International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 6 Issue 7 Ver. I ǁ 2024 ǁ PP. 40-45

A review paper on Intelligent control systems to improve the speed of the robotic arm for picking fruit

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Abstract
The use of robotic arms in fruit-picking tasks has gained significant attention in recent years due to their potential to increase efficiency and productivity. However, one of the key challenges faced in this domain is the need to improve the speed of robotic arms to achieve higher pick rates. Intelligent control systems have emerged as a promising solution to address this challenge This review paper discusses intelligent control systems designed to enhance the speed of robotic arms in fruit-picking tasks. It discusses the challenges in fruit picking and explores various advanced techniques, including sensing mechanisms, path planning algorithms, control strategies, decision-making algorithms, real-time processing techniques, and machine learning algorithms. The paper also provides insights into state-of-the-art techniques and future research directions to further improve the speed and efficiency of robotic arms for fruit-picking applications.
Keywords: intelligent control system, sensing mechanism, a planning algorithm, Machine learning algorithm
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Date of Submission: xx-xx-xxxx Date of acceptance: xx-xx-xxx

INTRODUCTION

The rapid development of innovation in the new digital world and the increasing integration of information, communication, and cyber-physical technologies have modified modern manufacturing, particularly in the context of Industry 4.0[1] . Numerous manufacturing industries are embracing many cutting-edge technologies. One technology which has gaining traction in the fabrication industry is a robotic arm manipulator. The utilization of this technology aims to enhance improved efficiency and productivity. The increase in performance and production is due to the robotic arm's increased speed and precision [2].Robots have been increasingly widely used in industry, medicine, military fields, and agriculture over the last 30 years[3]. currently, a number of research were performed on the use of robotic and automated technologies in agriculture., including planting, spraying, monitoring, Seeding, nurturing, and harvesting are crucial steps towards agricultural industrialization. Automated harvesting robotics has become one of the most important crucial parts of digital agriculture [4]. Replacing the time-consuming and labor-intensive task of manual picking with a consistently automated process would lead to decreased human exertion, ultimately enhancing field productivity. This objective can be accomplished through the utilization of robotic harvesting, which encompasses robot arms, gripping mechanisms, and software systems. Nevertheless, if control strategies are inadequately designed, it may result in agricultural production losses.[5]. Many studies have been conducted by researchers from all around the world on the robotic picking of different vegetables and fruits, such as the tomato picking robot, strawberry picking robot, watermelon picking robot, and lettuce picking robot[6]. contrasted with picking machines, these picking robots are more automated and smarter. They already completed achieved the basic process of picking the target, freeing people from onerous labor. Nevertheless, we need smart control and smart algorithms to speed up the robotic arm to harvest agricultural crops with high accuracy. This article provides a detailed overview of past and current research related to the issue of harvesting manipulator control. The goal of this article is to know the methods of the control system and the types of robots used in harvesting by identifying what has been done to suggest innovative control approaches to bridge the knowledge gap observed in the published literature in this paper, it was divided into three main sections. The first section is focused on agricultural harvesting robots; the second section is about deep learning and visual control, and the third section is on movement planning (motion planning).

An overview of agricultural harvesting robots and associated control systems

The world is facing several challenges, including the COVID-19 pandemic, population growth, climate change, and decreasing food production. During the pandemic, food-producing facilities halted production, leading to panic in parts of the world. This food insecurity problem was further compounded by population growth, with food production needing to be doubled in 2050 to feed the world's population of 10 billion. Though worrisome, many concerns, particularly food insecurity, can be mitigated by advances in science and technology that give solutions. Sensor technology, automation, and robotics are all advancing technologically [7].With the continued development of intelligent manufacturing and the ever-expanding application of robots, robots are being deployed in increasingly complex environments,, and the performance requirements of robots become more and more demanding agricultural robots have gradually begun to replace humans, to complete various agricultural operations, changing traditional agricultural production methods. Not only is the labor input reduced, but also the production efficiency can be improved, which invariably contributes to the development of smart agriculture [8]. The study of agricultural robots has received a lot of attention from academics, especially since the COVID-19 outbreak, as seen in Figure 1

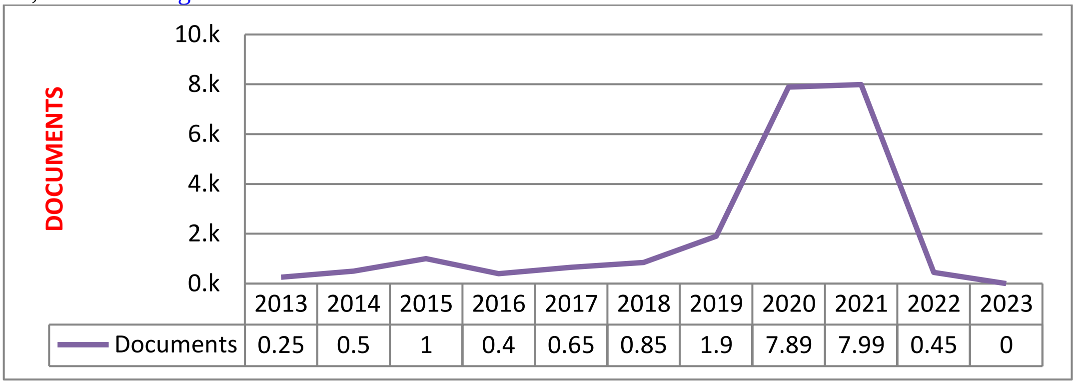

Figure 1: Indexed papers on the trend of agricultural robots. [4]

As is commonly known, an agricultural robot is typically an arm-type manipulator on an affixed base that performs a series of tasks within a local workspace. Robots are classified based on their mechanical structure into various categories. Linear robots, including Cartesian and gantry robots, Cylindrical Robots, Spherical Robots, Parallel Robots, SCARA Robots, and Articulated Robots [9]. artificial intelligence, the Internet of Things (IoT), sensors high-precision, and fast-speed are becoming the future pattern of agricultural robots facing more challenging tasks. The speed of the manipulator is still relatively slow in many agricultural applications However, Robot harvesting agriculture requires rapid computing of efficient and smooth robot arm motions between configurations.[5] .To increase speed, it is important to analyze the requirements of the application and select the appropriate approach. Examples include reducing system inertia, using more powerful actuators, optimizing the control algorithm, and using higher bandwidth communication. Robot control is the spine of robotics" highlights the importance of control systems in robotics, which are responsible for coordinating the various components of the robot to achieve a specific goal. Motion control is the most important link, and there are main types of visual servo control for picking robots: image-based visual servo control and position-based visual servo control [10]. The control of robot manipulators involves various aspects such as posture control [11][12].dynamic control (velocity-related control) [13]torque control (acceleration-related control)[14] and path planning[15] [16]. presently, the control sequence of a robotic manipulator is mostly accomplished by solving inverse kinematic equations to move or position the end effector with regard to the fixed frame of reference [7][8]The Motion control system of a robotic arm plays a crucial role movement of a robot's joints, end-effectors, and other components through the use of sensors, actuators, and control algorithms to increase the speed and ensure accurate efficiency of robotic arm movement. [17].The structure of the robot is depicted in Figure 2.

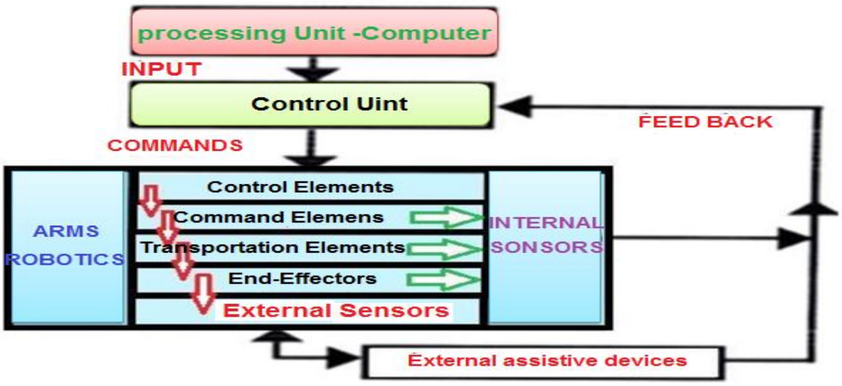

Figure 2. shows the structure of the robot

Robot control involves two main approaches: open-loop and closed-loop. Open-loop involves providing pre-defined movements to the robot without feedback from sensors, while closed-loop uses sensors to provide feedback and adjusts the control signals to achieve the desired movement[18]. The closed-loop control system consists of a set of basic components as depicted in Figure 3

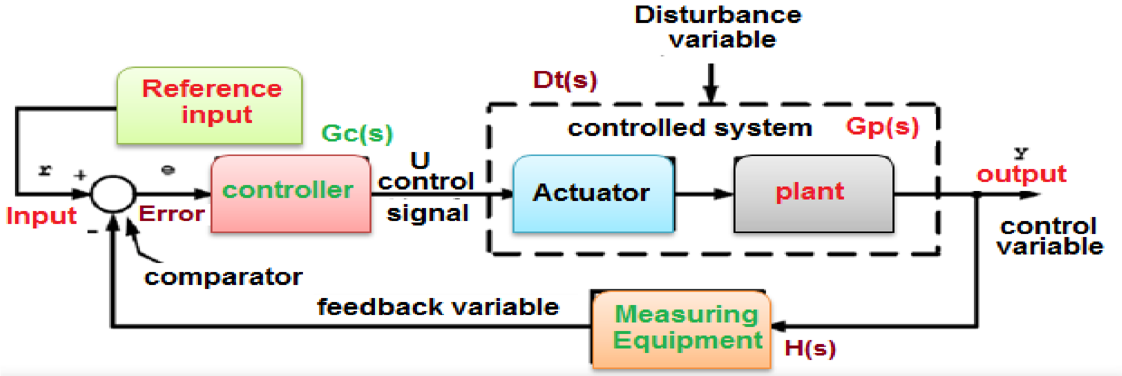

Figure 3-General diagram of a closed-loop control system

The most common control algorithm used in robot motion control is the proportional-integral-derivative (PID) controller. This algorithm adjusts the control signals based on the difference between the desired and actual positions of the robot[8]Researchers have been actively developing intelligent control for harvesting systems using artificial intelligence (AI) and machine learning algorithms. China, the US, japan, and other nations have achieved numerous breakthroughs in this field. New developments led to the design of an intelligent control system. And wide number of oriented control techniques have been used for controlling the positions of robots like Disturbance observer-based controllers.[19]Artificial Neural Networks (ANNs),Fuzzy logic control[20], and modifying the input to the system to increase flexibility. Other controllers used to improve the internal control system of robotic arms include adaptive fuzzy technologies or developed fuzzy PID controller systems[21].optimal control [22][23]adaptive sliding mode [24]-[25]and adaptive neural network tracking control[26]-[27].However, Increasing motion control for arm robotics in fruit harvesting is a topic of interest in agricultural automation. Several papers discuss different approaches to improve the motion control of robots in fruit harvesting systems. Harrell et al[28] developed a fruit-tracking system that estimated the size and position of a fruit region in real-time, which was used to control the motion of a fruit-picking robot. Dewi et al. [29]analyzed the motion control of two collaborative arm robots in a fruit packaging system, using kinematics modeling, image processing, and fuzzy logic control Huang Fan et al. [30] researched a control method for fruit tree picking robots using an image-based visual servo controller and a fuzzy PID controller, achieving accurate target positioning and high gripping success rate . Congjian Li et al [31] proposed a shape feedback control method for a fruit harvesting robot to enhance motion precision. Keyvan Asefpour Vakilian et al.[32] presented an analytical model and three proposed controllers for controlling the displacement and angular velocity of the fruit stem system in a robotic harvester. Tao li et al[33]. developed a multi-arm robot system for apple harvesting. the motion control system uses infrared positioning and visual conveying technologies to improve fruit tree picking efficiency and target tracking precision.

Recent developments of fruit and Vegetable picking robot

In recent years, fruit and vegetable picking has become an important sector of production, employing more than 60% of the labor force. With the aging population and urbanization further highlighting the labor shortage, a significant increase is seen in the cost of picking.[34].Therefore, intelligent agricultural fruit-picking equipment and smart picking robots that can improve picking efficiency and reduce picking costs have now become important research directions Robot technology has achieved unprecedented achievements in agriculture, since the 1960s [35].when citrus picking by machines was first suggested by Schertz and Brown in 1968, and research and development on robotic harvesting have been ongoing ever since leading to the development of fruit-picking robots. but only recently has it taken full advantage of advances in machine vision, artificial intelligence and robotics technology. Automated fruit harvesting robots have been developed over the past 30 years, According to a survey by Hongyu Zhou.et.al. [36].with 50 robots being created in total. Companies have played a significant role in developing arm robotics and motion control for these robots. The velocity and cycle time of picking are crucial factors in automated fruit harvesting, and their improvement is of great importance. The number of robotic picking systems varies depending on the fruit variety. The number of robotic picking systems by fruit variety is presented in Figure4

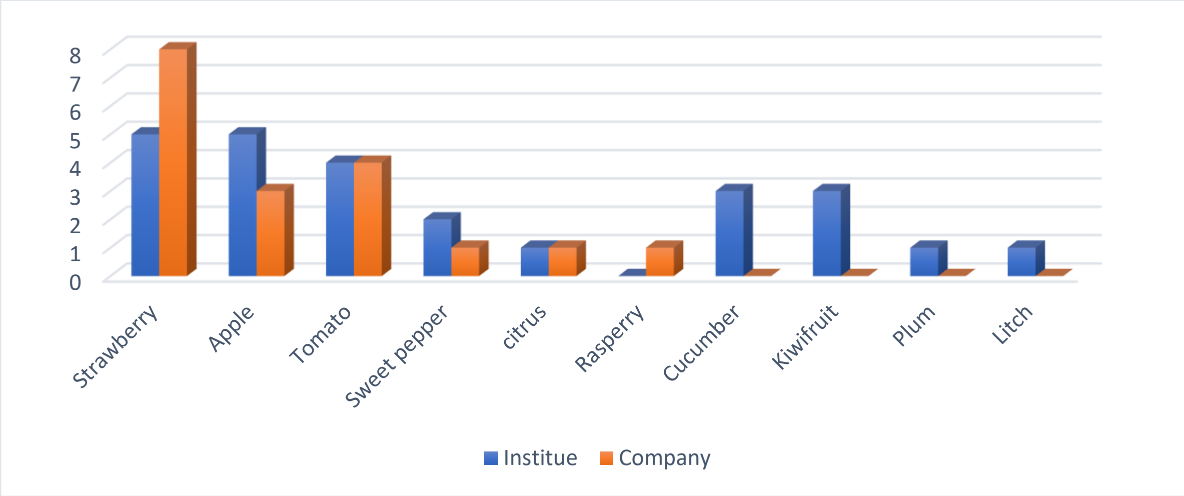

Figure 4 Number of robotic fruit harvesting systems by variety.[36]

APPLES PICKING ROBOTICS

Apple-picking robotics is a rapidly developing field that aims to revolutionize the way apples are harvested from orchards. It uses sensors, computer vision technology, and robotic arms or end- effectors to autonomously locate and pick ripe apples from trees, reducing physical strain on human pickers and improving the overall sustainability and profitability of apple agriculture. Recent research has focused on the design and development of intelligent control systems for robotic fruit picking. These systems aim to improve the speed and accuracy of fruit picking while reducing labor costs and improving efficiency. One approach involves using machine learning techniques to train the system to recognize and locate fruit Figure 4A illustrates the apple picking robot's control system. in 2016, California Abundant Robotics has developed a commercial fruit harvesting robot that uses a vacuum-based end-effector combined with computer vision and an efficient navigation system to pick up apples with an accuracy of over 90% and a speed of up to 1.2 seconds per apple. But this robot is very large and uses hydraulics in the apple picking process. as illustrated in Figure 5 [37] .

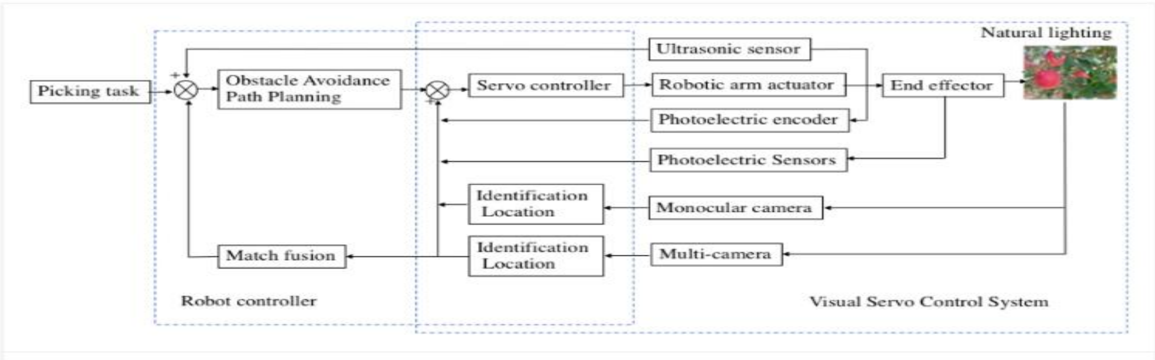

Figure 4： Ailustrates the apple picking robot's control system

.Also, In 2018, FFRobotics United States a popular commercial robot service [38] developed a fruit-picking robot that is 10 times faster than humans Ripe Australian company Australia developed another commercial model that employs a vacuum-based end -effector and AI to pick apples.

Figure5 apple picking robot [37]

R. Verbiest, K. Ruysen, et al [39]. At Automation Centre for Research and Education (ACRO) Institute developed a robotic apple harvester with a camera and off-the-shelf software, mounted behind a common agriculture tractor and supported by a Panasonic industrial robot The harvester includes a generator, stabilization unit, seventh external vertical axis, the safety scanning device, Siemens central control unit PLC, HALCON image processing software, and a vacuum-gripper for fruit picking The successful harvesting rate of the system was recorded as 85% with a harvesting time of 8 seconds However, the use of a tractor for large-scale harvesting can be expensive (Figure 6).

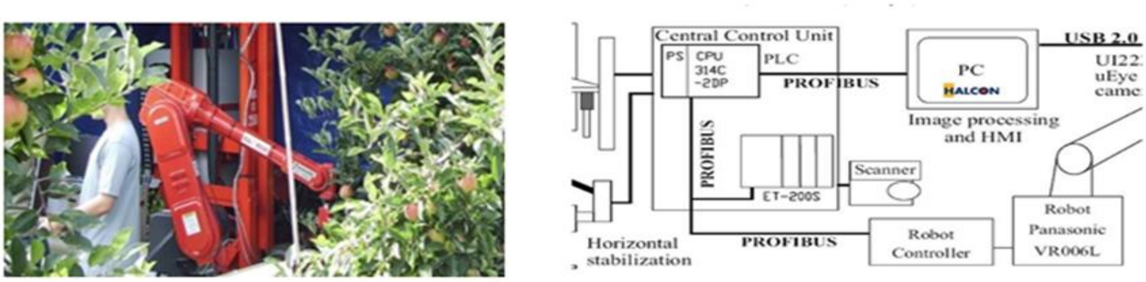

Figure 6 (ACRO) Institute robotic apple[39]

Joseph Ryan Davidson et al[40]from Washington State University designed an apple picking robot with 6 degrees of freedom (Robotics Inc., Irvine, CA)) for unstructured apple tree and orchard automation applications, focusing on improving obstacle avoidance during harvesting . The structure of the picking robot arm and end effector is shown in (Figure 7). This robotic arm is an open chain tandem manipulator with a rotary joint, with a maximum stroke of approximately 0.6 m. The robotic arm is controlled using a modular dynamic actuator called Dynamixel Pro, which is directly controlled from a Windows-based PC using the manufacturer's Software Development Kit (SDK) The PC's USB port is converted to RS485-level communication protocol using a USB2Dynamixel adapter Programming and high-level motor control are implemented in Visual Studio C 2010. The inverse kinematics algorithm was implemented in MATLAB and compiled into a C+ shared for controlling the robotic arm in the Microsoft Visual Studio development environment The efficiency of the picking robot for picking apples is 84.6%, with an average positioning time of 1.2 s and a picking time of 6.8

Figure 7 picking robot apple[40]

In the same vein , The apple picking robot was created by De-An, Zhao, et al [41]. used a manipulator with five degrees of freedom that have a PRRRP structure (Figure 8) and an end-effector that has a pneumatic gripper in the form of a spoon. The control system consisted of an AC servo driver and an industrial computer. The robot employed a pictures-based vision servo control algorithm for fruit localization and picking motion. Laboratory tests demonstrated a success rate of 86% and an average apple-picking time of 14.3 seconds. Field experiments in an orchard showed a picking success rate of 77% and an average apple-picking time of 15 seconds. The prototype robot proved its effectiveness in both laboratory and field settings, showcasing the capabilities of the designed control system and the overall performance of the picking robot

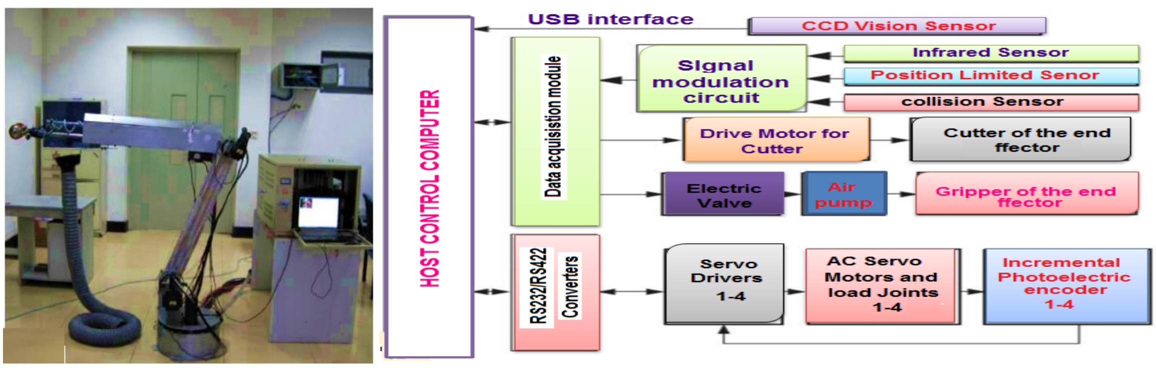

Figure 8 shows the apple-picking robot's structure and control system. [41]

Kaixiang Zhan et al [42]developed a motion control prototype for a robotic apple picking. It integrates a vision-based perception system and 3 DOF manipulator with a hybrid pneumatic and motor actuation system for flexible movements. The manipulator consists of two revolute joints and one prismatic joint, forming a pan-and-tilt mechanism. It is driven by NEMA 23 Teknic Clear Path Servos motors with a maximum velocity of 4000 RPM and peak torque of 2 N m. The two revolute joints are connected using a shaped aluminum plate, with the axes of rotation perpendicular to each other. The velocity of the servo motors can be adjusted through variable frequency pulses generated by an Arduino Uno microcontroller. To measure position feedback, an adscititious sensing scheme is needed. A Teensy 3.6 microcontroller is used to count the pulses and calculate real-time position information. and a vacuum-based end-effector is used to execute apple picking and a nonlinear control scheme to achieve accurate and agile motion control. Successful apple picking achieved 82.47% efficiency in 97% of harvesting tests. The overall cycle time necessary to pick an apple is around 8.8 seconds. (Figure9)

Figure 9. picking robot apple[42]

In a similar vein .The automatic apple picking robot manipulator developed by Yuki Onishi et al. [43].from Ritsumeikan University, Japan uses a UR3 robot arm is a 6 degrees of freedom (6 DOF) robotic arm manufactured by Universal Robots (Figure 10) The robot arm is equipped with a hand that can harvest apples without endangering the tree or its fruit. The detection of the 2D position of the apple is done using the fast and precise scheme Single Shot MultiBox Detector (SSD), while a stereo camera is used to determine the apple's three-dimensional location. Inverse kinematics is used to determine the robot arm's joints' angles and its path as it travels toward the target fruit. By rotating the hand axis, harvesting is accomplished. According to experimental findings, an apple may be harvested in 16 seconds and more than 90% of the apples can be identified in just 2 seconds. It is considered that this method of apple picking works for apples of a comparable species.

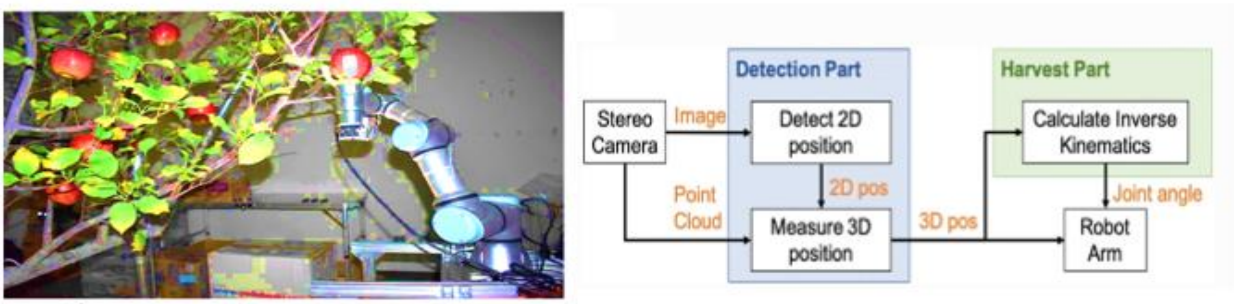

Figure 10.: picking target apple[43]

Ruilong Gao, et al.[44] from Jiliang University in China developed apple-picking robot system It consists of six-DOF collaborative manipulators developed by JAKA ,an end-effector with a 3D-printed three-finger grippe. The gripper also has a rubber layer inside that protects the fruit. a mobile platform, (Figure 11) the robot was controlled using a computer with an AMD R7-5800H CPU and 16 GB of RAM. An RGB-D camera mounted in an oblique upward position was used for fruit recognition, employing the YOLOv3 algorithm. The path planning and obstacle avoidance trajectory planning for the robot were done using a particle swarm optimization (PSO) algorithm, which showed faster convergence speed and improved fruit-picking success rate to 85.93% The picking cycle was reduced to 12 seconds with the proposed motion planning method.

Figure 11system architecture of the apple-picking robot[44]

Duke.Bulanonet ,et al. [45] developed apple picking robot (OrBot) using Visual Servo System control. The robot consists of six-degrees-of-freedom (DOF) manipulator (Kinova) with a maximum speed of 500 mm/s, two-finger gripper, color sensor, depth sensor, a Dell computer as the control unit, and a mobile platform. The primary control unit for the picking process is a Dell laptop computer and Kinova Kortex software platform which includes API, MATLAB, Digital Picture Processing. The visual serving system effectively detects and guides the robot towards the target apples. The fixation tests showed the robot's capacity to accurately identify the target apple in the picture. The visual servo velocity test showed that the robot requires a mean of 12 seconds to picking an apple. Actual fruit harvesting in a commercial orchard resulted in a picking success rate of 87% for the OrBot robot (Figure 12)

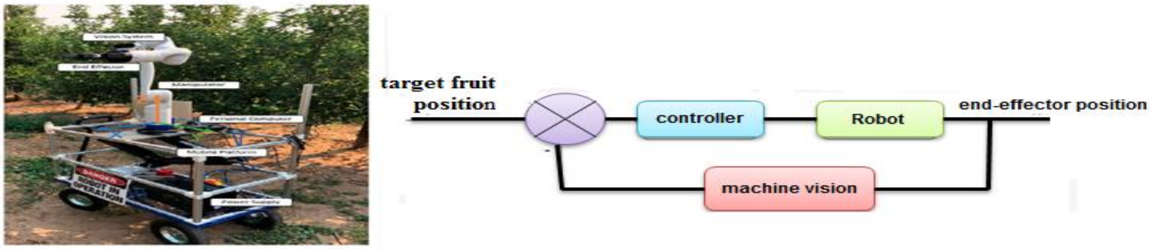

Figure 12Figure 1 shows the apple orchard RoBot and its components.[45]

A robot for picking apples was developed by Bulanon, D. M. et al. [46].using a feedback controller and machine vision for the robotic Since the detected fruit needed to be in center of the image in order to determine how far away it was from the camera, the camera had to be precisely installed on the manipulator. Two machine vision-based feedback control strategies have been created, put into practice, and simulated for this positioning method. A three-position on/off controller was used in the initial design to move the camera steadily while keeping track of the position of the fruit until it was in the center of the picture. The second method involved moving the camera using a proportional (P-) controller with variable gain that had a value proportionate to the mistake. Statistical outcomes Calculated findings demonstrated that both controllers could position the manipulator to place the fruit in the center of the picture demonstrating the viability of employing robot vision as a feedback sensor and the P-controller's quicker response time. (Figure 13).

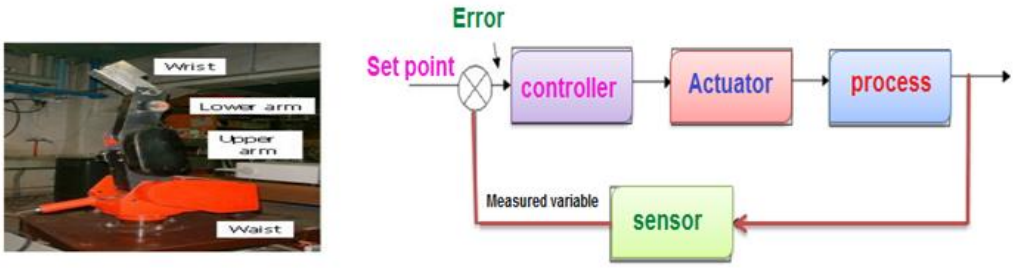

Figure 13 (a) Multi-joint vertical robot (b) Concept of feedback control[46]

Lingxin Bu [47]developed an apple-picking robot that utilized a 5-degree-of-freedom manipulator (XARM 5Lite) mounted on a mobile platform. The robot also included stereo cameras that used a ZED binocular vision sensor to capture images and calculate depths. A flexible three-fingered end-effector was used for the non-destructive grasping of apples. The motion of the manipulator, fruit detection, and data recording were controlled by a host computer running on Ubuntu 16.04 and using the Robot Operating System (ROS). The host computer communicated with an Arduino uno to control the grasping and releasing motions through a solenoid valve. The field experiment obtained a success percentage of 80.17% for anthropomorphic motion and 82.93% for horizontal pull with bending. The average time for motion was 12.53 ± 0.53s. Figure 13 describes the harvesting robot software architecture

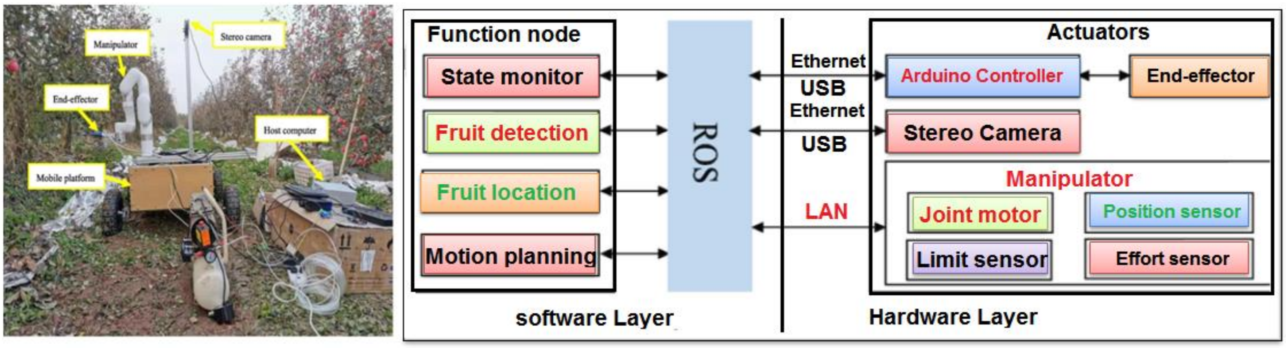

Figure 13 describes the harvesting robot software architecture [47]

Cameron J. Hohimer et al. [48]designed and developed a harvesting apple robotic arm with five degrees of freedom and an end effector with three pneumatic actuators to stabilize the apple during gripping. The detachment success rate on tested apples was 67%, with an average time of 7.3 seconds per fruit from separation to the storage bin.

Figure13B Robotic apple picking with soft end effector.[48]

FLOWERS PICKING ROBOTICS

Rose flowers (Rosa sp.) are a popular and widely grown decorative plant around the world. And one among China's top 10 flowers. It is used as cut flowers, potted plants, and garden ornamental plants, and is also used in medicine, food, and cosmetics products, [49,50,51]. flowers picking is one of the most time-consuming and labor-intensive steps in agricultural production, which is seasonal, high cost, and high strength. Therefore, an automated picking system has great potential to solve labor shortages, improve productivity, and ensure timely harvesting. flowers picking technology mainly includes semi-automatic picking technology and robotic picking technology. Presently, research on flower-picking technology at home and abroad is at the preliminary stage. In recent years, Multiple attempts have been made to automatize the flowers- picking process. the scholars have been conducted on the some researches on the robotics picking flowers technology Rath and Kawollek et al. [52] from Leibniz University of Hannover in Germany developed an autonomous picking robot system for Gerbera Jamesonii (kind of flower). (Figure 14) This robot consists of a machine vision CCD-camera control system and a standing robot with a 6 DOF Mitsubishi RV-E3NLM industrial manipulator and an end-effector with a knife pneumatic gripper. In the picking experiment 80%of all pedicels could be harvested but the average duration to harvest one plant reached about 10 min

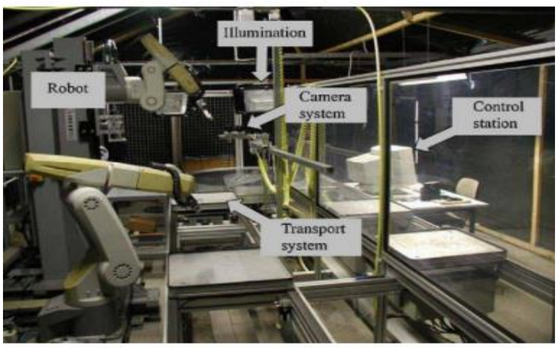

Figure13 Gerbera Jamesonii flower harvesting robot [52] Figure 14 rose flower harvesting robot[53]

Similarly, Cahit Gürel et al[53].from Atılım University in Turkey has developed of a Rose picking Robot .Figure

14.The robot has four main functions: analyzing the rose, cutting the stem, moving pot and operational control. A test platform has been set up, the robotic setup developed in collaboration with FESTO is a three axis gantry setup used to navigate stem tracking heads in XYZ Cartesian coordinates. It has a cycle time of less than two seconds and is controlled by a PLC. The desired position of the end effector is calculated from an image processing algorithm using MATLAB, and positions and commands are sent via OPC Server. .In a similar vein, Armin Kohan, et al[54]of Islamic Azad university Iran proposed an arm hand system for the picking of Rosa Damascena .This type of picking robot has four DOF manipulators and four DC motors with potentiometers that move the manipulator to the desired position, the vision system includes two CCD cameras forming stereo vision systems that can move matching , mounted , and an end effector end with curved shape Clipper which has two appendages covered with soft rubber to keep the flower after picking. The Clipper moved by an DC Motor. After being picked, flowers are placed at the site of collecting flowers by the manipulator The control commands required to carry out harvesting operation were supplied to the manipulator control circuit via the serial port of the computer The total success percentage of harvesting was 82.22%.
(Figure 15)

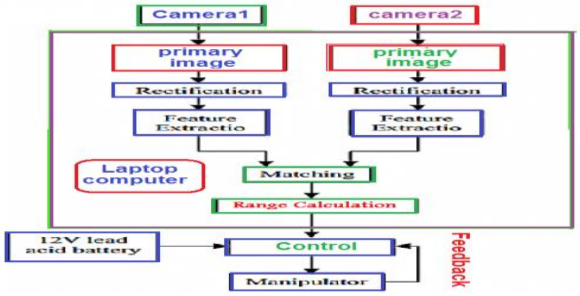

Figure 15: Block diagram of the harvester[54]

On the other hand, Ao.Jiang.et al[55]From Xiangtan University China developed a lily flowers picking robot with a 5-DOF manipulator placed in moving crawler car , end-effector that has a claw head gripper. DahengMEER500-7UC-L camera, and control system the structure of the picking robot arm and end effector is shown in (Figure 16). In the control system described in (Figure 17). uses a two-level control system with an upper computer and a lower computer. the system includes A mobile crawler car controller employing STM32F103, a robotic arm controller employing SMC-604, and the two controllers connect via each other employing the NRF24L01 + wireless component, and the two controllers connect using the IPC via Ethernal The mechanical arm consists of three stepper motors, 86BYG250H using the MA860H driver to provide more drive current The robotic mechanical equipment platform carried out the picking in experimental field in a natural environment. The results revealed that the manipulator position inaccuracy from the arm's end was 12 mm. Moreover, the picking success rate was 83.33%.

Figure 16. structure diagram for the manipulator. [55]

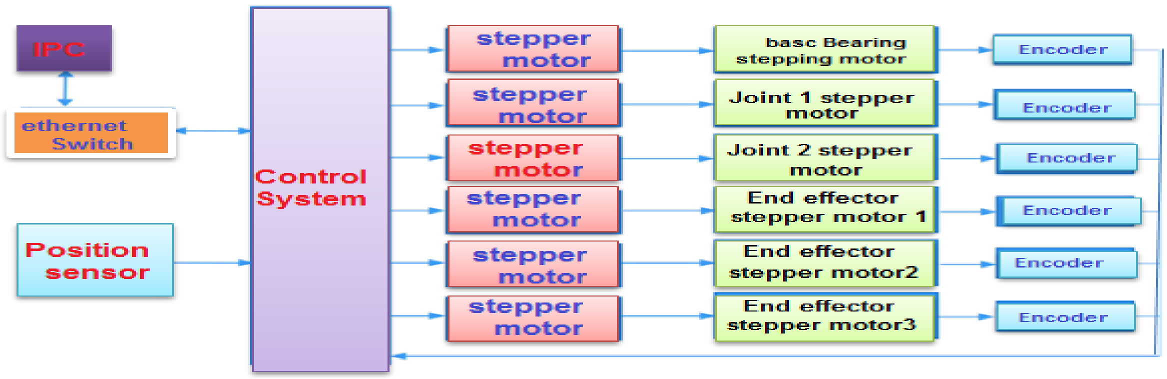

Figure 17. Block schematics of the manipulator control system[55]

Similarly, Abarna.et al[56]developed a Flower picking robot at VIT University, Chennai, India implemented a 3-DOF manipulator that had an articulated structure (RR), an end-effector that has a cutting tool, and a chassis .in this control system uses the Raspberry Pi for image processing techniques PIC16F877A controller and the USB camera tis connected to the raspberry pi module through USB port. The output of the raspberry pi module is given to the sensor1 in PIC module. Output from Port B of PIC16F877A is associated with the relay devices. The output of the relay modules will be given to the 3-DPF robot. (Figure 18). Color and pattern recognition algorithms are used to identify rose flowers. When a bloom is detected, a trigger is sent to the PIC controller to initiate the robotic arm for picking. The picking end effector was designed to grasp a knife and was operated via a servo motor for open and closing operation to cut the stem of the rose flower. Experimental results efficiency of the system is found to be 90% after 10 iterations for 50 flowers and found that the harvesting processing time is better with the use of Raspberry PI and PIC Controller, approximately 6 seconds per flower.

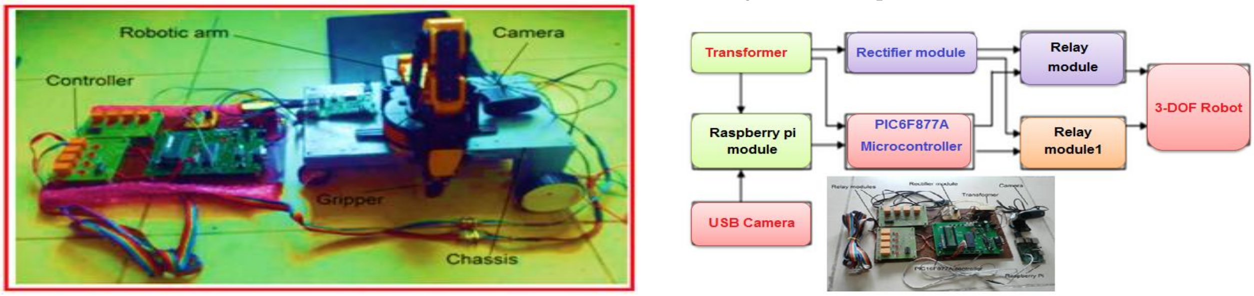

Figure 18. Rose flower harvesting robot.[56]

ROBOTICS STRAWBERRY HARVESTING

Robotic strawberry harvesting is an emerging technology that aims to automate the process of picking strawberries. Despite its potential benefits, commercializing this technology has been difficult. While academia has been researching and developing strawberry harvesting robots, commercialization has been limited to start-up companies. However, none of these companies have successfully commercialized their strawberry harvesting robots yet [57]. Except for academia, Xiong et al[58]from the Norwegian University of Life Science developed a harvesting robot for Strawberry equipped with a Mitsubishi serial arm with five degrees of freedom (DOF) , RGB-D camera, and end effector containing a finger gripper.The gripper, equipped with 3 internal infrared (IR) sensors, was able to detect and correct positional errors. It used a basic PID controller for control. To collect the picked strawberries, the gripper had an integrated container, which significantly reduced picking time; one can pick a strawberry in 7.5 s and 10.6 s at a success rate of about 96.8%. As shown in Figure 19 Another strawberry picking robot was invented by Y. Xiong et al.[59] The new robot consists primarily of a R200 RGB-D camera, a single-rail dual-arm manipulator, two grippers, a mobile platform, LIDAR navigation sensing, and a pun net station. All of the components are connected to a laptop with an Intel i5-6700 CPU and 16 GB RAM. Figure 20 The control architecture of the system utilizes the CiA 402 motion control protocol, with each motor connected to the host computer through a CAN to USB converter. A server node in ROS can be created to modularize the arm system and coordinate user nodes and arms, decoding and encoding commands for individual control. Six modes are established based on robot requirements, with the server node automatically adjusting acceleration and deceleration based on speed. The server node outputs arm status as ROS topics in 40 Hz, including current position, speed, and status, for feedback control Figure 21. The picking speed of the strawberry is 4.6s, with a success rate of about 97.1%. The picking speed of strawberries can vary depending on the harvesting method and technology used A company Agrobot[60] and Advanced Farm [61] have designed robots with multiple independent picking systems that can harvest strawberries at a rate of 3 fruits every 10 seconds . Another strawberry harvesting system developed by Harvest CROO is has sixteen robotics arm heads and sixteen arm-camera-gripper units., allowing it to harvest strawberries at a similar rate of 3 fruits every 10 seconds.

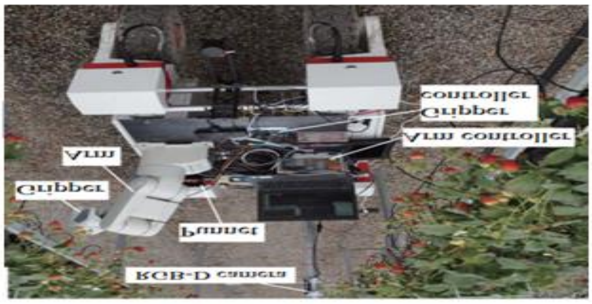

Figure 19 strawberry picking robot

Figure 20new strawberry-harvesting robot [59]

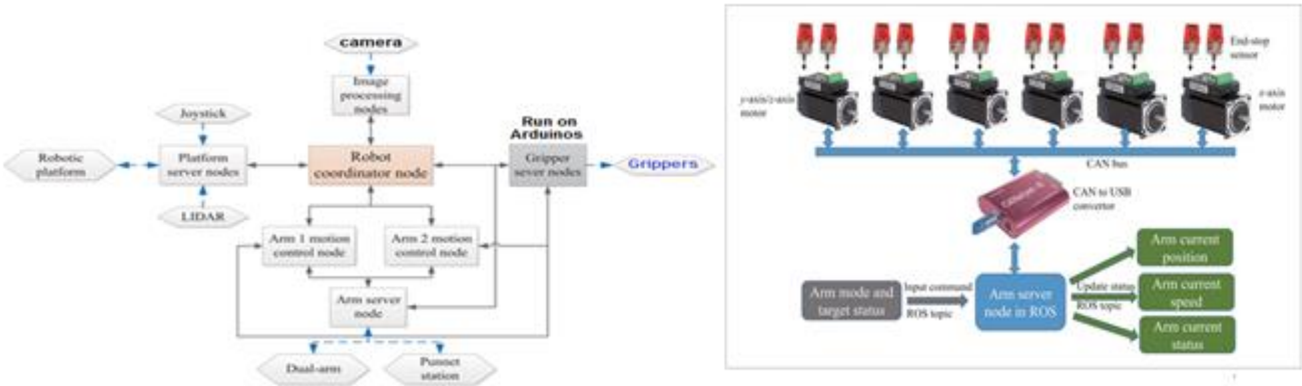

Figure 21 Single-rail dual Cartesian arm control design. [59]

A fast robot for picking strawberries has been developed by DE. Peter. et al. [62]. The robot consists of an autonomous vehicle, a custom robotic arm, an end effector with a gripper-like human fingers., color computer vision system-RGB-D. the logistic handling module and the quality monitoring software the robot is capable of detecting and recognizing strawberries based on 3D image and distance information obtained from cameras It can approach and harvest strawberries without damaging them, and has been shown to be effective in both lab conditions and farm settings. Custom robotic arm detects detected strawberries, performing similar to a human's working activity, taking only 4 seconds to reach, pick, and put them in a pun net Figure 21a

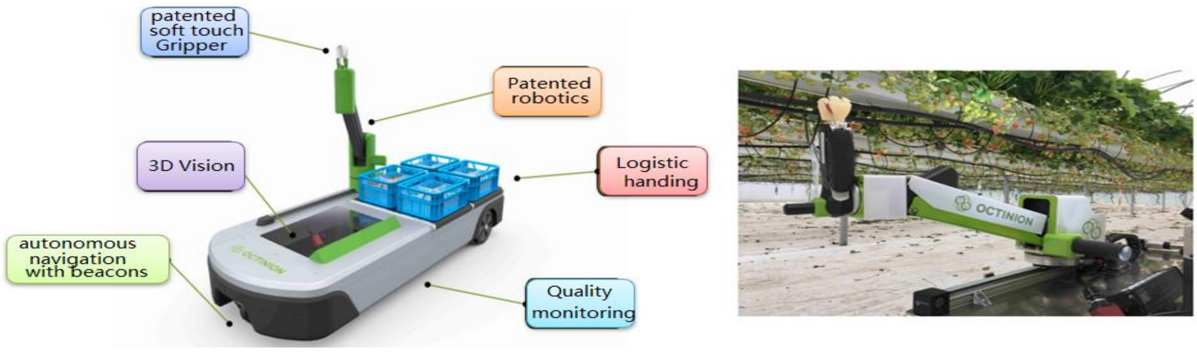

Figure 21a Picking robot concept design and its components

Hayashi et al. [7] developed a strawberry fruit picking robot that includes a cylindrical manipulator, an end-effector with a sucking equipment, an automated vision device, a container, and a traveling device. The fruit identification rate had been 60%, the successful picking rate had been 41.3% with sucking equipment and 34.9% without sucking device, and the harvesting period had been 11.5s.
Feng et al. [63] from the National Engineering Studies Center for Information Technology in Agriculture Beijing, China, introduced a novel strawberry-picking robot for elevated-trough culture that employs a sonar vision and an autonomous navigation system. A 6 DOF commercial manipulator (Denso VS-6556G) including end effector and a grasping and cutting tool was employed. To obtain fruit position data, the control system employs a PLC that connects with the robot controller through an RS232 interface. The successful picking rate had been 86%, with a mean picking time of 31.3 seconds and a mean inaccuracy for fruit position of less than 4.6 mm. Figure 22: (Figure 22)

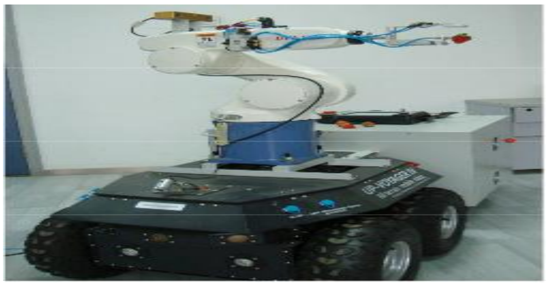

Figure 22 The functional model of harvesting robot[63]

TOMATO PICKING ROBOT

Tomato picking robots have been developed by start-up companies and academic institutions to reduce costs and increase efficiency in the farming industry. They are equipped with advanced cameras and sensors to detect ripeness and locate tomatoes.[64] Examples include Certhon Harvest Robot, Root AI's Virgo, and FARO.On the academic front, a group of scholars has created a robot. Li Biqing1,et al[65]from Wuhan University developed a cherry tomato picking robot composed of four parts: an IOT vision sensor, four manipulators, controller and transmission device. It uses image recognition and fuzzy control to scan the tomatoes and determine the movement locus of harvesting. The harvesting robot manipulator is composed of three levels: control system, stretching system and harvesting execution end. The computer control system uses PLC control technology to segment image. The picking experiments were carried out in the experimental results show that a robot arm picker is able to pick one tomato every 7 seconds. The results showed that the use PLC closed-loop feedback in the computer control system increase cherry tomato harvesting robots' productivity and reducing harvesting time. (Figure 23)

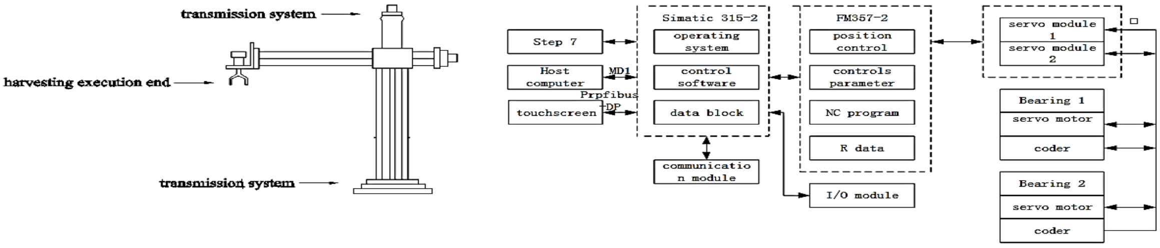

Figure 23. schematic of the picking manipulator's PLC equipment [65]

in the same vein. Jiahao,et al[66]designed a tomato picking robot used in a greenhouse, as shown in (Figure 24)Tomato harvesting robot consisting of a 6 DOF manipulator system, Chassis, Lifting device, end-effector and a controller system . In this work analyzes the effectiveness of the design parameters selected for a tomato picking manipulator, and verifies the rationality of the manipulator in motion planning for tomato picking. They employed 3D CAD. The robot manipulator's kinematics equation was demonstrated using the DH deducing approach, and the robot manipulator's kinematic modeling was carried out using MATLAB. They also employed a motion controller (Battleship V3), an industrial computer, and a manipulator control system with six different sets of motion devices. The motion unit (AQMD3608BLS) consists of motor drivers, joint drives, with Hall's sensors sets. The working model experiment shows that the recommended lightweight tomato picking manipulator has excellent kinematics efficiency and fundamentally meets with tomato picking activity requirements: the manipulator picks a tomato with a success percentage of 78.67% in a mean of 21 seconds. but the cutting speed is still slow.

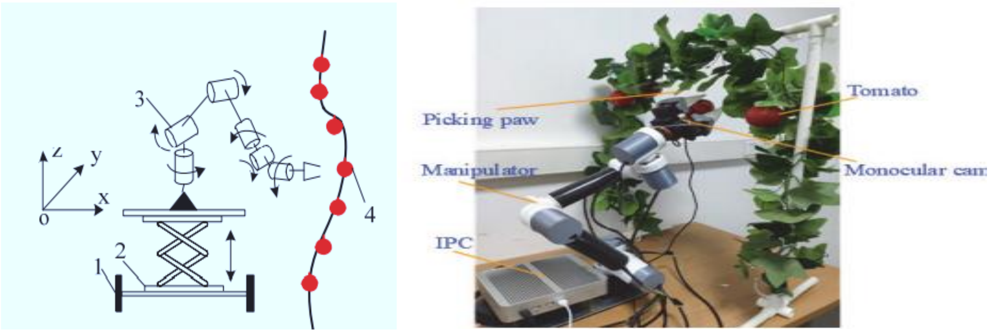

Figure 24Mechanical principle of the picking robot tomato[66]

Yi-Chich CHIU et al.[67] from Jeonju, Korea design an autonomous harvesting robot device for greenhouse-grown tomatoes that is composed up of four primary parts. As illustrated in Fig. 1, the robot arm 5 DOF Mitsubishi RV-M1 includes the end-effector apparatus comprises four claw fingers, machine vision, robot carrier, and control system comprise of four parts including the robot arm and end-effector control, processing of images, robot transport control, and central control unit PLC. The experimental findings revealed that the integrated picking rate for success had been 89.63%, with a mean picking period of 35.96 s/sample and a capacity of 100.1 samples/h. (See Figure 25.) (Figure 25)

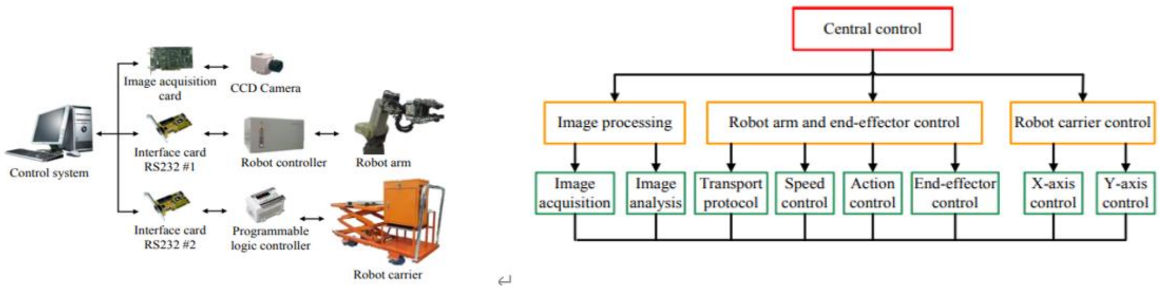

Figure25 Structure of the picking robot system and end-effector[67]

Yurni Oktarina et al[68] designed a picking robot capable of identifying and plucking red and green tomatoes. The robot is made up of a manipulator with four degrees of freedom, a vision system, an end-effector with scissors, and control system. The robot is outfitted using servo motors being actuators, an Arduino Mega 2560 microcontroller being primary controller, a Raspberry Pi for processing images, a PI camera mounted on the end-effector, and a proximity sensor to determine the robot's distance from the fruit. The experiment demonstrates that the average time for picking red tomatoes is 4.932 seconds and 5.276 seconds for green tomatoes. The time necessary for the robot to detect red tomatoes and return to the standby position is 9.676 seconds for red tomatoes and 10.586 seconds for green tomatoes. The time discrepancy is caused by the robot's distance from the tomato, not by its color (Figure 26)

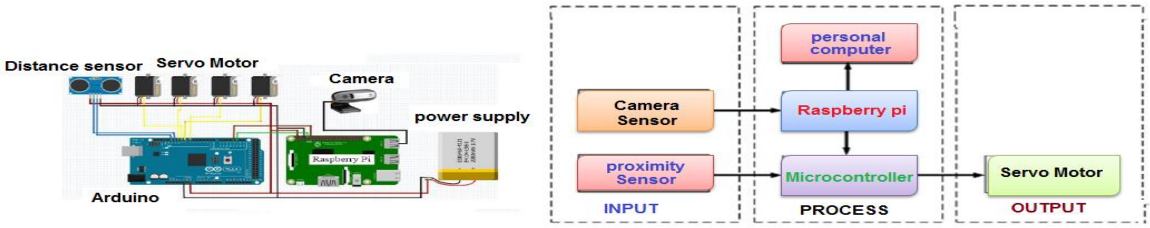

Figure 26 depicts the electrical connection between the harvesting robot's components. [68]

Wei Zhang et al. [69] from North-West A&F University, China, designed a tomato picking robot consisting of wheeled chassis, binocular camera with a four-degree-of-freedom manipulator made of carbon fiber tube, an end effector, and controllers. The manipulator used a DC brushless motor (42BL80S09-230TR9) The structure of the control system for visual servo picking is shown in Figure 23. The monocular and binocular cameras were connected to the visual controller (D12120P551) via a USB interface to form a visual system and to acquire and process image-related information on the fruit. The main controller (Battleship V3) obtained feature information from images processed by the visual controller via serial port 5. The main controller drove each motor of the joints of the picking robot by sending commands to the controller (AQMD3608BLS) via serial port 3. The main controller was connected to the steering gear controller (LSC-16-V1.3) via serial port 2 to control the movement of the steering gear at the joint of the wrist and fingers of the end effector. The main controller was connected to the chassis motion controller (DC-30A) through several pins to drive the hub motor of the chassis. The results show that the global-local visual servo picking system had an average accuracy of correctly judging fruit maturity of 92.8%, an average error of fruit distance measurement in the range of 0.485 cm, an average time for continuous tomato picking of 20.06 s, and an average success rate of picking of 92.45 (Figure 27).

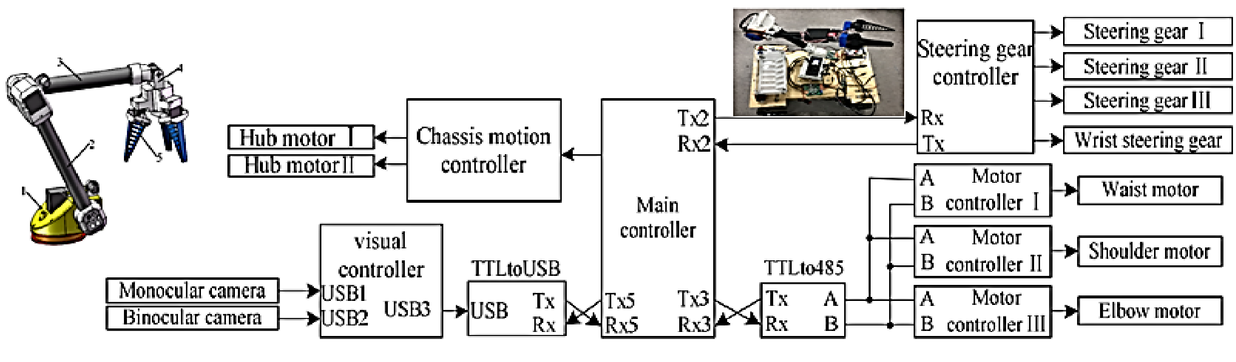

Figure 27 Structure diagram of the control system[69]

Azamat et.al[70]from Kazakh National University developed of Continuum Robot Arm and Gripper for Harvesting Cherry Tomatoes named it TakoBot.TakoBot used machine learning based on neural networks YOLO (You Look Only Once) to distinguish matured tomatoes from immature tomatoes and other comparable fruits.

TakoBot's control architecture is consists of two main parts: software and hardware (Figure28). The work process starts with the software Firstly, it scans ripe tomatoes. After detecting tomatoes, the camera measures the distance. Finally, the measured information helps calculate the robot's inverse kinematics. Calculated inverse kinematics sends the information and coordinates of the tomato to the Arduino board. Thus, the Arduino board sends data to the motors to drive the TakoBot to make the gripper get to the desired position. In the harvesting experiment the tomato recognition accuracy was 90% but average speed of the robot was 56 s for a single tomato. which is slower in comparison with human work

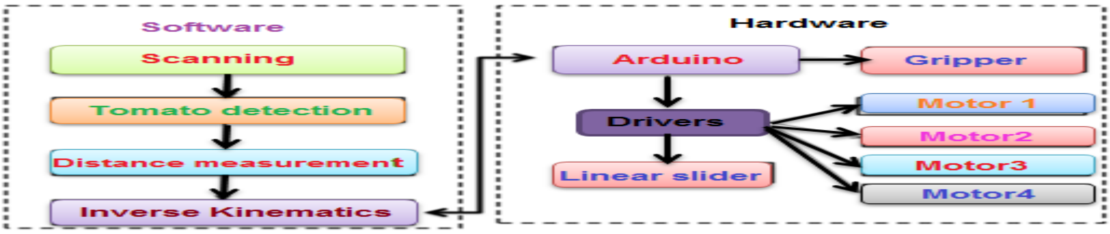

Figure28:Block diagrams of the control system for the TakoBot[70]

Jongpyo Jun et al[71]from Chonnam National University South Korea proposed an efficient tomato-harvesting robot that combines the principles of 3D perception, manipulation, and an end-effector. With this robot which consists of a 6-DOF manipulator (UR3), a custom end-effector and embedded board (Jetson TX2), and RGB-D camera (Intel Real sense D435). The RGB-D camera is attached to the end-effector and is used to transmit the pose data of the detected tomato to the embedded board via USB communication. With this robot, deep-learning-(YOLOV3) based detection and 3D perception are performed considering tomatoes as the target Figure29.Motion control of the manipulator was implemented based on 3D perception, whereas the developed end-effector comprised two parts: a grasping module and a cutting module. The grasping module grips tomatoes in a cluster and is based on a suction gripper using soft robotics. The suction gripper allows suction pads, which were based on the kirigami pattern, to grip unstructured shapes more easily. The cutting module, which has the shape of scissors, is equipped with a fractional cutting unit to overcome structural limitations and improve cutting. After approaching the fruit, the process of detaching the fruit was regarded as harvesting. The total cycle time was 5.9 seconds, and in the test bed, the fruit was located close to the robot arm, so the harvesting speed was relatively fast.

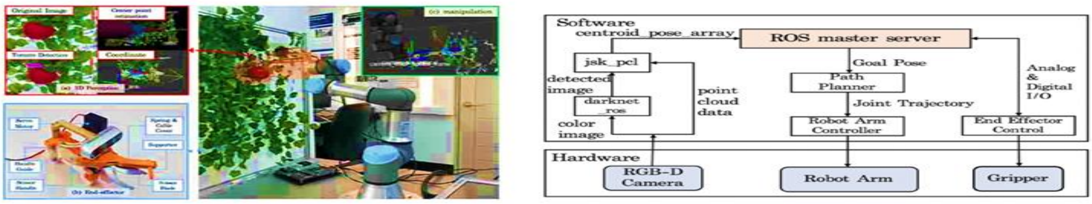

Figure29 tomato-harvesting robot[71]

Robotic Harvesting of Fruiting Vegetables

Kyusuk Y. et al. [72]At the University of Florida, Gainesville, designed an orange-picking robot based on a six-degree-of-freedom 6-DOF ARC Mate manipulator and an end-effector with a four-finger pneumatic gripper. (Figure 30) The robot mainly consists of a double-cylinder type pneumatic rotary actuator (DRQD-20-360, Festo Pneumatics Co., Japan), a custom-designed linear expandable linkage, a multi-directional swivel vise (Central Forge Co. Stafford England), an electrical telescopic lift, a flatbed garden cart (YTL International Inc. Cerritos CA), pneumatic control box, desktop computer and air compressor. PLC units controlled pneumatic valves, pressure regulators, and vacuum ejector modules. Desktop computer was prepared to monitor the end effector's operation stage in ladder logic and to collect sensed pressure and vacuum data through a PCI DAQ board and Labview solution. The time taken to orange and pick was around 4.5 s per orange, with an achievement rate of 90.8%.

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Figure 30 orange picking robot[72].

In the same vein Li Ma et al. [73]from Northwest A&F University, Yangling, China developed automatic picking robot for kiwifruit that adopted a 6-DOF manipulator with a UR5, Universal Robots, Odense, Denmark structure an end-effector with two 3D-printed lightweight grippers, photoelectric sensors and pneumatic components and vision system includes an RGB-D camera (RealSense D435i, Intel, Santa Clara,CA,USA) and an image-processing unit (Jetson Nano, NVIDIA, Santa Clara, CA, USA) in this work developed picking-robot control system based on the ROS-MoveIt (Robot Operation System Motion Planning Framework) as shown in (Figure 31)The RGB-D camera captures fruit color images and depth images and transmits the images to the image-processing unit. The image-processing unit first performs fruit target detection and grasping detection based on the deep-learning (GG-CNN2.yolov4) and then obtains the pose information of the target fruit relative to the robot base coordinate system based on the internal and external parameter matrices of the camera. The fruit-pose information is sequentially published in the form of topics and the robotic-arm control node subscribes to the topic. The rapidly exploring random trees (RRT) algorithm in the Open Motion Planning Library (OMPL) is used for path planning. The inverse kinematics solution is solved by calling the inverse solver IK Fast to form the dynamic trajectory of the robotic-arm kinematics group and drive the robotic arm to arrive at the target pose. After the robotic arm completes the current target-fruit picking task, the image-processing node updates the fruit-pose information until all fruit-picking tasks are completed. The experimental results show that the successful harvest rate of the kiwifruit picking robot is 88.7% The average time taken for picking a single fruit was 6.5 s.

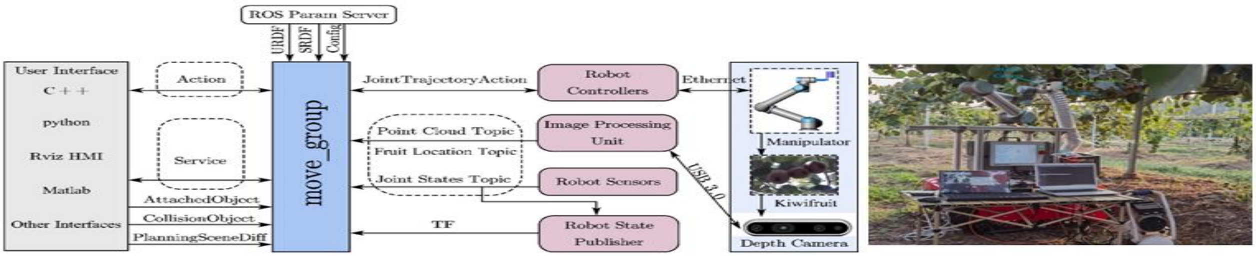


Figure 31picking robot for kiwifruit[73]

Osama M. et al[74]from the University of Jordan, Amman created a prototype for a synergistic smart robotic olive fruit harvester that uses an RGB-Dcamera for deep learning-based fruit localization and detection as well as a Raspberry Pi processor for nonlinear velocity control. A 6DOF manipulator with hybrid pneumatic/motor actuation, a vacuum-based end-effector, and a nonlinear velocity-based control scheme. the procedure adopted in this work focuses on picking a group of fruit in each stroke. The harvesting system consists of a robotic arm guided by a stereovision camera to enable 3-D vision. Once the fruits' location is detected, a reverse kinematics algorithm is initiated, yielding 3- points coordinates. These coordinates are commanded to the manipulator to move to the location and performs the picking process. The experimental manipulator was used to pick the fruits Preliminary results have been obtained. A trial was done using predefined angles in order for the robotic arm to reach the fruit. Different joint speed profiles are shown in Fig. 23.25s the picking success rate is 60% (Figure 32).

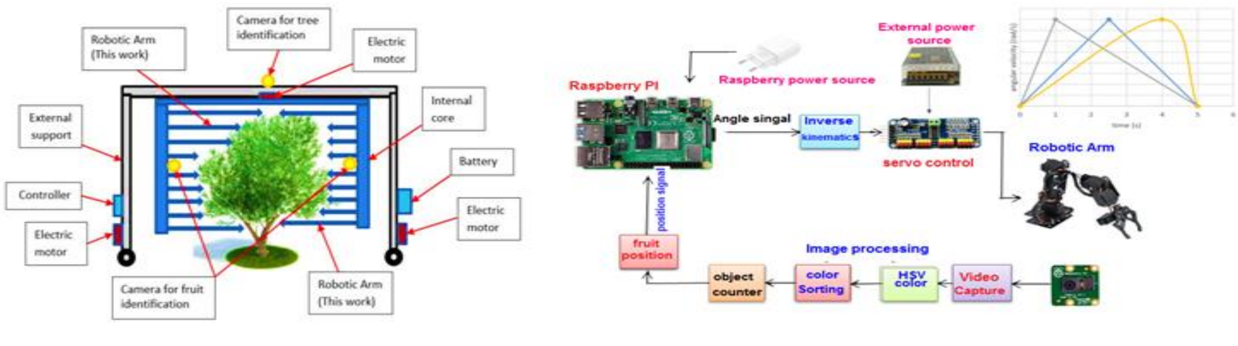


Figure32 Structure diagram control system of olive fruit harvesting robot[74]

Henten et al[75]From Wagemngen Netherlands Designed a 7-DOF manipulator for cucumber automatic picking robot. This type of robot consists of an autonomous car, a 7-DOF manipulator consists of a linear slide on the top, where also mounted a Mitsubishi RV-E2 manipulator with an anthropomorphic arm , a spherical wrist and driven by24 DC motors and servo controllers combined with absolute encoders., two camera vision systems, as well as various electronic and pneumatic hardware, cutting devices of the end effector used thermal cutting technology to pick the cucumbers with a picking success rate of 80% .On average the robot needed 45 s to pick one cucumber. and slow picking speeds systems for detection, Similar to this, Xiaomei Hu .et al. [76]from Shanghai University, Shanghai, China introduced the design and experiment of a new citrus picking robot. The robot is mainly composed of a 4DOF robot arm INKHOU LR6-R1200-4 equipped with Intel Real Sense D435 a depth camera is composed of RGB –D color camera, left infrared camera, right infrared camera and infrared dot matrix projector to measure depth and an end effector with scissors, a clamping device and an electric pusher, which converts telescopic motion into rotation harvesting. Coordinated control of various institutions and systems is carried out through the upper computer. (Figure33). The citrus picking robot achieves the whole process of autonomous harvesting. The control system of a citrus harvesting robot is written in C++ and executed in Visual Studio 2017 under Windows 10. It obtains image information and sends instructions to the executing agency The success rate of the citrus harvesting robot is more than 90% and the average period of citrus harvesting is 15s/fruit tested in laboratory environment

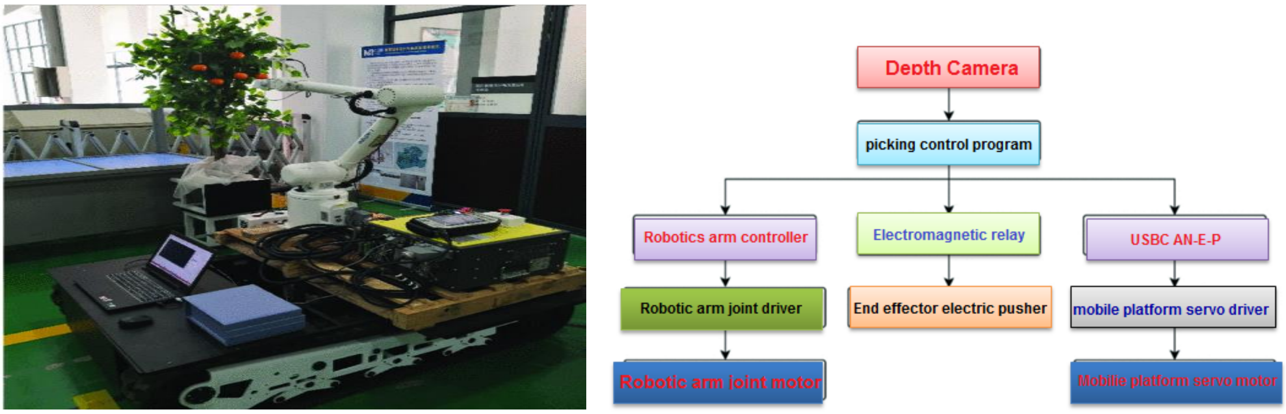


Figure33. Structure diagram control system of citrus harvesting robot[76]

Similarly, Shamshiri et al. [77]developed and simulation Robotic Harvesting of Fruiting Vegetables using the software programmers V-REP, Robot Operating System (ROS), and MATLAB. The study was carried out in two stages: first, the virtual robot experimentation platform (V-REP) was used to build a simulated workspace, and then ROS and MATLAB were used to design a communication and control architecture. An exact replica of the 6 DOF Fanuc LR Mate 200iD robot manipulator, models of sweet pepper fruit and plant system, and different vision sensors were created in V-REP to form the simulated workspace. Two control schemes were developed and evaluated; the first one was based on joint velocity control and the second one based on joint position control. A Proportional-Integral-Derivative (PID) control law was applied to both of the designs in order to minimize the offset error between the center of the camera frame and the image position of a detected fruit. Results demonstrated that the robot could self-adjust so that its tip RGB sensor displays maximum possible view of the largest detected fruit and fast stabilization. The stability was achieved in 2.5 seconds without overshoot and oscillations. (Figure 34)

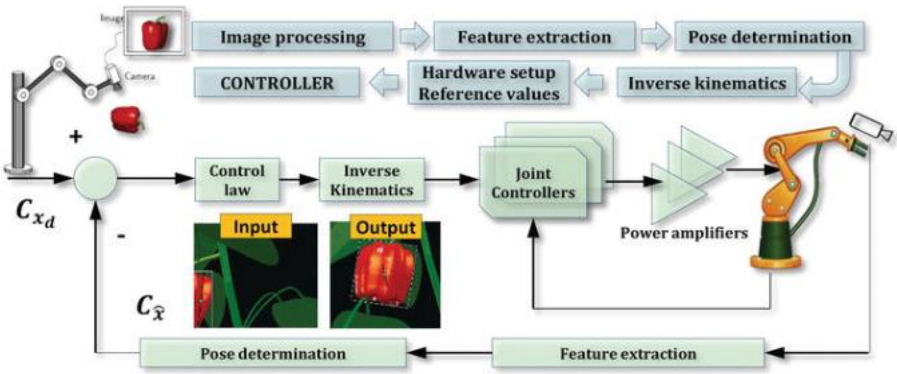
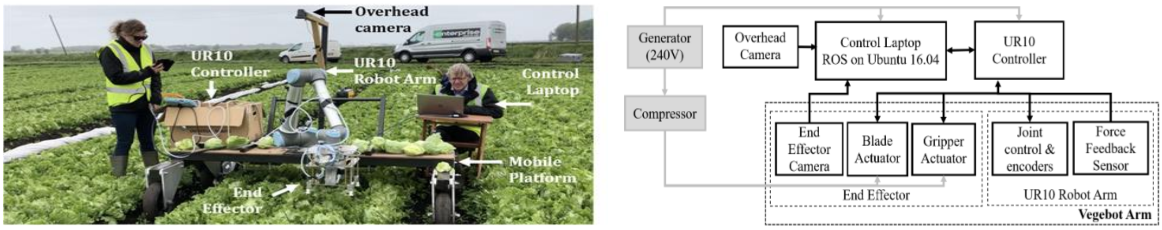


Figure34. Structure diagram control system of vegetable harvesting robot[77]

Similarly Birrell .et al[78]developed a lettuce harvesting robot. comprises a laptop computer running control software, a standard 6 degree of freedom (DOF) UR10 robot arm, two cameras with an end effector containing two pneumatic actuators, one for grasping and one for cutting. A block diagram showing the integration of the system is shown in Figure 35 Picking robot achieved success 91% localization and 0.82 classification accuracy, with an average cycle time of 31.7s, slower than humans due to the weight of the end effector. causes on the robot arm to slow down considerable



A block diagram showing the integration of the system is shown in Figure35[78]

Chang, S.J et al. [79]from South Korea developed a 3 DOF lettuce harvesting robot using machine vision and fuzzy logic control. This robot consists of a manipulator with end-effector, a lettuce-feeding conveyor, an air blower, a machine vision system, six photoelectric sensors and fuzzy log controllers. The robot showed effective performance with 94.12% harvesting success rate and took 5 s to cut the lettuce

Boaz Arad et al [80]at Ben-Gurion University of the Negev, Beer-Sheva, Israel presented the development, testing and validation of SWEEPER, a robot for harvesting sweet pepper fruit in greenhouses. The robotic system includes a six degrees of freedom industrial arm equipped (Fanuc LR Mate 200iD), with a specially designed end effector, RGB-D camera, high-end computer with graphics processing unit (GPU), programmable logic controllers (PLCs), sensors, other electronic equipment, and a small container to store harvested fruit. One Arduino-based PLC controlled the cart operations (motion along the row and cart elevation); another PLC controlled the low-level functions of the end effector. shown in Figure 4. All equipment was mounted on a cart that could drive on the pipe rail and also on the concrete floor. The SWEEPER robot is the first sweet pepper harvesting robot to demonstrate successful robotic harvesting in a commercial greenhouse, with an average cycle time of 24 s and a harvest success rate of 61% for best fit and 18% in current crop condition (Figure36)

Figure 36 shows a robot arm with four components: CB, CE, FC, PA, PC, and PW.[80]

Muhammad Umar Masood, et al. [81]from New Mexico State University developed a low-cost robot arm (5 DoF), used for harvesting of Chile peppers. A Braccio robot which includes of a 5-DoF robot arm and 3D vision Depth D435i sensor and cut cutting mechanism, The robot arm is based on DC Servo Motors and is controlled by an Arduino Due Development Board.is used as microcontroller for the hardware. The forward and inverse kinematics of Braccio robot was derived for workspace analysis and motion planning developed in MATLAB The developed harvesting robot showed promising results with localization success rate of 37.7%, detachment success rate of 65.5%, harvest success rate of 24.7%, damage rate of 6.9% and cycle time of 7 s. (Figure 37)

Figure 37 harvesting of chile pepper[81]

Xiuxia Zhang, et al[82]from Hefei of technology china carried out control system for wolfberry harvesting robot used fuzzy-PID control .This kind of robot comprised a self-propelled automated platform with one articulating arm, coupled with camera, sensors of all kinds for obstacle avoidance and picking manipulator 5dof . Two rotor bodies inside the manipulator, which were made of two silicone wheels, every silicone with three spiral silicon tube, carried on relative motion to realize the simulation of hand-picking to pick fruit. Pinhole imaging technology for identification and PID control method for the enhancement of control system's dynamic and static performances were employed to ensure the normal order of the picking robot. but the motion picking success rate was not high. Martin F. Stoelen .et al. [83] from University of Plymouth,UK developed Automated Sugar Pea harvesting robot consists mainly composed a five-degrees-of-freedom from Trossen Robotics , vision system includes an RGB-D camera and an end effector with sensors mounted on the robot hand. This arm is based on the Dynamixel daisy-chained servos, which provide high accuracy (down to 0.088°) and flexible control (adjustable PID and torque control). Robot Operating System (ROS) available for the robot's ArbotiX microcontroller Figure 38. The experimental results show that a robot arm picker is able to pick one sugar pea every 10 seconds.

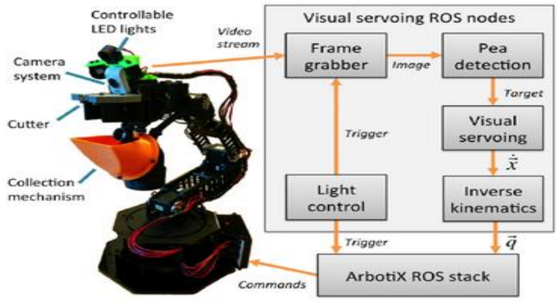


Figure 38 Automated Sugar Pea picking robot[83]

Ekruyota OGet al.[84]designed and develop an autonomous harvesting robot for various pepper and eggplant cultivars fruits. The autonomous robotic system is lightweight, small, and flexible, capable of harvesting bell pepper and eggplant fruits (Figure 39). It consists of a harvesting system, microcontroller, navigation system, storage box, and Pi camera. The Raspberry Pi controller coordinates navigation, while DC motors provide rotary motion. The system uses image processing and a robotic arm for fruit collection. The harvesting test was performed for 20 times, on two pepper cultivars and eggplant plant cultivars grown in the laboratory. Results obtained from the laboratory trial are presented. results show that the successful harvest rate of the pepper cultivars and eggplant plant cultivars picking robot is 86%

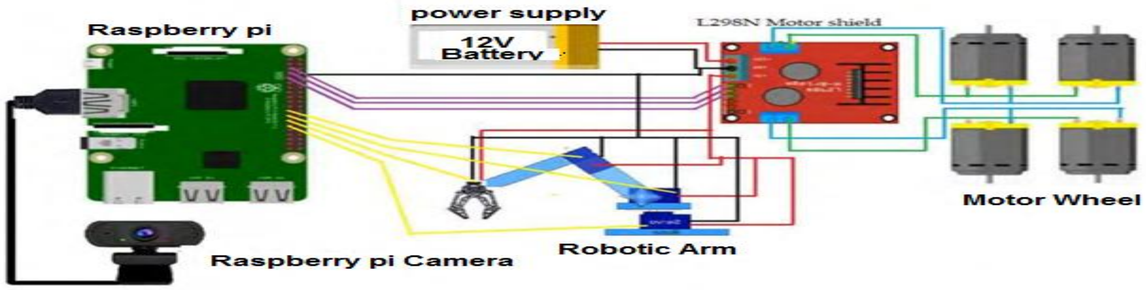


Figure 39,,The architecture of the prototype fruits harvesting robotic system[84]

Bin Zhang 1et al. [85]from Hainan University, China; Designed a 5-DOF manipulator for jujube trees pruning robot as shown in Figure40,This type of robot consists mainly composed of a machine arm with 5 degrees of freedom (5-DOF), an end-effector, vision system and control system. The manipulator's control system has a two-layer structure, with top and lower computers. A six-axis off-line motion controller is used in the lower computer control system (YJ-CTRL-A601; Shenzhen Yijia Technology Co., Ltd.; Shenzhen; China). Each joint's driving motor is an integrated closed-loop stepper motor (ESS60-P; Shenzhen YAKO Automation Technology Co., Ltd.; Shenzhen; China) Figure 40and 41shows the diagram for the jujube pruning manipulator's overall control system

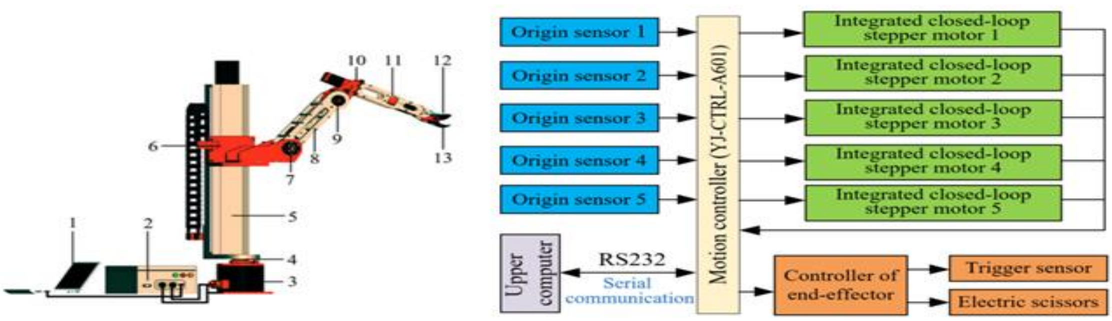


Figure40 the diagram for the jujube pruning manipulator's overall control system[85]

The kinematic equation of the jujube pruning manipulator was solved using homogeneous transformation of the DH parameter method, and the manipulator was mathematically simulated using the MATLAB Toolbox. The manipulator arm kinematics and pruning experiments were carried out in experimental filed in a natural environment by the robotic physical machine platform. The results showed that the manipulator position error from the end of arm was less than 10 mm, and the average pruning success rate of the manipulator was about 89.10%, and the average time was about 27.7 min. It was verified that control system of the pruning manipulator was reasonable and feasible.

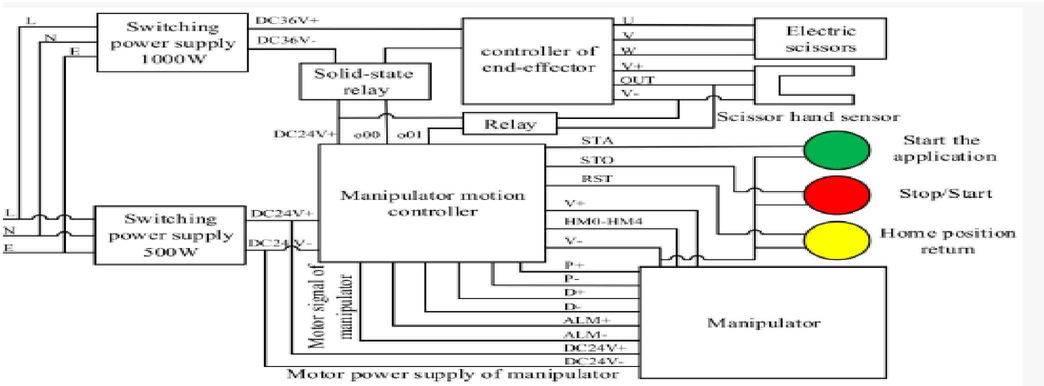


Figure 41The diagram for the electrical schematic of the jujube pruning manipulator.[85]

ANALYSIS FOR HARVESTING ROBOTICS

Computer, Control and, for harvesting robot

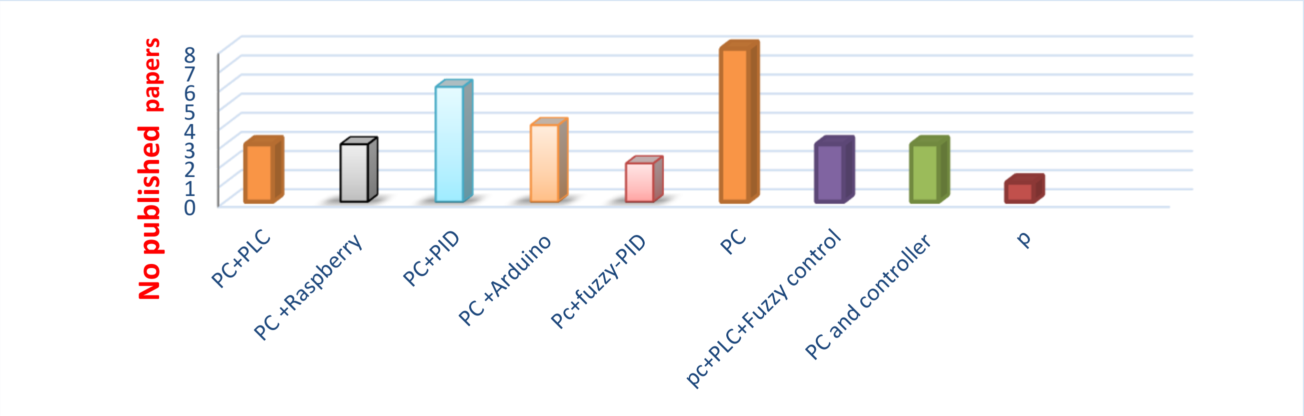
Harvesting robots require computer control and actuator mechanisms to function effectively. These systems must be designed to allow the robot to move and operate accurately and with precision while performing harvesting tasks. Actuators are a power mechanism used to affect motion or position of the robot while the control mechanism is typically a computer or microprocessor that receives input signals and sends output signals to the actuator mechanisms. These systems must be carefully designed and tested to ensure that they are reliable and efficient and can withstand the harsh operating conditions of a harvesting environment Fruit and vegetable robotics studies involve the use of computerized communication and control systems to perform autonomous tasks such as speed control, image processing, and robot manipulation. Harvesting robots utilize various actuators, control systems, and mechanisms based on their design and application. Electric actuation systems are commonly used in selective harvesting, as shown in Table 1. However, in cases where harvesting operations are performed at higher levels and must handle heavier payloads, fluid power [37][70] [39]Chang, S.J. et al. [36] and Kyusuk Y. et al[72]were utilized. Off-the-shelf manipulators commonly used servo AC/DC motor systems in harvesting operations [84][54]] [55]while custom-built manipulators used servo motors (Kaixiang Zhan et al. [48] stepper motors [48] stepper motors (Xiong et al.[59]), and a dynamic actuator (Dynamixel Pro) for actuation (Joseph et al. [40]and motor drivers (AQMD3608BLS) Jiahao, et al. [66]

Table1. Computer and Arm actuation sensors and camera and communication components used in fruit and vegetable robotics studies

Computer and Controller	Arm actuation	Communication components	sensors and camera	Ref
Orange				
PC +PLC unit controlled	pneumatic	USB+PCI DAQ board	RGB-D and deep-learning (GG-CNN2.yolov4)	[72]
olive fruit				
Pc+Raspberry Pi4 processor for nonlinear velocity control.	Electrical	USB+Servo Controller to control multiple servo motors.	RGB camera for deep learningbased fruit localization and detection	[74]
Cucumber				
two-computer	Electrical+ pneumatic	USB+24 DC motors and servo controllers combined with absolute encoders	device(CCD)-cameras mounted onto one wide angle optical system.+ Encoder (per arm joints)	[75]
citrus				
Pc	Electrical	communication with the upper computer through TCP/IP protocol,and CANopen	RGB –D color camera	[76]
Vegetables				

PC+(PID) control	Electric	USB+ROS and MATLAB were used to design a communication and control architecture.	Logitech C920 HD Pro USB/proximity Hokuyo URG04LXUG01+ RGB sensor	[77]
Raspberry Pi controller	Electric	USB	Raspberry cameras	[84]
lettuce				
Pc+UR10contorller	pneumatic	USB+ digital I/O lines routed through the UR10 arm	USB webcams and stream video to the control laptop. +YOLO3 algorithm	[78]
PC with BP-IS +PIC16C73	pneumatic	USB	machine vision and fuzzy logic control.CCD Camra (PULLIX)and Photelectric sensors	[79]
sweet pepper				
PC+PLCs+ IK-based	Electric	USB Wireless Adapter	RGB-D camera/Fotonic F80	[80]
PC +Arduino D435i sensor	Electric	USB+UART serial communication	RGB-D D435i	[81]
Wolfberry				
Pc+fuzzy-PID control	Electric	USB	Visual control, color collection	[82]
Sugar Pea				
PC+ PID ArbotiX microcontroller	Electric	USB Interface	RGB-D camera+ sensors	[83]
strawberry				
PC+PID controller CR1-571	Electric	RS232C	RGB-D camera And three internal infrared (IR) sensors	[36]
laptop (Intel i5-6700 CP and 16 GB RAM)	Electric	USB+ (ROS)+ CANbus network.	RGB-D camera/Intel R200 IR sensors +TRCT5000	[58]
……………………	Electric,	……………..	three CCD color cameras	[62]
PC + PLC	Electric,	RS232	Binocular camera + Sonar sensor, Camera	[63]
PC	Electric,	………………………	Vision processing	[7]
TAMATO				
The computer control system uses PLC+Fuzzy control	Electrical	MDI +PROFIBUS +DP	IOT vision sensor	[65]
industrial computer.	Electrical (motors 42BL50S03-230TR9)	USB+IPC	Monocular cameras	[66]
PC and PLC	Electrical	Interface card RS232#2	CCD cameras	[67]
PC and controller AQMD3608BLS , LSC-16-V1.3	Electrical	USB+	a binocular camera (3D-1MP02-V92+ monocular camera (QR-USB3MP01H)	[69]
PC +Arduino board	Electrical	USB	Camera+ machine learning based on neural networks YOLO4	[70]
embedded board (Jetson TX2)	Electrical	USB communication	RGB-D camera (Intel Real sense D435).+ deep-learning-(YOLOV3)	[71]
Arduino+ a Raspberry Pi	Electrical	USB	CCD cameras	[68]
Apple				
computer and AC+ IBVS	Electrical	USB Interface	CCD camera+GPS+Collision sensor +Photo-electric position sensor	[41]
Computer+ IK-based	Electrical	USB Interface	stereo camera ZED (STEREO LABS)	[43]

Arduino+ PC	a hybrid pneumatic	USB Interface	RGB-D camera	[42]
PC	Electrical	USB Interface	RGB-D camera used is the Realsense L515 LIDAR	[44]
control unit is a Dell XPS 15 9570 personal computer,	Electrical	USB Interface	RGB-D camera	[45]
PC using the manufacturer's Software Development Kit (SDK).	Electrical actuator (Dynamixel Pro)	A USB2Dynamixel adapter (Robotics Inc., Irvine, CA)	CCD camera/Prosilica GC1290CToF camera/Cam cube 3.0	[40]
Machine Vision Feedback P-based	Electrical	USB Interface	color CCD camera/ laser ranging sensor	[46]
computer with an Arduino uno	Electrical	USB Interface (ROS)	cameras used a ZED binocular vision sensor	[47]
computer	Electrical(custom)	USB	color CCD camera	[48]



Figur42, **the diagram depicts the various types of controllers utilized in the articles**

CYCLE TIME AND OVERALL SPEED FOR HARVASTING ROBOT

Cycle time and overall speed are important factors to consider when it comes to harvesting fruits and vegetables using robots. The recommended cycle time is the time needed to picking a single fruit with robotic. The cycle time can vary depending on the shape and size of the fruit, the robot's arm design, the complexity of the harvesting process, and the velocity and accuracy of the robotic arm. It is important to optimize the cycle time to ensure the practicality of robot harvesting. In this study, several fruit and flower harvesting robotics, including cycle time and overall speed for different kinds of fruit, vegetable, and flower harvesting, were analyzed, as seen in Fig. 44. Through research on flower harvesting robots, the cycle time for picking Gerbera jamesonii flowers was higher, although the used robot was a Mitsubishi RV-E3NLM. Jiang, Xiang Yao, et al.[52] [55]A special robot was designed to pick lily flowers, and the control system was strong for harvesting as the periodic time was reduced to seven seconds due to the efficiency of the arm and the use of very powerful actuators, and the image recognition system was very fast. Similarly, Abarna and Selvakumar et al. [56]developed a rose-picking robot. And found that harvesting processing time was better with the use of the Raspberry PI and PIC controller, approximately 6 seconds per flower. Most applications cannot compete with their human counterparts among the examined systems with reported cycle times. In this table, 1, 2, 3, and 4, the success rate of the harvesting robot, the cycle time of the harvesting, the type of control used in the robot arm, and the degree of freedom are listed. Apple harvesting robots are one of the systems that were evaluated, with cycle times recorded. These systems depend on a number of variables, including the hardware and software design of the harvesting, the method of apple detachment, and the harvesting success rate. According to studies, the cycle time for robotic apple harvesting equipment ranges from 8 to 10 seconds per fruit to about 9 seconds per fruit in efficient pick-and-drop scenarios. Robotic apple harvesting has been claimed to have a range of success rates, with some tests reporting a success rate of 85.25%. Apple growers can increase output and cut labor expenses by enhancing harvesting efficiency and cutting cycle time. Researchers and developers have also implemented multiple arms in a strawberry robotic system as well as robot fleet concepts to further enhance cycle time and productivity. Xiong et al. [57] reduced the cycle time of their robot from 6.1 to 4.6 s per fruit when switching from single to dual arms (Xiong et al. [57]Agrobot [51] and Advanced Farm[50] mounted many independent picking systems on a single mobile base, and Harvest CROO's strawberry harvesting system equipped with 16 robotic heads and 16 arm-camera-gripper sets can pick 3 fruits every 10 s and Cycle time and overall speed of the response were also evaluated, both in the fixation process and fruit and vegetable harvesting. It was shown that the fast speed configuration of the robot was suitable for different types of fruit harvesting as it maintained a consistent speed of between 4.5 to 45 s when harvesting a fruit from different arbitrary positions. Although this speed is slower compared to a human picker, And the harvesting speed is faster than the average of the reported speeds of currently developed harvesting robots, which is an average of 20 s. It should be noted that the harvesting speed is dependent on several factors, such as the actuator's angular speed, image processing speed, and the manipulator's work envelope.

HARVESTING SUCCESS RATE

The harvest success rate for 35 of the 41 applications has been observed. As shown in Fig. 43，48，51 although none of the existing robots has achieved a 100% harvest rate in apple, tomato, strawberry, flowers, kiwifruit, olive fruit, citrus lettuce, sweet pepper, sugar pea, orange, orange, wolfberry and cucumber harvesting, significant progress has been made in harvesting rates with multiple prototypes and products recording a higher than 90% harvest success rate. So far, the strawberry harvest is the best among the robots, and the success rate is very high, reaching 96%, as is the harvest rate in flowers. The success rate of the robot during the harvest was measured (Rath and Kawollek)[52], as the results varied according to the number of flowering stems. The results showed that the robot achieved 97% success in the presence of one or two flower stems. Due to the presence of 3 or 4 flower stalks, that percentage dropped to 89%; with 5 flower stalks, this percentage is 50%. Reported success rates for strawberry and sweet pepper harvesting are relatively low, citing environmental complexity as apossible reason, with harvest success rates significantly increasing after environmental simplification. Despite the successes in the rate of fruit picking, there are no robots in the commercial market. All studies were academic and in university laboratories.

Table2 Different Types Of flowers picking Robots

Types Of Flowers	DOF	Arm actuation	TYPE ARM	Speed Rate	Harvesting success Rate (%)	Reference
Gerbera jamesonii	6DOF	Electrical	Mitsubishi RV-E3NLM	10 min/ flower	80%	[52]
Rosa Damascena Flower	4DOF	Electrical	custom arm	No Result previewed	82.22%	[54]
lily flower	5DOF	Electrical stepper motors, 86BYG250H	Special arm	7 s/ flower	83.33%	[55]
Rose Flower	3DOF	Electrical	structure (RR)	6 S /flower	90%	[56]

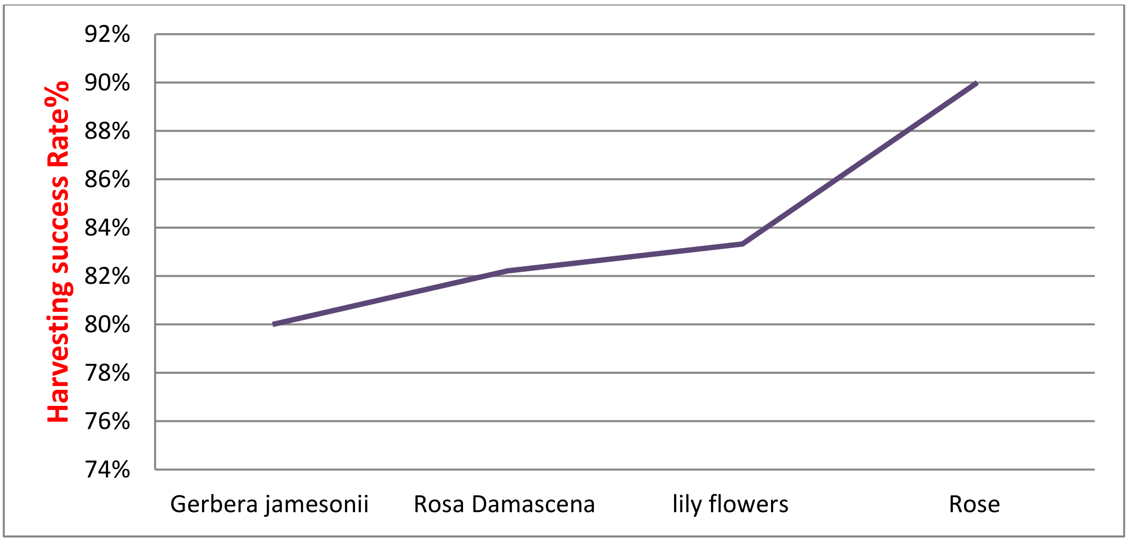


Figure43 explain relationship between the success rates for each researcher harvesting flowers Robots

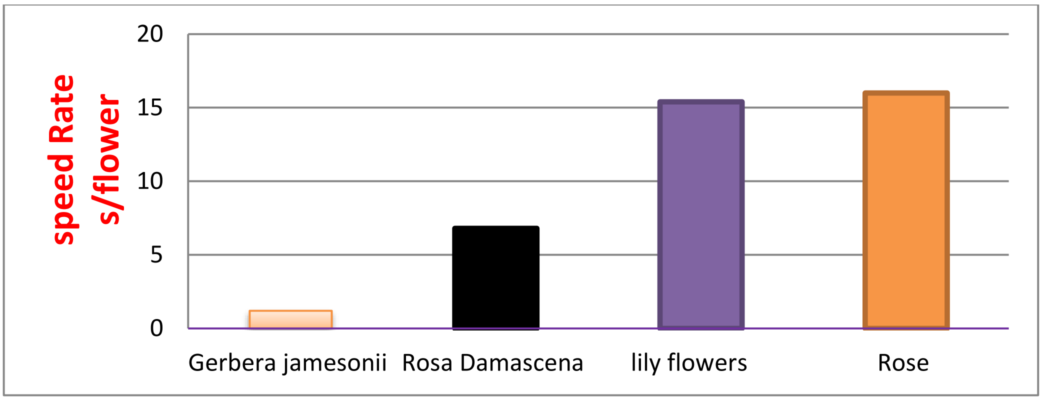
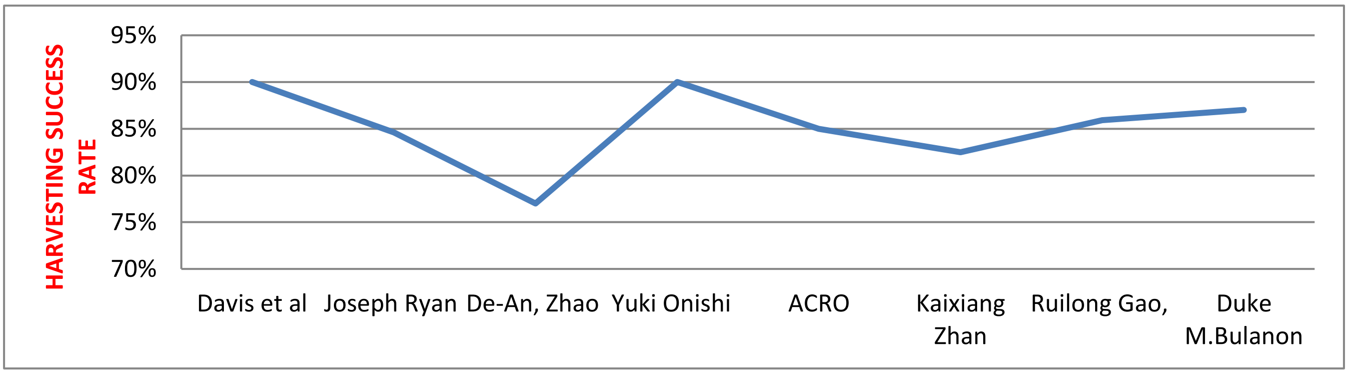


Figure 44 explain the relationship between the speed rate for each researcher harvesting flowers Robots

Table 3: Different Types Of fruit and Vegetable Picking Robots

Total Arm 6DOF	MANIPULATOR ARM	SPEED RATE	Harvesting Rate (%)	Reference
		Orange		
6DOF	ARC Mate manipulator	4.5 s per orange,	90.8% .	[72]
		kiwifruit		
6DOF	UR5, Universal	6.5 seconds	88.7%	[73]
		olive fruit		
6DOF	Custom manipulator	23.seconds	60%.	[74]
		Cucumber		
7-DOF	MitsubishiRVE2	45 seconds	80%	[75]
		citrus		
4DOF		15 seconds	90%	[76]
		Vegetables		
6 DOF	Fanuc LR Mate 200iD	2.5 seconds	…………………..	[77]
		lettuce		
6DOF	UR10	31.7 seconds	91%	[78]
3 DOF		5 seconds	94.12%	[79]
		sweet pepper		
6-DOF	Fanuc LR Mate 200iD	24 seconds	61%	.[80]
5 DoF		7 seconds	69%	[81]
4DoF	Custom manipulator	……………………….	86%	[84]
		Wolfberry		
5 DoF	Custom manipulator		…………….	[82]
		Sugar Pea		
5 DoF	Trossen	10 seconds	………..	[83]
		strawberry		
5DOF	Mitsubishi	10.6seconds	96.8%.	[58]

	dual-arm manipulator	4.6 seconds	97.1%,	[59]
4DOF	articulated mechanical arm	…………….	75%,	[62]
6DOF	Denso VS-6556G	31.3 seconds	86%	[63]
6DOF	cylindrical manipulator	11.5 seconds	41.3%	[7]
Multi DOF	Harvest CROOROBOT	10 seconds	……..	[61]
TAMATO				
3 DOF	Custom manipulator	7 seconds.	…………	[65]
6 DOF	Custom manipulator	21 seconds	78.67%	[66]
5 DOF	Mitsubishi	35.96 seconds	89.63 %	[67]
4DOF	Custom manipulator	10.586 s	……………..	[68]
4 DOF	Custom manipulator	20.06 seconds	92.45%.	[69]
continuum robot	TakoBot (Tako in Japanese means octopus, Bot comes from the robot)	56 seconds	80%.	[70]
6-DOF	manipulator (UR3)	5.9 seconds	80%.	[71]
APPLE				
5DOF	Articulated, PRRRP	15.4 seconds per apple	77%	[41]
6DOF	UR3 UNIVERSAL ROBOTS	16 seconds per apple.	90%	[43]
3DOF	Custom manipulator	8 .8seconds per apple	82.47%	[42]
6DOF	JAKA	12 seconds per apple	85.93%	[44]
6DOF	Kinova robotic	12 seconds per apple	87%.	[45]
6DOF	Robotics Inc., Irvine, CA	6. 8 seconds per apple	84.6%	[40]
Multi DOF	Custom manipulator made in Abundant Robotics	1.2 seconds	90%	[37]
7DOF	Custom manipulator made in (ACRO) Institute	8 seconds per apple	85%	[39]
5DOF	XARM 5Lite	12.53 seconds per apple	82.93%	[47]
5DOF	Custom manipulator	7.3seconds per apple	67%,	[48]



Figur45:explain the relationship between the success rates for each researcher harvesting apple Robots

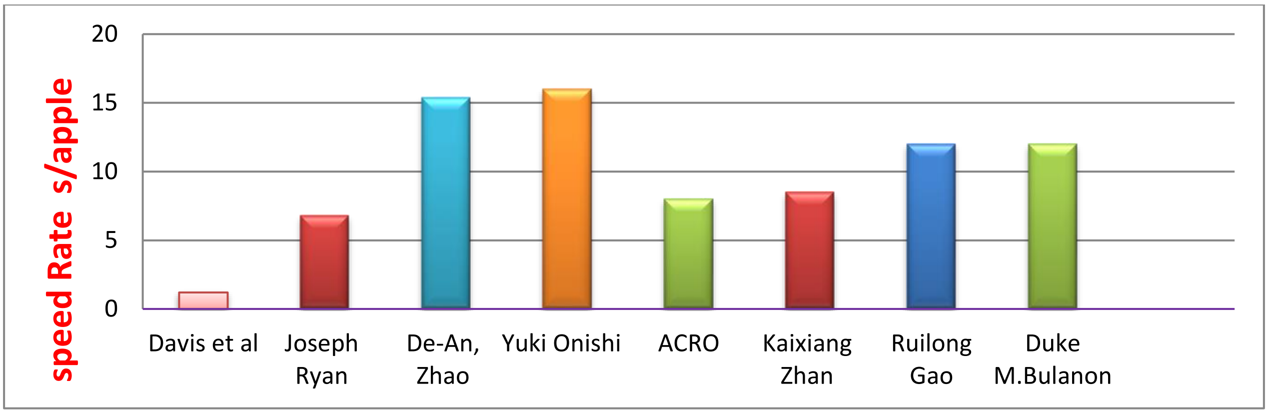


Figure 46 the relationship between the rate of apple picking speed for each researcher

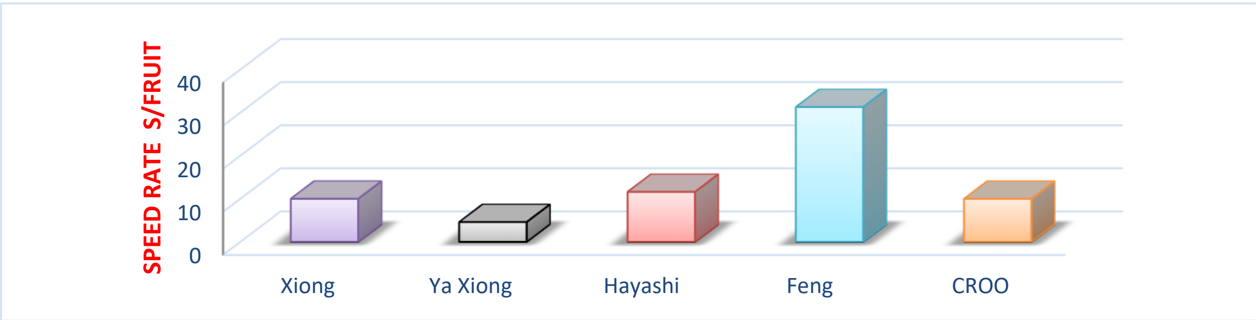


Figure 47, the relationship between the rate of strawberry picking speed for each researcher

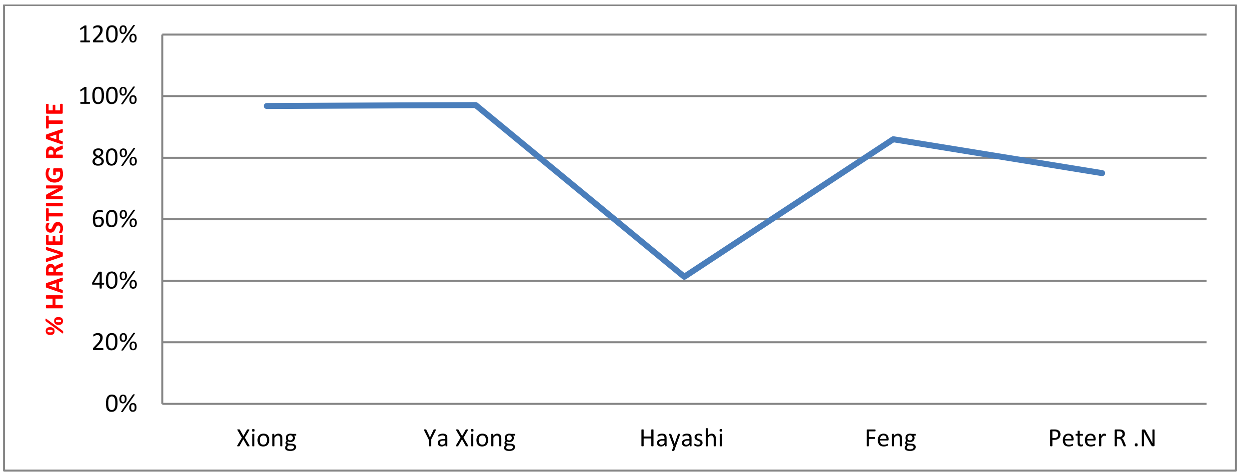


Figure48 the relationship between success rates of strawberry picking for each researcher

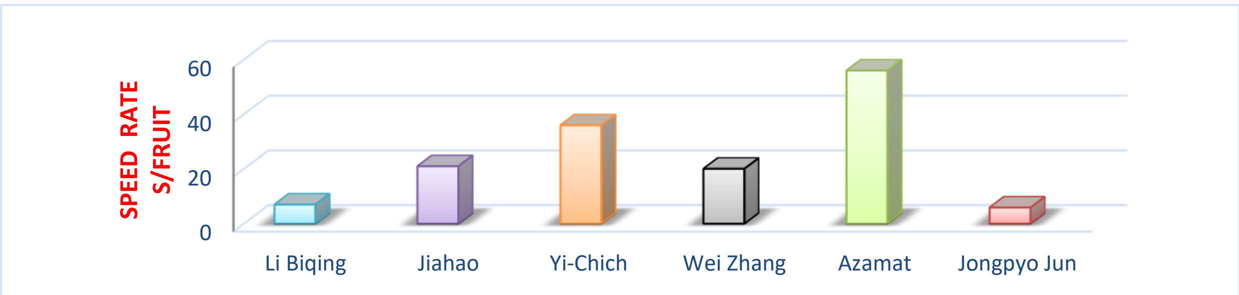


Figure 49, the relationship between the rate of Tomato picking speed for each researcher

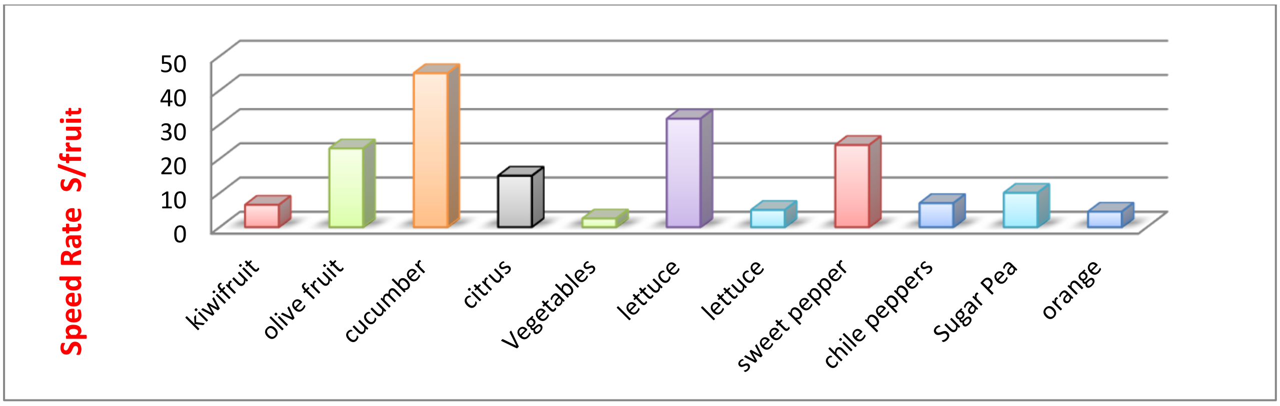


Figure 50: the relationship between the rate of others fruit picking speed for each researcher

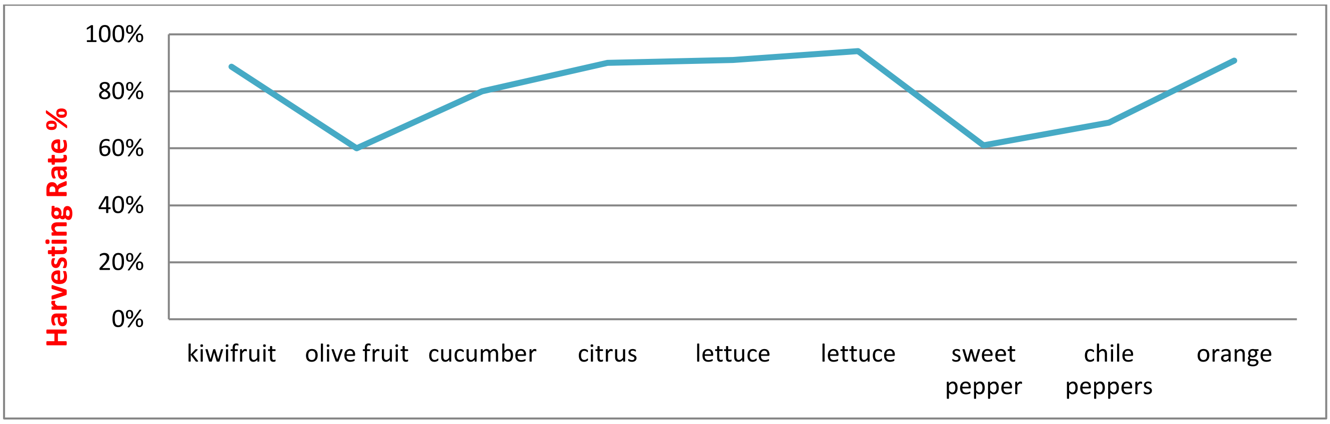


Figure 51, Results of fruit and vegetable robot picking rate

End Effectors in Agricultural Robotic Harvesting Systems

An end effector is a peripheral device attached to a robot's wrist, enabling interaction during a task. For harvesting robots, the end effector is considered the contact point between the robot and the fruit to be harvested. If not designed effectively, an end effector could damage the crop and deteriorate the overall performance of the harvesting system. Figure52 illustrates four end-effector types, which can be combined for fruit detachment in a harvesting system. These end-effectors can combine grasping, rotation, suction, cutting, and other techniques.

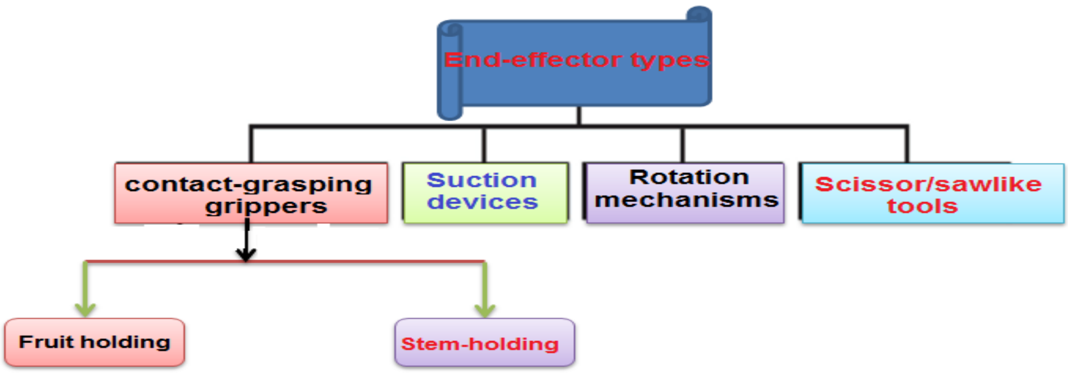


Figure52 depicts the four end-effector types studied in this paper.

this section article discussed robotic end effectors for harvesting crops like apples, tomatoes, sweet peppers, and cucumbers, focusing on fruit detachment requirements, end effector types, and sensory control techniques. Monkman et al. [86]introduced a classification of grippers into four groups: impassive, ingressive, astrictive, and contigutive. They are also classified by actuation control, magnetic, vacuum, hydraulic, pneumatic, and electric. Robotic grippers are categorized by finger count, with the right actuator selection based on the application and working environment conditions. Several end-effector configurations have been designed and employed for autonomous harvesting robotic applications. According to the reference's literature in the previous sections, multiple harvesting end effectors have been successfully built, applied, and evaluated under actual conditions,

usually on a limited scale. The present study analyses 30 robotic harvesting applications on 14 different fruit and vegetable
.

End Effector		DETACHMENT METHOD				Evaluation		
				strawberry				
Type	**Technique**	**Cut**	**Rotate**	**Grasp**	**Vacuum**	**Accuracy**	**Actuation**	**Ref.**
6 Fingers gripper/cut	Scissor type blade motion	✓	……	✓	………….	98.5 %	Electrical	63
2 Fingers gripper/cut	Thermal cutting	✓	………	✓	…………..	………….	pneumatic	[63]
Cutting with parallel blades	suction device	✓		✓	………….	…………..	pneumatic	[7]
3clamp griper	Mechanical clamp griper	✓	………	…	………..	Up to 90.7%	Electrical	[59]
				Rose flowers				
knife	Scissor type blade motion	✓	………..	✓	………..	80 %	pneumatic	[52]
hold a knife	Scissor type blade motion	✓		✓	…………….	87.79 %	Electrical servomotor	[56]
curved shape Clipper	Clipper with rubber appendages for holding flowers after picking	✓	………	✓	…………….	……………….	Electrical DC Motor	[54]
claw head gripper.	Claw, blade, step motor, asynchronous pulley, driven pulley move end picker to target flower.	✓		✓	……….		Electrical step motor	[55]
				apple				
3 Fingers gripper/cut	end effector or arm spin/ deflection (without blades)		✓	✓	……..	………..	Electrical	[40]
spoon-shaped	Rotary/spinning blade motion	…..	…..	………	✓	86%	pneumatic	[41]
4 Fingers gripper	Mechanical fingers		✓	✓	………	60%	Electrical	[43]
tube is covered with a soft silicone vacuum cup	Suction	……	………	………….	✓	97%	a hybrid pneumatic	[42]
three-finger gripper	gripper with a rubber layer inside the gripper that protects the fruit		✓	✓		85.93%	Electrical	[44]
two-finger gripper	Mechanical fingers	………	✓	✓	………….	87%	Electrical	[45]
A flexible three-fingered end-effector	Mechanical fingers	………		✓		82.93%	Electrical	[47]
Three finger gripper	Mechanical fingers	………	……….	✓	…………..	67%,	pneumatic	[48]
				TOMATO				

2-finger gripper		✓	………	….	……….		pneumatic	[65]
3-finger gripper	flexible finger was composed of a dual-axis steering gears		✓	✓		92.8%,	Electrical	[66]
four fingers	finger sis mounted with foam-like soft coating material	………	✓	✓	………….	…………..	Electrical	[67]
scissors,		✓	……		………….	……….	Electrical	[68]
4 fingers	custom end effector		✓	✓		92.45%,	Electrical	[69]
semi-spherical shape with cuter	semi-spherical shape for grasping	✓		✓		90%		[70]
blade is used to harvest the fruit.	Scissor type blade motion	✓	……	…	………….	…………	Electrical(servo motor)	[71]
orange								
four-finger	Mechanical fingers	……..	✓	✓		90.8%	pneumatic gripper	[72]
kiwifruit								
two lightweight grippers	The grasping-detection network GG-CNN2 was used to predict the grasping angle of the gripper.	✓	……	✓	…………	76.0%	Electrical	[73]
olive fruit								
8 fingers known as jaws	Mechanical Gripper	✓	….	….	✓	………	Electrical	[74]
cucumber								
Laser cut	thermal cutting	✓		✓	……………	………	Electrical - heated wire	[75]
Sugar pea pods								
two I fingers grippers		✓	-----	✓	---------	……	Electrical	[83]
citrus								
scissors, a clamping device and an electric pusher	Scissor type blade motion	✓	…..	✓	……….	…..	Electrical	[76]
lettuce								
hand with knife	custom end effector	✓	……	✓	………..	……………	two pneumatic actuators,	[78]
								[79]
sweet pepper								
Stem fix devices/cutter		✓	….	…	…..	Up 61%	Electrical	[80]
knife	Scissor type blade motion with gear	✓	…	✓	………….	……….	Electrical	[81]
two I fingers grippers	custom end effector	✓				86%	Electrical	[84]

Number Harvesting robot for vegetable and fruit

According to previous research literature relevant it is obvious Various robotic harvesting applications for different types of crops have been successfully designed, controlled used, and evaluated in real-world situations.

In this work, 40 robotic picking applications on 14 different types of fruit are studied from 2013 to 2023, The distribution of the previous literature on fruit type is depicted in Figure 52A

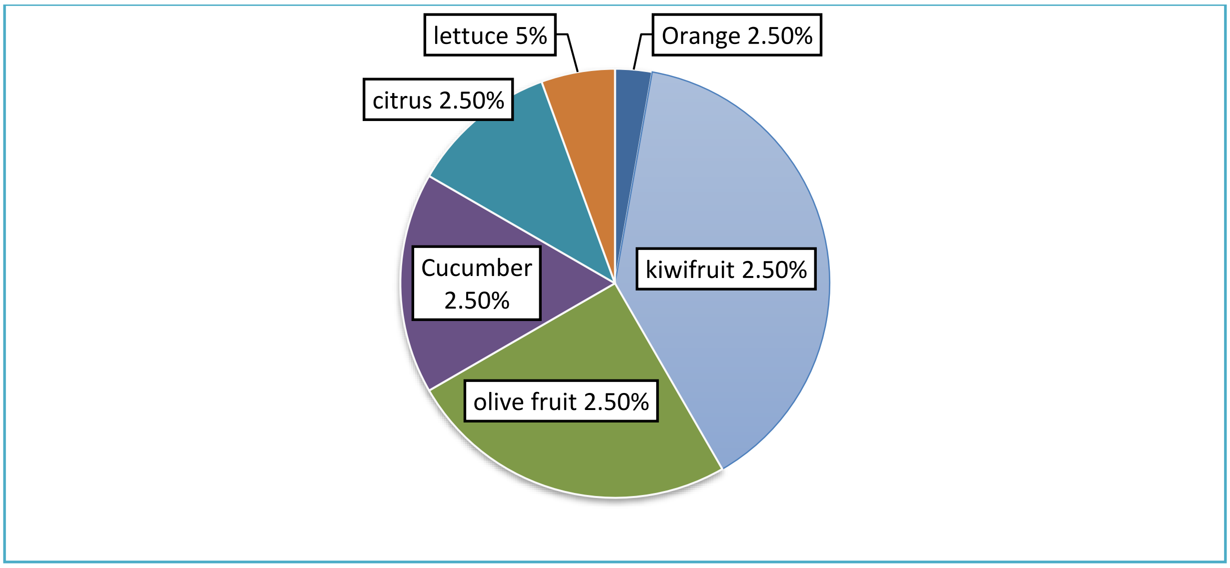


Figure 52A The distribution of the previous literature on type fruit

Most robotic picking applications focus on apples (25%), followed by tomatoes (17.5%) and strawberry (15%), which are high-demand agricultural products around the world This can be ascribed to the fact that all three fruits are strong, don't vary greatly in size and weight, are generally hard so they can withstand mechanical manipulation without suffering damage, and grow well in all nations

Actuation and sensing of picking robot and End-Effectors

Of the 40 papers previously reviewed, five did not report the kind of actuators that were employed in the manipulator (we could not determine the kinds of actuators from the image in the papers). Twenty-seven of the forty technologies used commercially available robotic manipulators with electric actuators .Five technologies developed their own manipulators and employed pneumatic actuators Two technologies used a combination of pneumatic and electric actuators .The remaining one technologies developed their own hybrid pneumatic actuators .Figure 3 depicts a summary of manipulator actuators in 40 robot Many of the technologies did not explain the reasoning chose that the manipulator actuators The majority of technologies (68%) that created their own manipulators relied solely on electric actuators. Electric servomotors and stepper motors are generally advantageous for harvesting activities where the weight of the manipulator structure and agricultural payload is expected to be low since they are reasonably easy to control and give fast response times. Also, the number of actuators employed in the end-effector models ranged from one to five actuators in their designs The majority of the actuators were either pneumatic (20%) or electric (63%)– only one hybrid pneumatic (2.5%) actuator was employed in the manufacture of the end-effector. (figure) Also, it is important to highlight that the source for the compressed gas (tanks, compressors, etc.) was not located on the robot and end-effector

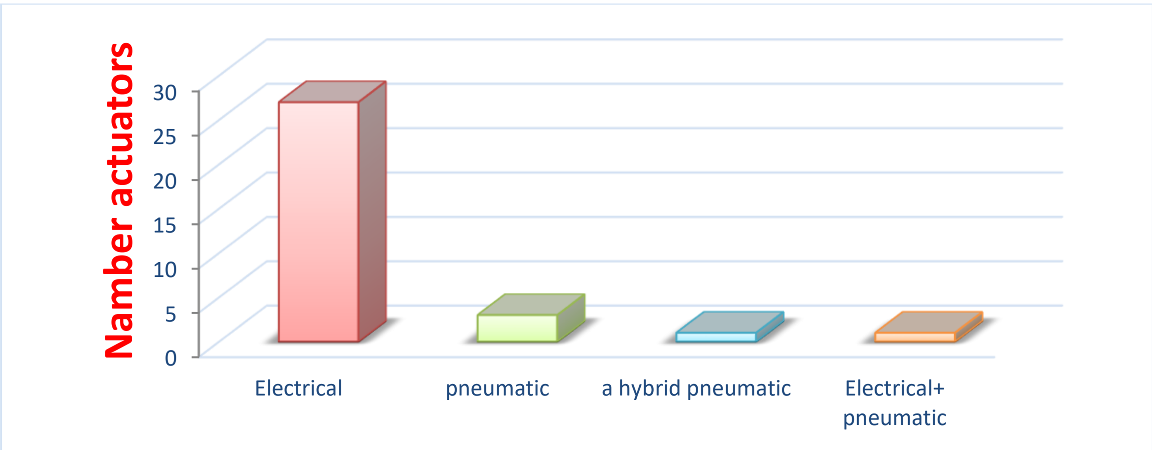


Figure 52 C Kinds end manipulators actuators employed in reviewed papers

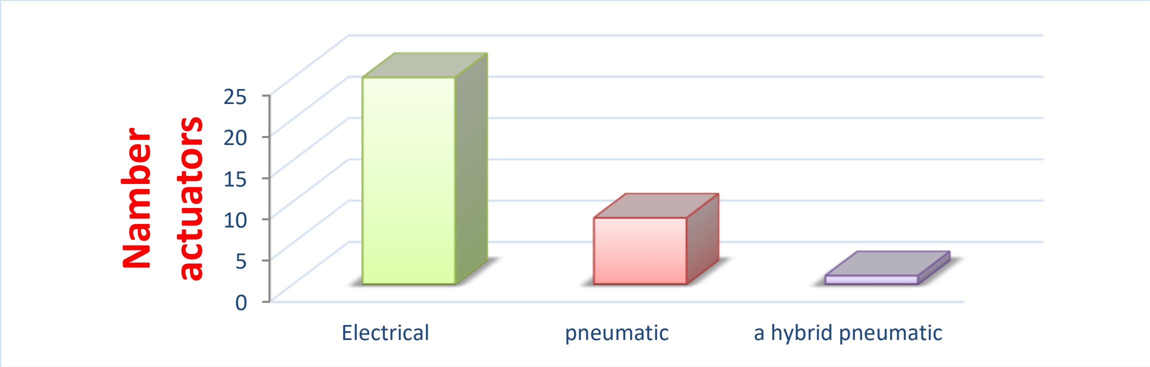


Figure 52D Kind’s end effectors actuators employed in reviewed papers

Detachment methods play a significant role in the end effectors s of the fruit-picking process Detachment techniques involve, grabbing vacuuming, rotating, and cutting. Different detachment strategies have been used, either alone or in combination. Figure 50 all combinations in the previous literature are presented. five combinations are reported: (1) cut, (2) cut-grasp, (3) vacuum, (4) rotate -grasp (5) cut-vacuum and (7) Figure 50 shows that the most typical way of detachment is a mix of grabbing and cutting. Grasping and cutting can protect both the harvested fruit and the crop from damage caused by excessive pulling.

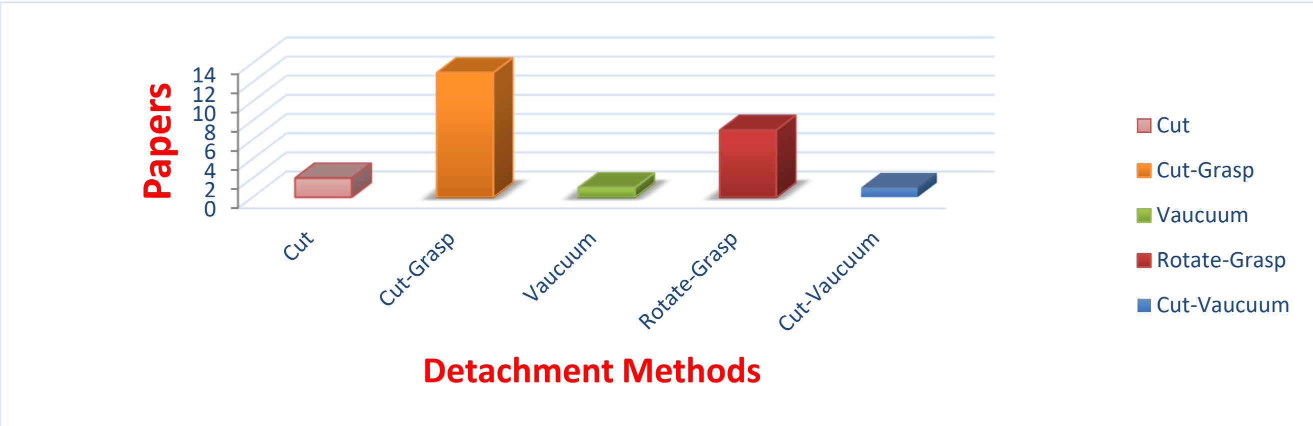


Figure 52F, shows the distribution of research papers in the referred literature according to detachment method

VISION BASED ROBOT CONTROL AND DEEP LEARNING MOTHED FOR HARVESTING

Visual servo systems, commonly referred to as vision-based robot control, has been known from the early 1980s, however the phrase "visual servo" was not first used until 1987[87] .Visual servo control is a method of controlling the movement of a robot using feedback from a vision sensor. As seen in Figure 52b

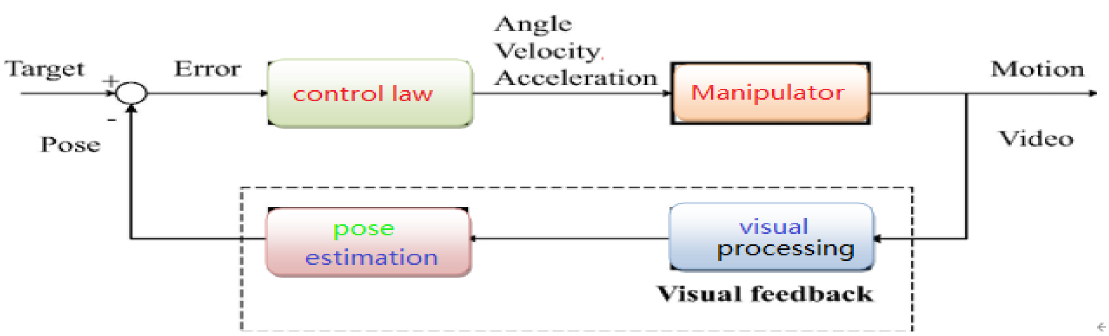


Figure 52G structure of visual servo [88]

Currently, stereo vision systems mostly use two types. The first is an optical geometry-based binocular vision system. Traditional optical concepts and optimization algorithms are used to determine the target's 3D position. The second is an RGB-D camera depend on the time-of-flight (ToF) approach, that employs an infrared sensor to determine the target's depth. The stereo-vision system, based on optical geometry, utilizes multiple cameras positioned at a predetermined distance. Prior to detecting the target, the cameras undergo calibration and capture multiple images of the same object. Through image processing and classification, the system identifies the target object. The 3D representation of the target is then reconstructed by establishing a relationship between its spatial coordinates and those of the robot, enabling the extraction of physical parameters necessary for target identification and localization[89],[90] Binocular stereo vision has been used in agricultural harvesting robots for the identification of various crops such as apples, sweet peppers, and tomatoes. The use of this technology allows for accurate height measurements of the crops, which can be used for detection and localization purposes. Additionally, the depth measurement capabilities of binocular stereo vision have been utilized to develop an illuminance measurement method for intelligent lighting in agricultural environments.

Stereo cameras were used in each arm of an orange picking robot by Plebe and Grasso [91] . They performed stereo matching of the oranges' centre-of-mass to locate oranges in a 3D coordinate system .Si et al[92]used a stereo camera to detect and locate mature apples under a canopy, with accuracy of 89.5% and accuracy of less than 20 mm when measuring between 400 and 1,500 mm. Despite its ease of use and success in straightforward test cases, it is still one of the most popular control methodologies in the literature. Yuanshen Zhao et al[89]presented a review of open-loop visual control techniques vision schemes for harvesting robots Initial techniques relied on accurate machine vision to increase the probability of reaching the target fruit. For example, Inoue et al[93]used several visual sensors, Hayashi et al., [7]adopted a three-camera system, with the center camera calculating inclination and the other two performing stereo vision, and Han et al[94].included the use of a laser device to improve accuracy Makky et a[95]proposed a stereoscopic 3D vision sensing system for a palm oil-collecting robot project. The team obtained two stereo images using a mobile digital camera and used image processing algorithms for target recognition, thereby detecting palm fruit-based on image color analysis and fruit maturity-based features. The method can calculate the distance, size, and tangential position of the palm fruit. For red fruit dense images and yellow-green apple images, the fruit recognition rate was between 65 and 70%, with a ranging error of ~±5%

Different methods have been presented for fruit detection and localization utilizing visual sensing. From traditional morphological techniques to cutting-edge Convolutional Neural Networks (CNNs), these are available. Morphology, color-based, thresholding and geometrical approaches are examples of traditional methodologies. Modern outcomes have been attained in recent years using Deep Learning (DL)-based methods. Deep learning methods based on the artificial neural network have become increasingly popular in recent years. With multiple-layer perceptron, deep learning methods can form more high-level attribute features. A convolution neural network (CNN) is a supervised deep learning method that involves convolution and back-propagation to extract features of the targets, which greatly improves the accuracy and generalization of the recognition algorithm[96]Fruit recognition can be done using depth images captured by an RGB-D camera. While Convolutional Neural Networks (CNNs) are effective in image-specific tasks like classification, they may not perform well in pixel-wise image understanding, which requires semantic segmentation. Regional CNNs, on the other hand, have shown to be more successful in this regard. For fruit detection and localization Sa et al[97]presented Fruit Detection System Using Deep Neural Networks They utilized bounding box detection through the fusion of Faster R-CNN, RGB, and Infrared (IR) images. Faster RCNN is an optimized version of RCNNs that enables real-time segmentation Gene-Mola et .al[36]used Kinect v2 depth images to recognize apples using Faster R-CNN with Visual Geometry Group (VGG) 16, with an average precision of 0.613. This is because the depth images are more sensitive to the ambient conditions compared with the RGB images. To overcome the degradation of the depth image Liu et a[98]applied Mask RCNN and YOLOv3 for bounding box detection in citrus fruit harvesting. Mask RCNN relied on ResNet-52 and ResNet-150 as the backbone, and ResNet-150 provided the best performance.Liu.et al. [99]presented a novel method to apply the RGB-D sensors and fused aligned RGB and near-infrared (NIR) images a taken from Kinect v2 applied faster-RCNN with VGG16 to detect kiwifruits, and an F1-score of 0.884 was obtained. Yu et al[100]applied the Mask-RCNN to determine the strawberry shapes and then applied GA to localize the picking point Mask RCNN combined with the logical green operator was employed by Liu et al[101]to enhance cucumber detection's overall performance. A combination of HSV and RGB images were used by Ganesh et al. Ganesh et al [102]to enhance the overall performance of Mask RCNN for orange detection. In a recent study, Tafuro et al.,[103]applied the Detection 2 a Mask-RCNN architecture to detect/estimate strawberry picking point, ripe-ness, and weight and provided two fresh datasets for strawberry picking. Similarly, Bargoti et al [104]applied faster-RCNN on yield estimation of apples, mango and almonds, a F1-score of 0.9 .

Motion planning for selective picking agriculture

Motion planning is to insert a sequence of intermediate points for control between the given path endpoints to achieve smooth movement along the given path endpoints. Motion planning consists of path planning (space) and trajectory planning (time),[105] as shown in Figure 53,

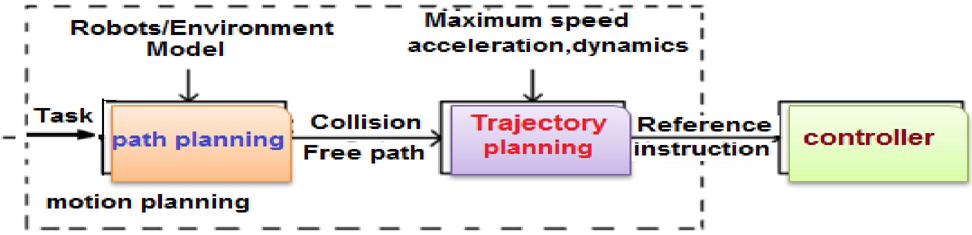
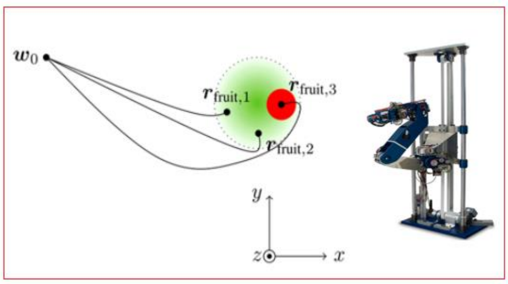


Figure 53, Motion Planning, Path Planning and Trajectory Planning

Motion Planning is a crucial field in intelligent robot research, and the selection of an optimal path planning method is vital for efficiently determining a viable route from an initial configuration to a desired configuration. This greatly enhances the overall performance of robots [106]. In order to successfully complete the task of fruit picking, automatic obstacle avoidance path planning of the harvesting manipulator is one of the key technical issues of fruit harvesting robots. However, the success of a robotic fruit picker is heavily dependent on the reliability and speed of its motion planner. [107].In the past few years, Many methods have been developed of motion planning algorithms are categorized into two main classes: classical techniques and heuristic techniques). Classical techniques primarily include Dijkstra, A*, and Artificial Potential Field(APF) In the t heuristic techniques use Probabilistic Road Map (PRM), Fuzzy logic, Rapidly exploring Random Trees (RRT),and improved Rapidly exploring Random Trees (RRT*). Furthermore, meta-heuristic algorithms like Genetic Algorithm (GA), Ant Colony Optimization (ACO) algorithm, Particle Swarm Optimization (PSO), Neural network, Neuro-fuzzy in fruit harvesting robots, path planning has mostly been done by classical and heuristic methods in reality, the success rate of robot is not the true test of success of the path planning algorithm. The success rate of the robot depends on many factors. The fruit detection model, kinematic model, path planning algorithms and grasping technique are some of the major factors attributed to the success of the fruit harvesting robot. The success of path planning algorithms depends on its ability to detect a path, ability to avoid collision, ability to give an optimized path, the path detection time as well as the computational time. In recent years, Research and development in harvesting robots has focused on economically viable crops, but open field robots require smarter solutions. Schuetz et al. [108]developed an optimal control strategy for generating a trajectory for a 9-DoF redundant fruit-picking manipulator CROPS manipulator for sweet pepper harvesting while reducing collision and dynamical costs Figure54 .Lufeng luo et al. [109]developed for collision-free path planning in grape harvesting with a6-DoF robot based on artificial potential field approach combined with energy optimization The potential field method generated a path that avoided obstacles while guiding the harvesting point towards the grape clusters Figure55 also for picking grape Jin et al.[110] proposed a far-near combined technique for picking-point positioning which included first recognizing and generally finding the grape clusters in a distant view and then guiding the robot to a near-view point to correctly position the peduncle. These approaches show that intelligent motion planning methodologies can overcome the constraints of selective picking, resulting in efficient and precise picking performance. ZuoliangTang et al. [111]developed Collision-Free Motion Planning for intelligent citrus-picking robots used novel improved APF algorithm. and ETS. ETS method. The ETS method is used to model the kinematics of the EC63M manipulator, and the Jacobian matrix of each point on the manipulator relative to the base coordinate frame can be obtained easily by this model. The improved and original algorithms were both used to carry out the motion of the EC63M manipulator mounted on the intelligent citrus-picking robot Compared with the original method, the improved one reduced the operation time by 54.89% and the total joint error by 45.41% **Figure56**



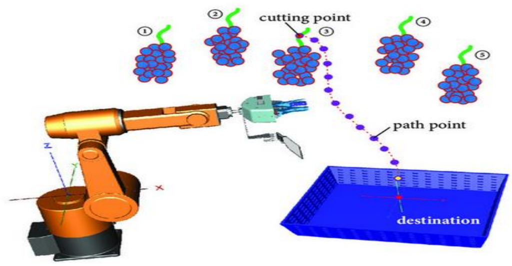


Figure 54 Strategies for fruit harvesting in distributed environments using a heuristic method. for initialising an optimal problem (sweet-pepper)[106] Figure55 The proposed path-planning method luo et al. [98]

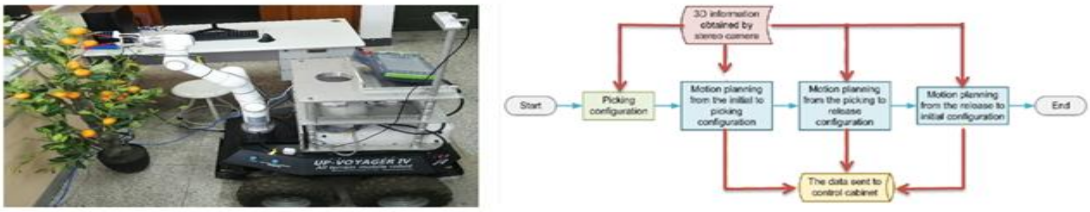


Figure 56. Flow diagram of motion planning for the picking manipulator[111]

Recent research by Xiong et al. [59]propose active obstacle-separation path planning strategies to pick fruits in clusters, using a cup-shaped end effector with opening blades to push away surrounding fruits and swallow a target fruit. They calculate the entry direction of the end effector into the cluster. move the head straight towards the center of the target while actuating the fingers, and inducing pushing actions on the surrounding obstacles before reaching the target. However, the bulky picking end effector damages the fruits using this heuristic motion planning. (Figure58) In the same vein Yamamoto et al[112]developed an air-blowing mechanism to separate the target from its neighboring fruits, which relies on two nozzles: vertical and horizontal. as seen in Figure57

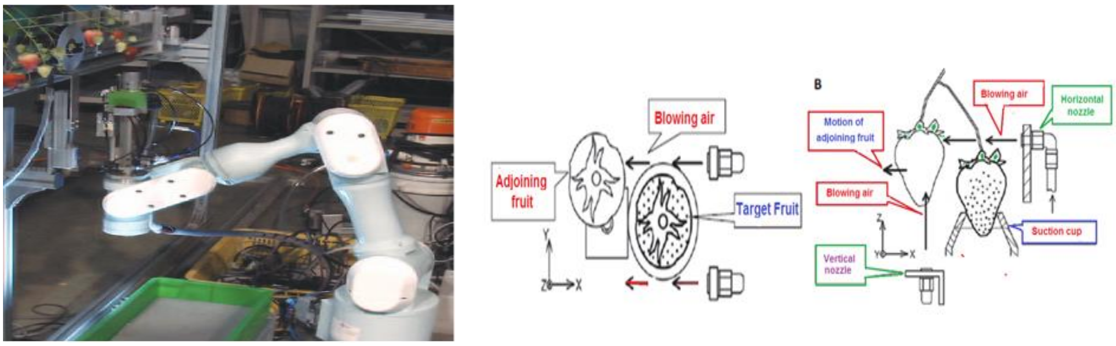


Figure57Separation of adjoining fruit by blowing airA) top view, B) side view [112]

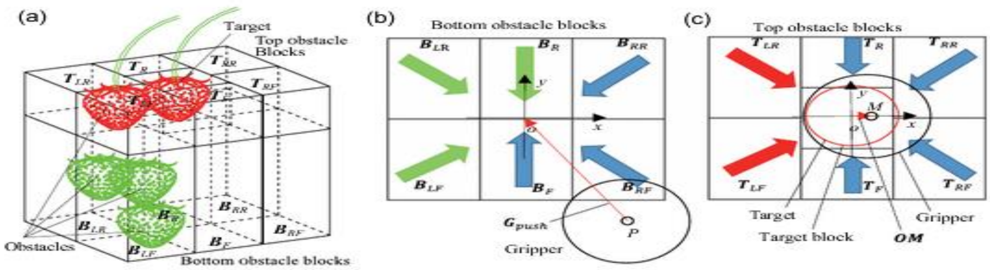


Figure58 shows gripper finger actuation pushing bottom obstacles along a straight line, using a active obstacle-separation algorithm.[59]

Robotic fruit picking requires a collision-free motion of the manipulator and end-effector, Bac et al[113]addressed the problem of collision-free motion planning for a 9-DoFs sweet pepper harvesting robot using bi-directional rapidly exploring random trees (bi-RRT) with a success rate of 63% .This approach is less affected by the number of degrees of freedom compared to other planners like CHOMP. After generating the path, a path-smoothing algorithm is applied due to the tortuous nature of sampling-based techniques. The authors place particular emphasis on selecting the azimuth angle of the end effector, where the optimal pose minimizes the difference between the fruit azimuth angle (with respect to the stem, in the horizontal plane) and the end effector azimuth angle (with respect to the fruit, in the horizontal plane) for picking strawberries, Figure59

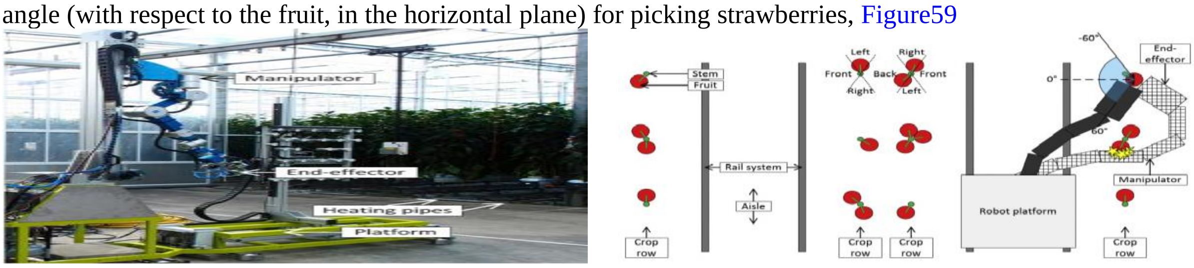
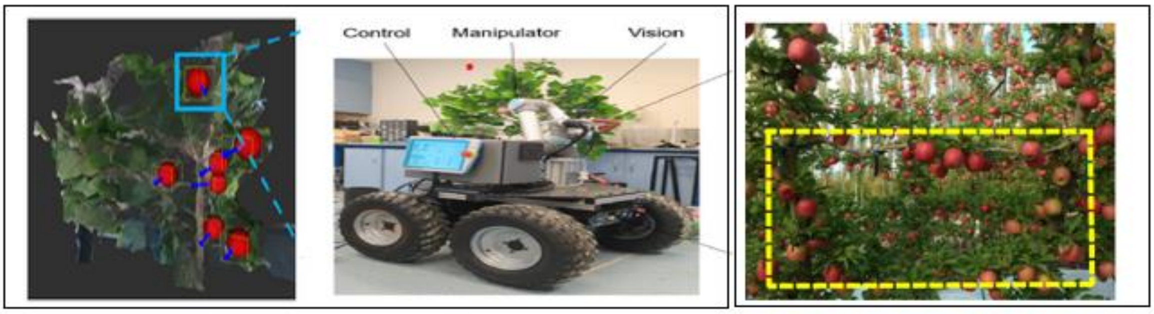


Figure59Sampling-based (bi-directional RRT) with desired end effector azimuth angle.[113]

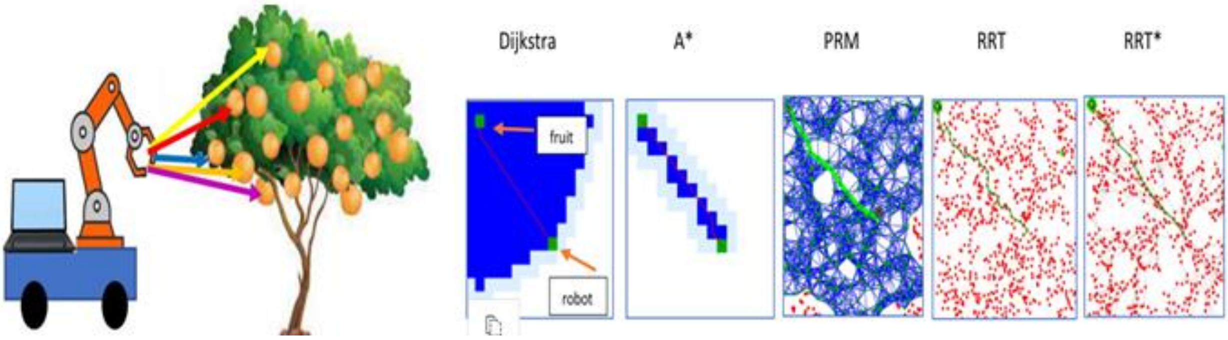
Xiaoman Cao et al. [107]proposed an improved RRT for litchi-picking robots which first uses target gravity to improve the exploration efficiency, then uses a genetic algorithm and heuristic smoothing algorithm to optimize the RRT path. These methods can be used to plan collision-free paths, but they are somewhat inefficient computationally. In certain situations, obstacles are not avoidable (e.g., strawberries in clusters). Figur60

Figur60 Xiaoman Cao et al .an obstacle avoidance experiment with the litchi-picking manipulator.[107]
Sariah Mghames et al. [114]proposed an Interactive Movement Primitives framework for fast-planning simple quasi-static pushing movements. The proposed motion planning is easily generalizable to other fruit and cluster configurations. This method generates systematic pushing actions based on the orientation of single-occluding objects (including unripe fruits and stems). This was the first attempt to construct interactive motion planning, which is required for fruit picking. An optimized version of this strategy enables the robot to find a way to avoid non-pushable obstacles. Shaym et al[115].proposed a probabilistic primitive-based optimization technique to generate smooth and fast trajectories for motion planning for harvesting tomatoes, while Zhong et al. [116].proposed a fruit grasp planning for litchi picking based on YOLACT. Apples present less issues for motion planning due to their less crowded fruits .According to Joseph R. et al [40]the region between the trellis wires in apple harvesting is deemed collision-free, posing fewer obstacles for motion planning. This makes it easier for a target in this region to be reached by an under-actuated end effector. Figur61b Wang et al].[117] propose an end-to-end network architecture-based RGB-D data for grasping an occluded target, and a modified PointNet is used for geometry aware grasping estimation. Experimental results show that the developed vision method can perform highly efficient and accurate to guide robotic harvesting. Overall, the developed robotic harvesting system achieves 0.8 Figur61a



Figur61a Robotics harvesting system and Grasping estimation of apples [117] Figur61b The region between the trellis wires is relatively free of obstacles

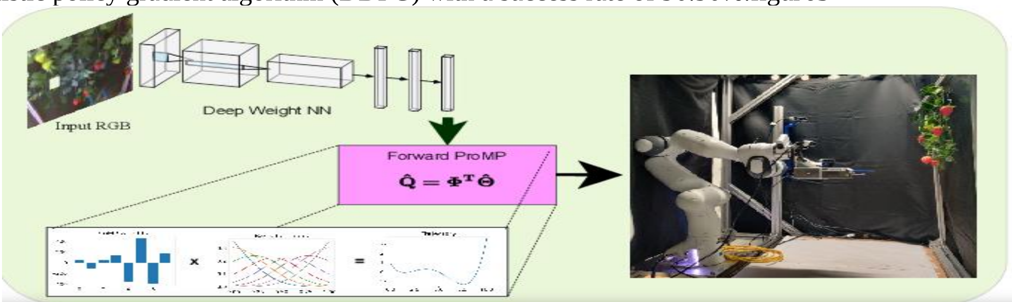
In a similar vein. Van Henten et al.[118]A method for picking cucumber was developed that uses A*(a shortest-path finding algorithm from a specified source to a specified target) algorithm to explore the configuration space for a path and checks the feasibility of each point on the path by a collision detector. A* is deployed in a six-dimensional space discretized into a large number of grid points, however, so the computation is extremely slow. Successful fruit detection and path planning for a fruit harvesting robot result in a higher success rate for fruit picking. Wang et al[119].developed Litchi picking using RRT algorithm and detection using YOLO5 with a success rate of 88.46% Additionally, Lehnert et al[120]using the RRT* algorithm for path planning and a neural network for fruit detection during the harvest of sweet pepper increased success rates by 18.5%.Similarly, Yoshida et al a[121]developed apple picking was done using RRT algorithm and detection using SSD with a Accuracy of more than 95% .showed that path planning to harvesting target can be performed relatively quickly in less than 0.5 s Similarly, Sadaf Zeeshan et al.[122] studied path planning for Fruit picking was done using four algorithm A*, PRM, RRT, and RRT* It was found that improved RRT* performed better in terms of path length and gave an optimal path as compared to the other algorithms due to its rewiring feature by an average of 21%. Run time of Rapidly exploring Random Tree was better than the other three algorithms Figur62. Similarly, Chen, Y et al[123]developed an improved RRT-Connect algorithm for obstacle avoidance in fruit tree pruning manipulators. The algorithm simplifies the manipulator and obstacles, allowing collision detection models to consider obstacles, and the manipulator. The algorithm reduces path planning time and length by 55% and 60%, with a 100% success rate. average path time 20.6 s, Qin, Z., et al. [124]developed a Cauchy target gravitational bidirectional (CTB-RRT*)algorithm, for tomato harvesting manipulators utilizing heuristic sampling and dynamically adjusted step lengths to improve local search speed. Simulation experiments showed a 5.5% reduction in path cost, 71.8% reduction in search time, and 64.2% reduction in sampling nodes compared to the RRT*-connect algorithm. The algorithm achieved a 99% success rate and 0.33s running time



Figu62Comparison of performance of path planning algorithms for varying distance in path within workplace. Green lines represent the path formed in PRM, RRT and RRT*, whereas red line represents path formed in A

Learning from demonstration (LfD) is a useful technique for robot harvesting, allowing the robot to learn how to properly pick fruits without prior knowledge. (LfD) is another popular approach for planning the picking actions in robot harvesting. For instance, Tafuro et al. [125].suggested method called Deep Probabilistic Motion Planning (d-PMP) (which is based on Deep Movement Primitives (d-MP).Sanni et al [126].Using an auto encoder and fully connected layers, d-PMP maps visual sensory readings to the weight of robot movements. d-MP extends the deterministic nature of d-MP and enables a robot to generate a distribution of possible trajectories for tasks such as picking strawberries.

Deep reinforcement learning (DRL) has recently been explored by researchers to enable dextrous manipulators to fulfill certain tasks. Mnihet al. [127].for example, combined deep learning and reinforcement learning to create a deep Q-learning algorithm (DQN) .DRL uses a neural network to predict actions, making it more efficient than traditional collision-free path-planning algorithms. in of Harvesting guavas Guichao lin a.al [128]presented a deep reinforcement learning based collision free path planning method using recurrent neural network and deep deterministic policy gradient algorithm (DDPG) with a success rate of 90.90%.figur63



Figur63shows how the visual sensory data is converted into robot motions using Deep-MPs.

Motion planning algorithms have been tested for generating an optimal reduced path, a smooth path avoiding obstacles, and algorithm that generates a path with minimum run time. All these parameters play a significant role in choosing the path planning algorithm for a fruit-harvesting robot. A list of some recent path planning algorithms used for picking fruits by robots is summarized in Table 6

Table 6 summarizes motion planning techniques for robotic picking fruit that have been developed over the literature.

Fruit	**Structure**	**DoFs**	**Technique for Motion Planning**	**Reference**
	Serial	7	Air blowing	[112]

Strawberries	Serial	3	Cluster entrance angle Cluster entrance angle calculation with active fingers	[59]
	Serial	7	Probabilistic	[125]
	Serial	7	Covariant Hamiltonian Optimization for Motion Planning (CHOMP)	[104]
	SCARA arm	3	Interactive Movement Primitives (IMP)	[114]
Grape	Serial	6	Minimum Energy + Artificial Potential Field	[109]
	Serial	6	Random Tree RRT algorithm	[110]
Apple	Serial	6	Trapezoidal velocity profiles	[40]
	UR5	6	RRT algorithm and detection using SSD	[121]
Tomato	Serial	7	Covariant Hamiltonian Optimization for Motion Planning (CHOMP)	[86]
	AUBO i3	6	(CTB-RRT*) algorithm	[124]
Sweet Pepper	Serial	9	Bi-RRT	[113]
	Serial	9	iterated linear quadratic Gaussian (iLQG)	[77]
	UR5 (universal Robots)	6	RRT* algorithm for path planning and a neural network	[103]
guavas	Serial	6	deep deterministic policy gradient algorithm (DDPG).	[128]
litchi	Serial	6	Random Tree RRT algorithm +genetic algorithm	[107]
	Serial	6	RRT algorithm and detection using YOLO 5	[119]
citrus	Serial	6	novel improved APF algorithm.	[100]
cucumber	Serial	6	A*(a shortest-path finding algorithm from a specified source to a specified target)	[118]
Fruit	Serial	5	A*, PRM, RRT, and RRT* algorithm	[122]

CONCLUSION

The objective of this review is to provide a comprehensive overview of the latest harvesting robot technologies and their practical implementation and evaluation in real-world applications, intended as a useful resource for designers and researchers. In the future, advancements in speed robot designs will necessitate the use of more advanced sensors, alternative materials, and intelligent control methods to enhance effectiveness. this review paper has focused on the implementation of intelligent control systems aimed at enhancing the speed of robotic arm operations for fruit picking. The study has provided an overview of various approaches and techniques that can be employed to optimize the performance and efficiency of fruit picking robots. By utilizing intelligent control systems, such as advanced algorithms and sensory feedback, the speed of robotic arm movements can be significantly improved. These systems enable the robot to quickly and accurately identify and locate ripe fruits, adjust its trajectory and grasp the fruit with precision, and efficiently detach it from the plant. The research indicates that intelligent control systems have shown promising results in improving the speed of robotic arm operations for fruit picking. By incorporating real-time data processing, deep learning algorithms, advanced sensor technologies, motion planning algorithms, and using smart actuation the robots can make faster and more informed decisions, leading to enhanced productivity and reduced harvesting time. also, A comprehensive overview is provided, covering the types of end-effectors, detachment methods, and sensory control strategies employed. The research findings indicate that grasp-and-cut is the most effective detachment technique, while contact-grasping grippers with two or three fingers are commonly utilized in practical applications. The focus of harvesting automation primarily revolves around tomatoes and apples. This choice can be attributed to their widespread cultivation, uniformity in size and weight, durability against damage, easy detectability due to their distinct color and shape, and their simple circular structure, which allows for effective grasping using a limited number of fingers (two or three). These factors collectively contribute to facilitating the automation of the harvesting process

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