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Field Performance of a Dual Arm Robotic System for Efficient Tomato Harvesting

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Abstract – The robot device that is being addressed in this research has two arms: one for picking the fruit and the other for chopping it. The arms find and locate pods with the help of a complex vision system that employs cameras. In this human-robot workflow, the operator chooses the tomatoes they want picked, and then the robot does the actual picking. The robot management and communication system use the EtherCAT bus to create a link with the graphical user interface (GUI), enabling human administration and control. The objective of this project is to create and assess a robotic system for harvesting tomatoes, equipped with dual arms. This system incorporates a mobile model equipped with two robotic arms and an end effector to enhance the efficiency of tomato harvesting. The system uses a GUI to enhance interaction between the robot and the human operator. Additionally, it employs a vision model to streamline the process of fruit detection. Findings from this study demonstrate that HMI may significantly improve the accuracy of tomato harvesting robots. Finally, there were some difficulties in developing 3D models because this study included outdoor experiments.

Keywords – Tomato Harvesting, Dual-Arm Robotic System, End-Effectors, Vision System, Communication System, Motion Control, Graphic User Interface.

I. INTRODUCTION

The global market for agricultural goods is witnessing a significant surge. To meet the global population's needs for nutritional supplements, fuel, and textiles, it is imperative to achieve a projected 50% growth in agricultural output during the next three decades [1]. Although the population is expected to increase by around ten billion individuals by 2050, there is a simultaneous shortage of workers in the agriculture industry [2]. The shortage may be ascribed to the increasing age of farmers and the phenomenon of urbanization. Moreover, agricultural labor sometimes requires substantial physical exertion and is marked by repetitive and monotonous tasks. Further automation and robotization are required in agriculture to address the increasing demand and alleviate labor shortages. Crops such as wheat, maize, and potatoes exhibit uniform growth in the field, facilitating easy harvesting by huge machinery. Conversely, larger crops like as apples, tomatoes, and broccoli need optimal conditions for producing completely mature fruits, necessitating cautious storage.

Perennial crops such as apples and grapes must also preserve plant integrity during harvest. Selective milling has proven to be difficult to operate, so it is now largely man-operated. Presently selective harvesting is considered a labor-intensive and expensive task on the farm. This makes it essential to design robot systems, which will enhance the process of such harvesting making it a better option in minimizing costs and labor. While humans may exhibit variable levels of performance, robots continually function without any individual or temporal fluctuations. In addition, robots may simultaneously perform crop inspection alongside the harvesting activity to identify illnesses and monitor crop growth. This capability enhances farm management and optimizes the food production process.

The primary obstacles hindering the widespread use of harvesting robots in commercial settings are their suboptimal productivity and exorbitant expenses. Utilizing a synergistic combination of human labor and robots is a feasible strategy to enhance the effectiveness of robotic harvesting. The Agribot project included the design and construction of a robot prototype for a unique artificial harvesting approach in unorganized surroundings, which involved the division of tasks between humans and machines. The operator used a laser range finder to identify and accurately determine the position of fruits. In their 2014 study, Zhao, Gong, Huang, and Liu [3] proposed an assistant-mark technique to accurately identify and determine the precise location of the picking-point for robotic harvesting. Gongal, Amatya, Karkee, Zhang, and Lewis [4] established and executed a collaboration between a robot and a human operator to recognize fruit targets. The experimental findings by

Seng and Mirisaee [5] demonstrated that the fruit identification system, which relied on the cooperation between humans and robots, achieved a detection rate success of 94% and consumption time reduced by 20%.

In order to achieve the objective of effective harvesting robot, a practical solution is to construct a harvester robot that is multi-armed. The mobile robot platform is outfitted with many manipulators, each specifically intended to retrieve a certain type of fruit. Kurtser and Edan [6] developed a multi-arm robot for harvesting melons, resulting in the highest possible yield. Noguchi, Will, Reid, and Zhang [7] developed a master-slave robot system for sector activities as part of their concept of multi-robot collaboration in fruit harvesting. This multi-robot system has reached a significant degree of autonomy, enabling the robots to effectively handle unforeseen occurrences and impediments. According to Li, Ling, Zhang, and Zheng [8], modular design is a viable and practicable approach to decrease the required investment for a harvesting robot.

This article offers a thorough examination of the progress and uses of robotic automated agricultural harvesting, with a special emphasis on fruits and vegetables. The related works section examines several strategies for automated harvesting, such as bulk and selected techniques, with a specific focus on the selective approach in light of technology improvements. The research examines several robotic methodologies for the collection of various crops, including apples, oranges, strawberries, tomatoes, cucumbers, eggplants, and grapes. The report outlines the development and evaluation of a dual-arm robotic system aimed at enhancing the efficiency of tomato harvesting. The system comprises a mobile platform, robotic manipulators, a vision system, and specifically engineered end-effectors. The research outlines the use of a human-robot collaboration technique for fruit identification, in which the operator recognizes the specific tomato to be harvested, and the robot independently carries out the harvesting procedure. The study also examines the control and communication system, which incorporates the use of the EtherCAT bus for accurate motion control and data interchange.

The remaining sections of the paper have been structured in the following manner: Section II presents previous literature works related to the research. Section III presents a discussion of the tomato harvesting robot, and its structure. Section IV reviews the modular robot system, which includes discussions of the dual-arm manipulator, end-effectors, vision system, communication system as well as motion control, and the graphic user interface. Section V presents a detailed experimentation of the tomato harvesting robot, presenting its field tests, and limitation of the robotic system. Lastly, Section VI presents a conclusion and recommends future scope for the research.

II. RELATED WORKS

According to Vásconez, Kantor, and Cheein [9], the use of robotic automated crop harvesting, especially for vegetables and fruits, has had a significant effect on agricultural output. This job has been under investigation and consideration since the early 1960s. Automated harvesting by robots may be categorized into two fundamental concepts: bulk and selective. The bulk notion entails the complete gathering of all fruits, often using techniques such as shaking the tree trunk or limbs. Nevertheless, using bulk approaches has the risk of causing damage to the crops. In recent years, the selective approach has been mostly embraced because to advancements in technology and the resulting opportunities they provide. The robotic system in selective crop harvesting employs a sensory/vision system to identify ripe fruits, and then determines the harvest targets before proceeding to harvest them. This activity often entails thoroughly surveying the whole crop in a greenhouse or an orchard, identifying and pinpointing specific targets, harvesting them by cutting or selecting, and then storing them in a designated container, such as a crate. Within the current body of research, a diverse range of advanced solutions of the robot have been suggested to achieve this objective.

According to the research conducted by Slotine and Sastry [10], typical robotic models integrate (a) a mobile system or vehicular control system, which bears the robotic manipulator that is responsible for getting close to, grabbing, and cutting fruits or vegetables; (b) scanning crops by a system of vision, identifying, and locating targets; (c) a specially end-effector designed robot to improve the process of grabbing and collecting the desired targets. There are several apple harvesting robotic systems documented in [11] and [12]. Due to their uniform circular shape and firm texture, apples are often plucked with little fruit damage. Certain more advanced robotic systems have shown harvest durations of 6 seconds or 8-10 seconds per fruit, achieving a success percentage of 80% or greater. According to the findings in [13], a similar level of performance is documented, with an average harvest time of 7 seconds and a success percentage of 90%. Other harvesters, such as the fruit harvester described in [14] that was tested on apples discussed in [15], could exhibit a longer harvesting time of around 15 or 16 seconds. The presence of these harvesters underscores the necessity for harvesting robots to possess real-time obstacle avoidance skills, due to the intricate and unpredictable nature of their working habitat.

The article presents a prospective technique, as described in [16], for decreasing the total cycle time in the robotic harvesting of tree fruits, primarily focusing on apple collecting. This approach employs a pick-and-catch system. A picking manipulator with an excessive number of degrees of freedom (DoF) is employed for the purpose of harvesting apples. The apples are then dropped onto the catching end-effector of another robot with 2 DoF, which is positioned at the place where the fruit is detached. Experiments conducted in a controlled laboratory environment, using a simulated apple tree, indicated that the pick-and-catch harvesting strategy resulted to approximately 49% reduction in the cycle duration, in comparison to the pick-and-place strategy.

In the past ten years, there have been several robotic solutions developed for harvesting strawberries. These solutions have shown good performance, with a rate of success of over 75% for individual strawberries. The mean time it takes to harvest one strawberry ranges from 6 to 10 seconds [17]. Some of these robotic systems also include operations for packing the harvested fruits. The contrast in color between the cherry fruit and its surroundings is also used to facilitate its detection.

A 4-degree-of-freedom (DoF) arm was used to harvest the cherry trees, combined with a special end effector and a 3-D vision sensor. The aim of this robot is to grasp the cherry trees by their peduncle. The robot was able to locate the cherries and calculate the best option for the end effector without any obstacles Besides, in the case of watermelon, the "STORK" robot showed that the researchers explored the possibility of harvesting large fruits such as melons. The feasibility of increasing the cutting cycle time of the robot by simultaneously performing multiple hand cutting operations has been investigated in [18]. Zion et al. [19] primarily addresses the problem of alcohol allocation for melons in the model of melon farms. A fruit harvesting robot called Agribot uses a similar technique, using two robotic arms working simultaneously to harvest a designated target. One uses a point laser rangefinder to detect and label these targets.

According to Navas et al. [20], tomatoes are widely cultivated and found almost worldwide. The dual-arm (bi-manual) robot harvester is unique in that it employs two manipulators, with one cutting the fruit and the other picking it up. This sets it apart from most other agricultural robotic systems, which typically use just one arm (uni-manual). Lio and Liu [21] discusses the significance of designing and adjusting novel agricultural methods with high productivity. This involves altering the crop and its surrounding environment to make it more suitable for robotic harvesting. The cucumber example in [22] specifically considers the high-wire system. The issue is also addressed and examined in [23] within the context of the SWEEPER2 project. Sophisticated cultivation systems have the potential to augment agricultural automation by streamlining and expediting the mechanized harvesting process for commodities such as apples. For example, the V-trellis fruiting wall for apples architecture improves access to target fruits and reduces obstructions that may interfere with harvesting.

According to Khajepour et al. [24], automated harvesting equipment have been programmed to target not just fruits but also vegetables as part of the harvest. A cucumber harvesting robot that operates independently is suggested in [25]. The study reports an impressive success rate of approximately 79% in harvesting and cycle timeframe of less than 1 minute for every target harvest. The success rate of the eggplant instance described by Sahoo, Bergman, Alanya-Rosenbaum, Gu, and Liang [26] is 62%, with an average time of harvesting of 64.1 seconds. Additional literature on radicchio and asparagus may also be found. Lehnert, English, McCool, Tow, and Pérez [27] indicate that there are relatively low rates of success in detachment of crop. Sa et al. [28] evaluated an autonomous harvester designed for crops with peduncles (such as fruits or vegetables) on both real and plastic crop scenarios. The harvester achieved a success rate of 67% on plastic crops and 52% on actual crops. Interest in research has been shown for sweet peppers as well, as seen in [29] using the "Harvey" robot and in [30]. More precisely, Kootstra, Wang, Blok, Hemming, and Van Henten [31] are participating in the EU project SWEEPER, which seeks to create and evaluate a practical robot harvesting approach for sweet peppers in real-life scenarios. The project reports an average duration of 24 seconds per pepper for harvesting.

Birrell, Hughes, Cai, and Iida [32] state that most harvesting robotic systems are designed for fruits that have characteristics such as color, form, size, rigidity, which makes robotic harvesting an easy endeavor. The absence of any recorded strategy of grape harvesting, despite the great value of this crop, indicates the existence of specific issues in this particular situation. However, there are numerous research studies available on the topic of grapevines. The Agri.q UGV was created as part of the PIC4SeR3 program for Smart Vineyard Medicare, as documented by Quaglia, Visconte, Carbonari, Botta, and Cavallone [33]. Its functionality has also been expanded to include other kinds of orchards. This solution of the robot explores the potential of multiple robotic systems, like a UAV and a UGV (drone), to work together in order to overcome slopes or irregularities of terrain and perform various tasks like fertilizer application, plant/ soil sample collection, and crop health monitoring. The goal is to achieve coordinated field servicing and monitoring. Tang et al. [34] presents a first endeavor to create a versatile farm robot categorically designed for vineyards. This robot is capable of doing several activities like harvesting, bagging, spraying, and berry thinning.

The robotic manipulator created in [35] was also used to specifically handle the duty of applying chemicals underneath grapevine trellises for the goal of enhancing crop health and removing diseases. The research objective of Praba and Krishnaveni [36] is to detect diseases and selectively spray crops to improve production quality. This objective is also part of the EU-project CROPS4, which aims to demonstrate, optimize, and advance a versatile robotic system of agriculture. Project CROPS made an effort to accomplish grape picking, however there were no documented instances of success. The GRAPE5 project likewise focused on targeting a similar use, namely grape protection. The advancement of GRAPE involved the construction of a self-governing terrestrial robot equipped with a mechanical arm. This robot was designed for the purpose of surveillance of one's well-being and the automated distribution of pheromone dispensers to stop the spread of plague. The authors' research works encompass activities such as weeding, which refers to the elimination of unwanted plants in certain sections of a vineyard. Another job is monitoring, which is the process of determining the location and mapping of a vineyard for the purpose of crop surveillance. Lastly, pruning involves selectively removing older canes or branches of grapevines while preserving the healthy ones. The current EU sponsored project BACCHUS6 [37] intends to contribute to the restricted field of automated grape harvesting by using two separate robots that operate together - one for harvesting and the other for inspection.

This work introduces the development and evaluation of a dual-arm structure with two manipulators with three degrees of freedom each, as well as two different types of end-effectors. The purpose of this frame is to efficiently pick tomatoes. The collaboration of two end-effectors has the potential to greatly enhance the efficiency of the harvesting process. The use of the EtherCAT bus-based control and system of communication enhances the velocity and reliability of motion control and data exchange. In relation to software of control, a graphical user interface was created to facilitate the exchange of instructions from the operator and to visually present the current status information of the robot. The field test performances demonstrated the efficacy of the created robot system, while also revealing several deficiencies that need to be addressed in future endeavors.

III. TOMATO HARVESTING ROBOT STRUCTURE

The proposed harvester robot's hardware includes a sensor rig and a dual-arm robotic system. The robotic arms that were selected include two Kinova MICOTM models that include the Ki-nova Gripper KG-3. The arms are energy efficient and have a lightweight design. The six-segment robotic arm can support a maximum weight of 2.1 kg while operating continuously in the mid-range and has six degrees of freedom (6DoF). The gripper and aubergine harvesting are both made possible by this load capability. The grippers have three flexible fingers that are not yet fully activated. Three linear actuators regulate the opening and shutting action of the fingers. The fingers can provide a grasping force of 40 N thanks to the one actuator in each finger. To remove aubergine peduncles, a specific tool may be fastened to the upper parts of the grippers. With its humanoid torso design, the robot is able to make full use of its dual-arm platform for accurate harvesting operations. Additionally, to achieve the best possible performance of the robotic arm when performing dual manipulation tasks, it is equipped with both left-handed and right-handed configurations refer **Fig 1**.

Fig 1. Prototype of a Robot Designed for Harvesting with Two Arms. The First Image Depicts the Lateral Perspective, but the Next One Portrays the Front View.

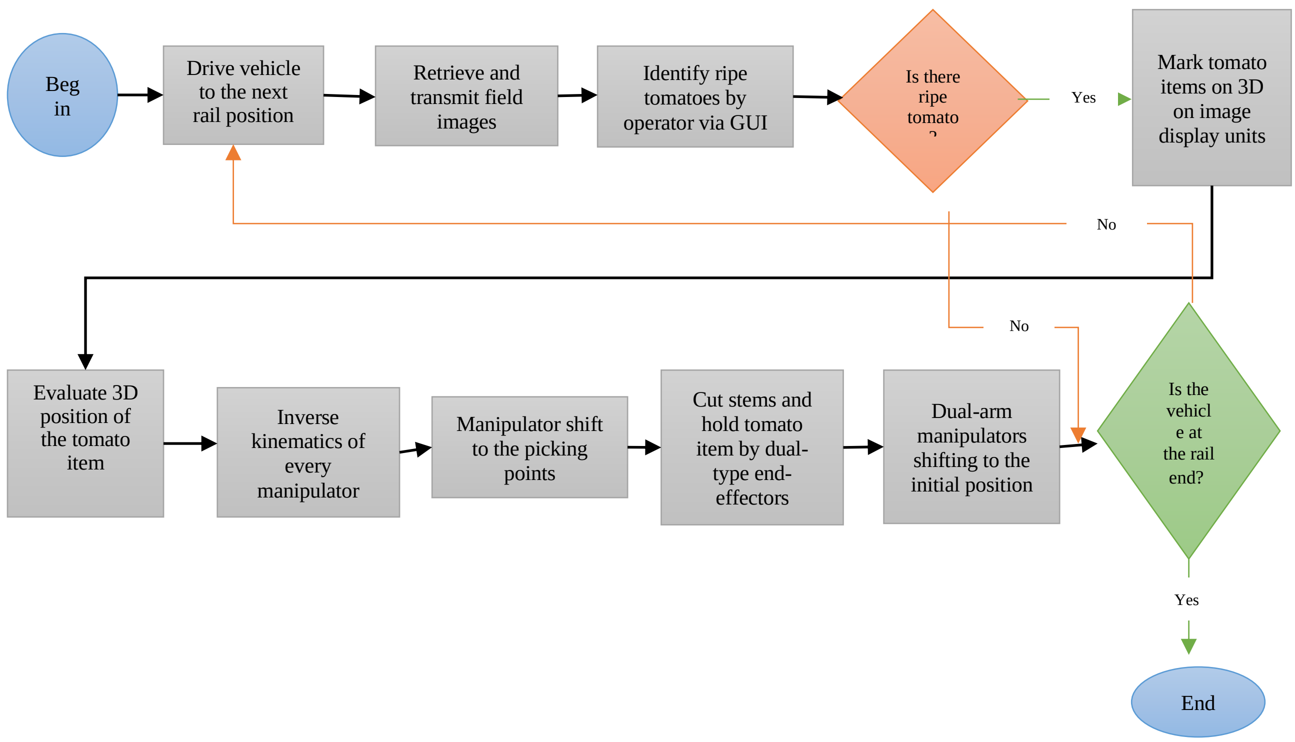

Fig 2. The Operational Process of The Robot for Harvesting Tomato.

Two cameras make up the vision system. One takes high-resolution color pictures and the other creates point clouds. The Mesa SwissRanger SR4000 takes the former. The Prosilica GC2450C camera complies with all GigE Vision requirements and has a 5.0-megapixel resolution. It is equipped with a high-quality sensor that delivers exceptional little noise, image quality, a maximum frame rate of 32 fps at full resolution, and high sensitivity. The Mesa SwissRanger SR4000 camera is a tool utilized for the acquisition and analysis of three-dimensional information from objects that emit infrared (IR) light inside their environment. The capacity to estimate distance is derived from the concept of time-of-flight (TOF). Under typical operational circumstances, it is feasible to attain a level of accuracy that is lower than 0.01 m across a working distance of 10 m, while capturing 50 frames per second. A software triggering mode is used by both cameras, whereby they remain in a state of readiness until they receive a “acquire” instruction to commence synchronized picture capturing. Both cameras transmit data over an Ethernet connection.

The most challenging challenge to improving the effectiveness of robotic harvesters is better fruit recognition, due to the unreliable nature of autonomous fruit identification in uncontrolled conditions. To address the aforementioned challenges, a human-robot cooperation method was implemented inside the suggested system structure. The operator performed the fruit identification job by indicating the screen interface of the target tomato that showed the operating location. Subsequently, the stereo camera was used to determine the precise spatial location of the designated tomato. In addition to fruit identification, the operator also provided instructions for the sequence of carrier vehicle driving via the user interface. The remaining procedures were executed autonomously by the robot. The whole sequence of tasks for the picking operation performed by the dual-arm robot is shown in **Fig 2**.

IV. THE INTEGRATED ROBOT SYSTEM

Dual-Arm Manipulator

Fig 3 (a) depicts the robotic manipulator that is dual-armed that has been designed as a spring-damper closed-chain system in the Cartesian space. This study aims to create a model of a robotic platform that can do a wide range of basic tasks using both arms. The model will be designed to be adaptable and flexible, taking into consideration both absolute skills (skills that can be performed independently) and relative skills (skills that need coordination between the two arms). In order to achieve this objective, let us examine the kinematic chain that is closed. Each arm, denoted by $i = \{L, R\}$, gets in touch with object O in the workspace W, which belongs to the N-dimensional Cartesian subspace. The term "absolute skill" refers to the locomotion of object O inside the specified workspace W. In contrast, "relative skill" refers to the specific actions carried out by each end-effector i in relation to the $\{O\}$ of the object. The closed-chain dual-arm configuration is centered around {O}.

The present arrangement of the closed-chain dual-arm system is determined by the acceleration, velocity, and location of the system's frame {O} in each DoF of W. These values are represented as $(xo, \dot{x}o, \ddot{x}o)$n, where n ranges from 1 to N. The behavior of this system is estimated by modeling it as a spring-damper system that operates between the frame $\{O\}$ of the item and its desired configuration go. The dynamical system generates movement trajectories x_0 with velocities $\dot{x}_0$ and accelerations $\ddot{x}_0$ in each degree of freedom (DoF).

$$T\ddot{x}_0 = \alpha[\beta(g_0 - x_0) - \dot{x_0}] \tag{1}$$

In conditions of severely dampened dynamics and zero velocity, where $\alpha > 0, \beta > 0$, and $\beta = \frac{\alpha}{4}$, the location of the model's attractor is where the system converges. The dynamical system described in equation (1) produces a linear displacement towards the target configuration go, regardless of the original system state. Any additional dynamic behavior may be represented by an external force exerted on the system's frame $\{O\}$ as:

$$T\ddot{x}_0 = \alpha[\beta(g_0 - x_0) - \dot{x_0}] + f_0(.) \tag{2}$$

The coupling term $f_0(.)$ represents the characteristics of the external force that influences the inherent behavior of the system. Put simply, $f_0(.)$ characterizes the behavior of the system and may thus be used to encode and retrieve a basic skill.

To ensure sufficient coverage of the workspace, the 3 DoF Cartesian robot manipulators were outfitted with two rotating joints and one prismatic joint. **Fig 3** (b) illustrates the outcomes of the simulations conducted to determine the possible workspaces for the robot manipulators that are dual-armed. A total of 6000 blue and red dots were used to represent the potential selection points for each arm, with each color corresponding to a certain arm. The same region occupied by both blue and red dots corresponds to the workplaces. The intended spacing of 400mm between each selecting point on the heating pipelines was determined by the simulation results' breadth. The dual-arm manipulator's frame is capable of rotating 180 degrees around the central axis.

End-Effectors

The harvesting robot used is seen in **Fig 5**. Four RGB-D cameras are integrated into the harvest robot to detect and localize crops, in addition to two end-effector-equipped robot limbs utilized for the operation of the harvesting mechanism. Additionally, there is a computer that controls the whole system. Using Universal Robots' UR3 and UR5 robot arms, Yoshida et al. [38] conducted their research. To increase its operating productivity, the robot is equipped with two appendages. It is the job of the upper robotic arm, UR5, to pluck the fruit from the tree's upper branches. In contrast, the lower robot arm, known as UR3, is tasked with gathering the fruit on the bottom side. When developing the robot arm to handle different types of fruits, we consider the arm's operational range and the requirements of the fruit trees.

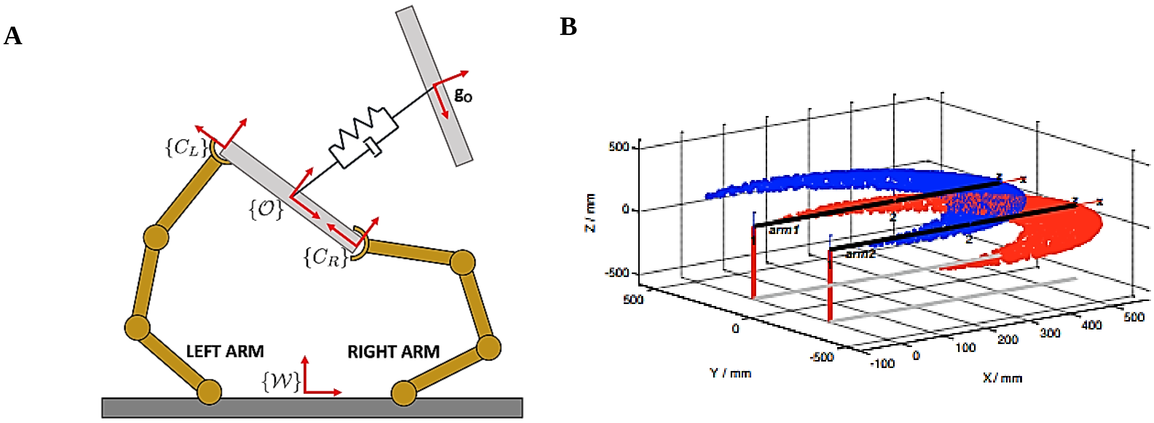

Fig 3. Dual-Arm Manipulator Structure: (A) The Manipulator Represented In Cartesian Space As A Closed-Chain System With A Spring Damper; (B) Dual-Arm Robot Manipulators Workspace.

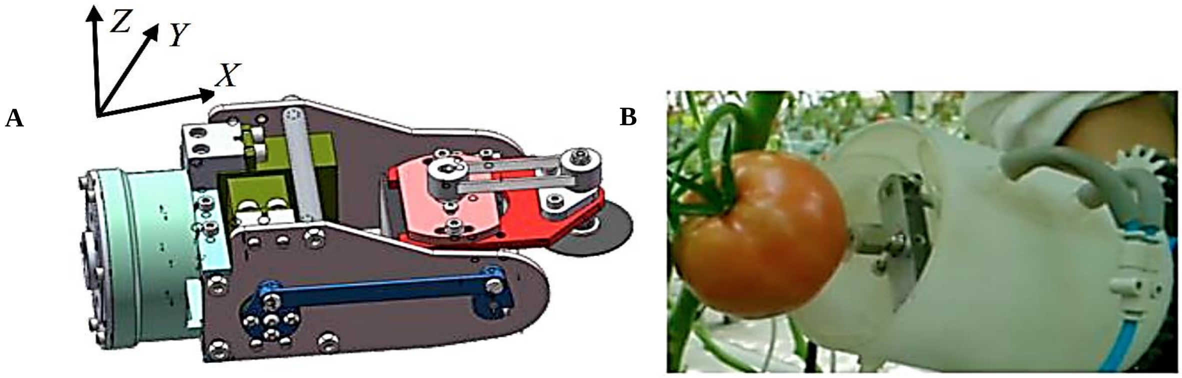

Fig 4. Types Of End-Effectors for The Robot with Two Arms. (A) End-Effectors of The Saw Cutting Type And (B)

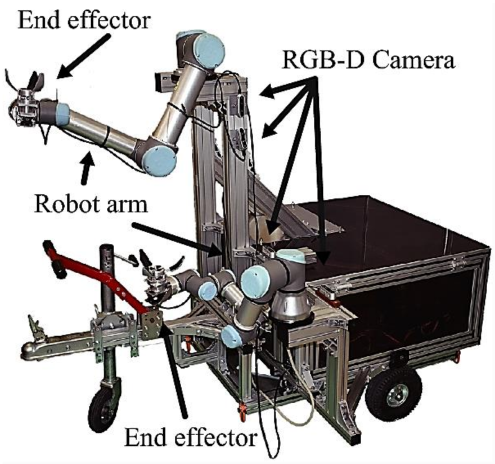

Fig 5. Elements of Harvesting Robot.

Fig 6. Fruit Harvesting Using an End-Effector

For the RGB-D camera, Brahmanage and Leung [39] utilized an Intel RealSense D435 device. The configuration of the robot's four RGB-D cameras is depicted in **Fig 5**. Two cameras were positioned immediately below the fruit tree, one camera was angled diagonally upwards, and one camera was positioned to the side. In an effort to minimize the presence of fruits in obscured areas behind leaves and branches, we strategically positioned cameras to capture several angles of the fruit tree.

The end-effector automatically recovers the fruit by spinning it in tandem with its own motion, as shown in **Fig 6**, once it reaches a certain vicinity. A peduncle is the stalk attachment mechanism for fruits like apples and pears. Therefore, the fruit will be precisely aligned with the end-effector's center regardless of how little the end-effector's arrival point differs from the fruit's center due to the end-effector's spin and the force applied by the fingers. There is no way for the end effector to know when the fruit harvesting procedure is complete without a sensor. The bulk of the fruit may be collected by turning it around four times, according to research by Pothula, Zhang, and Lu [40]. Because of this, the current study makes use of this particular value.

The end-effectors were designed in a modular fashion to facilitate the collaborative operation of two robotic arms. The purpose of the end effector was to possess a low weight and be readily interchangeable. **Fig 4** illustrates the installation of two distinct types of end effectors on each manipulator: a vacuum cup for grabbing the target tomato and a cutting device for fruit separation. **Fig 4** (a) depicts the schematic illustration of an end-effector that utilizes a saw cutting method. The actuator of the end-effector, which is used for saw cutting, is driven by a belt pulley. The pulley is connected to the output shaft of the motor on the opposite side. The micro control unit was responsible for managing the motor's control. The cutter's location was adjusted along two axes: the X – and Y-axis.

The adjustment in the X direction was achieved using a four-bar linkage mechanism. The range of adjustment ranged from -45 degrees to 45 degrees relative to the Y direction. The Y adjustment was enabled by actuators under the control of the MCU system. **Fig 4** (b) illustrates the pneumatic end-effector, including a plastic socket and a vacuum suction mechanism. Initially, the plastic socket was positioned at the central location of the tomato item, after which the vacuum suction cup securely grasped it to avoid any movement. The end factor that is pneumatic can be placed at a distance of 20mm to 50mm away from the center of a ripe tomato, along the stem axis. The cup possessed a diameter measuring 100mm, while the suction force was calibrated to support weights spanning from 100gf to 1kgf. The cutting of the stem operation was repeated many times until the gripper that is pneumatic effectively seized the appropriate tomato.

Vision System

The visual system of the robot used a Bumblebee2 color stereo camera, manufactured by Point Grey in Vancouver, Canada. The camera had a resolution of 480 pixels in height and 640 pixels in length, and operated at a frame rate of 48 frames per second. The system of stereo vision had two identical color of sensors of CCD, strategically placed atop a dual-arm frame to guarantee the requisite field of view. Image processing was carried out by the main computer (Lenovo Intel Core(TM) i3-370 CPU with a RAM of 4GB. The work of identifying and pinpointing mature tomatoes was accomplished in two distinct phases. Initially, the operator identified and highlighted a mature tomato in the 3D reconstructed picture using the graphical user interface. The location $P(x, y, z)$ of the tomato item in three dimensions was determined using the method of triangulation, as described by Zhu et al. [41]. This calculation was based on the two pictures obtained by the stereo camera. The use of a human-robot cooperation technique for detecting and locating ripe tomatoes has significantly enhanced the resilience and efficiency of robotic harvesting.

Communication System and Motion Control

The objective of motion control was to guarantee precise and fast execution of the picking operation by the built robot. The motion control and communication system facilitate the transmission of the operator's commands to the machinery's control unit, as well as the reception of signals indicating the status of task execution by the machine. The host computer served as the primary element of the communication and control system. It was equipped with a visual user interface and many software modules that were responsible for coordination and control. The host computer sent the operator's instruction to the G-MAS via Modbus to distribute each joint motor kinematic parameter. Subsequently, the signal of control was conveyed using the bus of EtherCAT. The output component comprises seven DC and their associated contemporary drivers.The primary attribute of the bus of EtherCAT is its ability to transport data in parallel, resulting in enhanced flexibility and velocity for control of motion and information interchange.

The Graphic User Interface

This interface is a visual control panel that allows operators to submit control commands and see the present condition of a robot. The visual user interface had four components: a unit for displaying 3D reconstructed images, a unit for simulating robot movements, a unit for basic command interface, and a unit for control command interface. The tomato item may be identified on this monitor by operators using a small red circle, with the circle's center representing the location of the object of the tomato. The position of the robot in a computer-generated three-dimensional virtual environment is displayed in the upper right corner of the screen. This virtual realm is employed to replicate the interaction between humans and computers. The principal command interface unit, used for system initialization, is located in the lower left corner of the screen. The control command interface unit, positioned in the lower right corner of the screen, is especially designed to adjust the diverse motion characteristics of the robot. The programming advancement tool used for creating the visual user interface software was Visual C++. Uzayr [42] provided a comprehensive description of the created user interface software.

V. EXPERIMENTATION

Filed Tests

In order to assess the dependability and flexibility of the harvesting robot that is dual-armed, the entire system that is advanced underwent testing at the Shanghai farm in 2015 [43], as in **Fig 7**. The tomato harvesting robotic arm incorporates a pneumatic actuator, which mimics the function of an artificial muscle. This driver is part of a pneumatic control system that includes control circuit, an air tank, control valve, and vacuum pump or air compressor. The purpose of this system is to transform energy from pressure in the air into mechanical energy, enabling the robot's arm to perform various movements such as shaking, rotation, and linear motion. Liu, Li, and Li [44] developed a manipulator for harvesting spherical fruits without causing any loss, which incorporates a pneumatic suction clamp see **Fig 8**. The suction cup successfully performed both the pulling back and clamping claw closing motions. This was achieved by a progressive movement stimulated by a single active cylinder. Additionally, the manipulator's key structural characteristics were determined.

Fig 7. Testing a Dual-Arm Tomato Picking Robot in a Greenhouse.

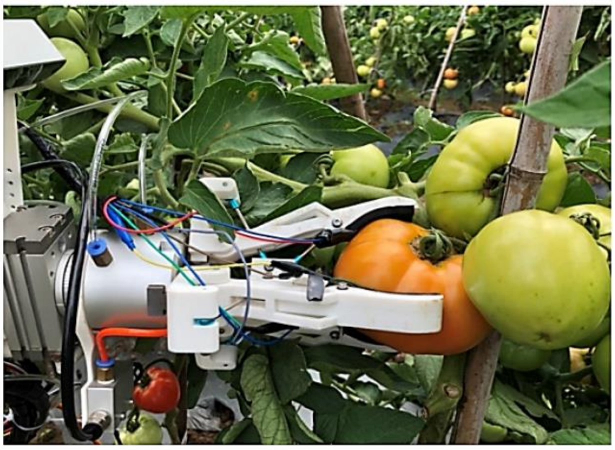

Fig 8. End-Effector for Harvesting Tomatoes using Non-Destructive Pneumatic Clamping Control.

Yoshikawa [45] developed a multi-finger flexible manipulator that utilized an asymmetric-bellow flexible pneumatic actuator at the bending joint. This design enabled the intelligent grasping of objects of different shapes. Utilizing air as a medium has the benefits of cleanliness and safety, compact machine dimensions, and simple upkeep. However, achieving precise position and speed control is a challenge owing to air compressibility. Pan et al. [46] designed a needle-shaped tool that uses pneumatic actuation to transplant plant seedlings. They evaluated its efficiency and assessed the extent of damage to the root ball.

Gao et al. [47] presented a pneumatic finger end-effector specifically intended for a robot that picks cherry tomatoes. The end-effector was controlled by air pressure and could effectively and consistently harvest tomato fruit by combining rotation and clamping. It demonstrated exceptional adaptability to demanding operating conditions and underwent field testing in a commercial greenhouse. The findings demonstrated that accurately establishing the spatial orientation of the fruit bunches in relation to the stem is crucial for achieving successful harvesting outcomes. Key research topics for increasing robot harvesting performance include boosting the end-effector flexibility, identifying the attitude of fruit bunches, and improving positioning accuracy.

Practically, once a tomato item was correctly labeled in the recreated 3D image made by an operator, the robot was capable of independently picking the labeled tomato. Once all the mature tomatoes were collected, the robot proceeded to the next operational location under the guidance of the operator via the control command interface unit. The field testing revealed many deficiencies in the robot system.

Limitations of Advanced Robot System

The reconstruction of the 3D image relies on picture matching as its foundation. Nevertheless, the intricate nature of the natural surroundings led to the unsuccessful matching of images in some exceptional circumstances. The process of reconstructing 3D images is time-consuming, which has a direct impact on the time it takes to complete the choosing cycle. The proposed harvesting robot utilizes a control method of visual open-loop that relies on accurately recognizing the location of the fruit item in a 3D. The camera that is stereo utilizes triangulation theory to accurately determine the spatial distance between the end factor and the target fruit. By accurately measuring the distance, the manipulators' movement parameter may be determined by computing the kinematics equation. The accuracy of manipulator control is greatly influenced by the calibration of the vision system and the precision of the kinematic model. Due to the mobility of robots and changes in the working site, the vision system and manipulators may experience mistakes, which might potentially lead to a failure in the harvest process.

VI. CONCLUSIONS AND FUTURE SCOPE

Recent years have seen notable progress in the field of robotic automated agricultural harvesting, namely in the area of selectively picking fruits and vegetables. Robotic solutions have been developed for different crops such as apples, oranges, strawberries, cucumbers, tomatoes, and grapes. Typically, these systems include a mobile platform carrying a vision system, a robotic manipulator for scanning the crop, and a specially designed end effector for efficient tearing and harvesting Success rates and harvesting times vary depending on crop against its specific robotic control system. For example, robots designed to harvest apples have shown a success rate of more than 79%, so each fruit is completed in 6-10 seconds. Strawberry harvesting robots have achieved a success rate of more than 75%, thus strawberries each harvest. The process is completed in a period of 6 to 10 seconds. The cucumber harvesting robot has achieved a commendable success rate of 80% with a cycle length of 45 seconds per harvest.

A dual-arm robot enhanced the process of picking tomatoes. This system has two switches, one for cutting and one for receiving, to increase efficiency and improve results. Increased reliability and motion control speed and data exchange using sophisticated controls function on the communication technologies such as the EtherCAT bus. Stereo cameras and RGB-D cameras have been used for the purpose of detecting and pinpointing mature fruits, hence enabling accurate and self-governing harvesting. Notwithstanding the progress made in automated agricultural harvesting, there are still obstacles that need to be surmounted. The intricate characteristics of the natural environment might impact the precision of 3D picture reconstruction, a critical aspect for fruit identification. Furthermore, the progress in creating robotic systems for grape picking remains restricted, despite the existence of studies on grapevine surveillance and safeguarding.

Future research in the field of robotic agricultural harvesting should prioritize the enhancement of end-effectors' flexibility, the improvement of fruit identification and locating algorithms, and the augmentation of the overall efficiency and productivity of the systems. Furthermore, it is essential to intensify endeavors in the advancement of robotic solutions specifically tailored for crops that presently lack automated harvesting alternatives, such as grapes. In general, the ongoing advancement and utilization of robotic automated crop harvesting systems have the capacity to transform the agricultural sector and enhance efficiency.

Data Availability

No data was used to support this study.

Conflicts of Interests

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

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Competing Interests

There are no competing interests.

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