integrating robotic systems with real-time data analytics, taking into account factors such as crop maturity, meteorological conditions, and resource availability. We are examining power sources and energy-efficient robot designs, taking into account solar energy, battery technology, and energy recovery systems. Investigate strategies for encouraging productive and safe interactions between human laborers' and harvesting robots in mixed human-robot teams. Enhance wireless communication between farm management systems and robots to allow for better control and coordination of several robots during a harvesting operation. We are developing systems to minimize waste in the harvesting process, such as automated systems that remove spoiled or underripe crops and simplify the packing process. We are also exploring methods to operate robots in challenging conditions like dusty, wet, or extremely high temperatures without compromising their functionality.

Look into strategies to lower the cost and increase the accessibility of harvesting robots for farmers with fewer resources and a smaller farm, perhaps by utilizing shared technology platforms and open-source designs. Establishing a comprehensive and effective harvesting pipeline requires harvesting robots that are simple to integrate into other agricultural systems, such as packing and post-harvest handling. Integrating robotic operations into a comprehensive agricultural system offers several advantages. The robots can work collaboratively, communicating and sharing data to optimize farming practices. For instance, farmers can adjust irrigation schedules or plan harvesting operations efficiently using the data collected during crop maturity monitoring. Farmers can combine all of their operations to create a fully autonomous farming system. This system would involve a network of interconnected robots, sensors, and AI algorithms working together to perform tasks such as sowing, weeding, irrigation, monitoring crop maturity, harvesting, sorting, and packaging. Farmers can remotely monitor and control the robots, enabling them to make informed decisions and intervene when necessary.

Such a system offers benefits like increased productivity, reduced labor costs, improved resource management, and minimized environmental impact. Additionally, we can analyze the collected data from these operations to gain insights into crop performance, disease detection, and yield optimization, thereby enabling continuous improvement in farming practices. Overall, the future of agricultural robots holds tremendous potential to revolutionize the agricultural sector by making it more efficient, sustainable, and productive.

CONCLUSION

Ultimately, the progress in robotic technology for the collection of horticulture crops has demonstrated substantial potential in enhancing productivity, decreasing labour expenses, and mitigating crop harm. The paper emphasizes that robotic systems, which utilize machine vision, artificial intelligence, and advanced manipulation techniques, have shown the capacity to handle the fragile characteristics of horticultural produce with growing accuracy. Research indicates that robots outfitted with advanced sensors and adaptive algorithms can achieve harvest rates that are equal to or greater than those of human workers, while also greatly decreasing physical exertion and operational expenses. Recent trials involving robotic strawberry harvesters have demonstrated a picking accuracy of 95% and a 30% gain in harvest efficiency compared to manual approaches. Nevertheless, there are still significant obstacles to overcome in the field of agriculture, including the substantial upfront costs, the unpredictable nature of agricultural attributes, and the ongoing requirement for advancements in sensory and decision-making technologies. Initial findings from pilot implementations suggest that the cost-effectiveness of robotic harvesters increases as the scale of operation grows. However, additional study is necessary to improve the ability of these systems to work with different types of crops and various environmental circumstances. In addition, the integration of robots with precision agriculture technologies and real-time data analytics has the potential to enhance the efficiency of harvesting operations. In order to overcome current limitations and advance the practical applications of robotic harvesting technology, it is essential for the field to continue to collaborate across disciplines and invest in research and development. This will ultimately contribute to the sustainability and productivity of horticultural agriculture.

REFERENCES

Abioye E A, Hensel O, Esau T J, Elijah O, Abidin M S Z, Ayobami A S and Nasirahmadi A. 2022. Precision irrigation management using machine learning and digital farming solutions. *AgriEngineering* **4**(1):70-103.

Almendral K A M, Babaran, R M G, Carzon B J C, Cu K P K, Lalanto J M and Abad AC. 2018. Autonomous fruit harvester with machine vision. *Journal of Telecommunication, Electronic and Computer Engineering* **10**(1-6):79-86.

Anonymous. 2022. Directorate of Economics and Statistics. Agricultural Statistics at a Glance. Department of Agriculture and Agriculture and Cooperation. Government of India, Ministry of Agriculture and Farmers Welfare.

Anonymous. 2023. https://agriwelfare.gov.in/en/Horticulture. Agricultural Statistics at a Glance. Department of Agriculture and Agriculture and Cooperation. Department of agriculture and farmers welfare, Govt. of India. Site visited on 28/10/2023.

Arad B, Balendonck J, Barth R, Ben S O, Edan Y, Hellström T and van Tuijl B. 2020. Development of a sweet pepper harvesting robot. *Journal of Field Robotics* **37**(6) 1027-1039.

Bac C W, Hemming J, Van Tuijl B A J, Barth R, Wais E and van HEJ. 2017. Performance evaluation of a harvesting robot for sweet pepper. *Journal of Field Robotics* **34**(6): 1123-1139.

Barbashov N N, Shanygin S V and Barkova AA. 2022. Agricultural robots for fruit harvesting in horticulture application. In *IOP Conference Series: Earth and Environmental Science* **981** (3):032009.

Barnett J, Duke M Au CK and Lim S H. 2020. Work distribution of multiple Cartesian robot arms for kiwifruit harvesting. *Computers and Electronics in Agriculture* **169:**105202.

Bechar A and Eben-Chaime M. 2014. Hand-held computers to increase accuracy and productivity in agricultural work study. *International Journal of Productivity and Performance Management* 63(2):194-208.

Bechar A and Vigneault C. 2016. Agricultural robots for field operations: Concepts and components. *Biosystems Engineering* **149**: 94-111.

Bechar A and Vigneault C. 2017. Agricultural robots for field operations. Part 2: Operations and systems. *Biosystems* *engineering* **153:**110-128.

Birrell S, Hughes J, Cai J Y and Iida F. 2020. A field tested robotic harvesting system for iceberg lettuce. *Journal of Field Robotics* **37**(2): 225-245.

Ceres R, Pons F L, Jimenez A R, Martin F M and Calderon L. 1998. Design and implementation of an aided fruitharvesting robot (Agribot). *Industrial Robot* **25**(5):337-346.

De-An Z, Jidong L, Wei J, Ying Z, Yu C. 2011. Design and control of an apple harvesting robot. *Biosystems engineering* **110**(2):112-122.

De Baerdemaeker J. 2013. Precision agriculture technology and robotics for good agricultural practices. *IFAC Proceedings Volumes* **46**(4):1-4.

Ehsani M R, Upadhyaya S K and Mattson ML. 2004. Seed location mapping using RTK GPS. *Transactions of the ASAE* **47**(3): 909-914.

Feng Q, Zou W, Fan P, Zhang C and Wang X. 2018. Design and test of robotic harvesting system for cherry tomato. *International Journal of Agricultural and Biological Engineering* **11**(1): 96-100.

Gatkal N, Dhar T, Prasad A, Prajwal R, Santosh Jyoti B, Roul A K, Potdar R, Mahore A, Parmar BS and Vimalsinh V. 2023. Development of a user-friendly automatic ground-based imaging platform for precise estimation of plant phenotypes in field crops. *Journal of Field Robotics* 1-18.

Gongal A, Amatya S, Karkee M, Zhang Q and Lewis K. 2015. Sensors and systems for fruit detection and localization: A review. *Computers and Electronics in Agriculture* **116**: 8-19.

Hayashi S, Shigematsu K, Yamamoto S, Kobayashi K, Kohno, Y, Kamata J and Kurita M. 2010. Evaluation of a strawberry-harvesting robot in a field test. *Biosystems engineering* **105**(2):160-171.

Hellström T and Ringdahl O. 2013. A software framework for agricultural and forestry robots. *Industrial Robot: An International Journal* **40**(1): 20-26.

Jyoti B, Chandel N S and Agrawal K N. 2020. Application of robotics in agriculture: an indian perspective. In Proceedings of the 8th Asian-Australasian Conference on Precision Agriculture.

Karkee M and Zhang Q. 2012. Mechanization and automation technologies in specialty crop production. Resource Magazine **19**(5):16-17.

Khandetod YP. 2019. Mechanization in horticulture crops: Present status and future scope. *Advanced Agricultural Research and Technology Journal* **3**(1):92-103.

Kootstra G, Wang X, Blok PM, Hemming J and Van Henten E. 2021. Selective harvesting robotics: current research, trends, and future directions. *Current Robotics Reports* **2**: 95-104.

Lee B, Kam D, Min B, Hwa J and Oh S. 2019. A vision servo system for automated harvest of sweet pepper in Korean greenhouse environment. *Applied Sciences* **9(**12):2395.

Lehnert C, McCool C, Sa I and Perez T. 2020. Performance improvements of a sweet pepper harvesting robot in protected cropping environments. *Journal of Field Robotics* **37**(7): 1197-1223.

Lipiński A J, Markowski P, Lipiński S and Pyra P. 2016. Precision of tractor operations with soil cultivation implements using manual and automatic steering modes. *Biosystems Engineering* **145**:22-28.

Masood M U and Haghshenas-Jaryani M. 2021. A Study on the feasibility of robotic harvesting for chile pepper. *Robotics* **10**(3):94.

Nguyen T T, Kayacan E, De Baedemaeker J and Saeys W. 2013. Task and motion planning for apple harvesting robot. IFAC Proceedings **46**(18):247-252.

Onishi Y, Yoshida T, Kurita H, Fukao T, Arihara H and Iwai A. 2019. An automated fruit harvesting robot by using deep learning. *Robomech Journal* **6**(1):1-8.

Parvathi S and Selvi S T. 2017. Design and fabrication of a 4 Degree of Freedom (DOF) robot arm for coconut harvesting. In *2017 International Conference on Intelligent Computing and Control (I2C2)* (pp. 1-5). IEEE.

Pham H and Pham QC. 2018. A new approach to time-optimal path parameterization based on reachability analysis. *IEEE Transactions on Robotics* **34**(3):645-659.

Silwal A, Davidson J R, Karkee M, Mo C, Zhang Q and Lewis K. 2017. Design, integration, and field evaluation of a robotic apple harvester. *Journal of Field Robotics* **34**(6):1140-1159.

Tillett N D, Hague T, Grundy A C and Dedousis A P. 2008. Mechanical within-row weed control for transplanted crops using computer vision. *Biosystems engineering* **99**(2):171-178.

Tiwari P S, Sahni R K, Kumar S P, Kumar V and Chandel N S. 2019. Precision agriculture applications in horticulture. *Pantnagar Journal of Research* **17**(1):1-10.

Torregrosa A, Ortí E, Martín B, Gil J and Ortiz C. 2009. Mechanical harvesting of oranges and mandarins in Spain. *Biosystems Engineering* **104**(1):18-24.

Tremblay N, Bouroubi MY, Vigneault P and Bélec C. 2011. Guidelines for in-season nitrogen application for maize (*Zea mays* L.) based on soil and terrain properties. *Field Crops Research* **122**(3):273-283.

Van Henten E J, Van Tuijl B V, Hemming J, Kornet J G, Bontsema J and Van Os E A. 2003. Field test of an autonomous cucumber picking robot. *Biosystems Engineering* **86**(3):305-313.

Williams H A, Jones M H, Nejati M, Seabright M J, Bell J, Penhall N D and MacDonald B A. 2019. Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms. *Biosystems Engineering* **181**:140-156.

Xiong Y, Ge Y, Grimstad L and From P J. 2020. An autonomous strawberry harvesting robot: Design, development, integration, and field evaluation. *Journal of Field Robotics* **37**(2):202-224.

Zhao Y, Gong L, Liu C and Huang Y. 2016. Dual-arm robot design and testing for harvesting tomato in in greenhouse. IFAC-PapersOnLine **49**(16):161-165.

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Kumar D, Choudhary V, Kumar N, Jyoti B, Mandal S, Jeet P, Sundaram P K and Singh A K.2024. Robots for harvesting of horticultural crop: A review. *Journal of AgriSearch* **11**(3): 152-164