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6-DOF Robot Arm for Harvesting Fruits in Modern Agriculture Farms

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Abstract**:** The modern agricultural needs and lack of skilled work force made the farmers automate their agriculture operations in the fields, with a special focus on fruit harvesting methods. The proposed research method design and develops a 6-DOF robotic arm as an intelligent solution for harvesting fruits in the indoor agricultural forms. The robot system design controls the components such as robot arm, servo motors, microcontrollers, gripper, and the sensors along with along with the raspberry pi code to establish automation for fruit assessment and precise fruit harvesting with reduced human manual efforts. The robotic arm achieved efficient detection and harvesting of fruits during simulated tests which allowed it to address major agricultural hurdles specifically related to selectivity and delicacy and operational flexibility. The proposed research takes a practical approach towards robotic abilities for precision agriculture with low computational processes and latency.

Keywords**:** Robotics, 6-DOF arm, automation, modern agriculture, robot armx.

1. Introduction

Robotics involves the design and creation of machines capable of performing tasks autonomously or semi-autonomously. Robots integrate hardware, software, and mechanical systems to interact with environment through sensors, actuators, and control units. A typical robot consists of a power source, sensors for environmental data acquisition, communication interfaces, and mechanisms for movement.

Robotic arms, especially those with six degrees of freedom (6-DOF) are widely used in many industrial applications for their accuracy and adaptability. These arms can perform intricate movements, increasing safety and productivity by functioning independently in dangerous or inaccessible settings. The 6-DOF robot arms have advantage of high accuracy in their operations and fast compliance. However, it needs high programming skills to customize their applications and extract the maximum benefit of it. A model of 6-DOF robot is shown in Figure 1.

Due to global ecological changes and social lifestyles, the agriculture forming systems around the world are being changed. Among them, the indoor forming is on the front in many countries [1–3]. Some of the other names for indoor forming are vertical forming [4–7], and horizontal forming [8]. These kinds of forms are important for especially unban area agriculture forms. In these forms, robotic technology is used to bring precision and fast operations in agriculture harvesting systems. For instance, robotic technology is used for surveying the form conditions, the crop health condition, water level conditions, and the temperature conditions in the form, which may take few minutes to assess with high accuracy, whereas the manual systems may take several hours to days depends on the area to assess the same elements.

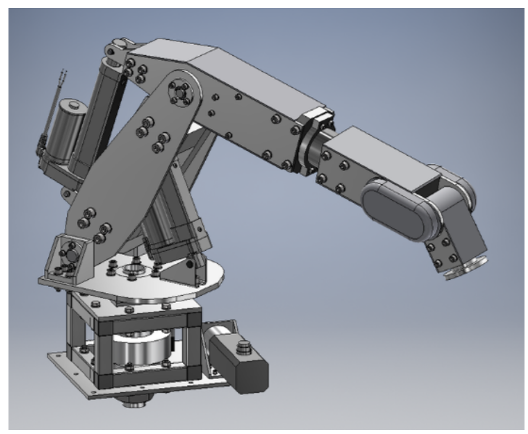

Figure 1. 6 DOF Robot Arm

In the indoor forms, 6-DOF robot arms are used in many contexts with sufficient hardware and software for specific functions of agriculture [9, 10]. Some robot arms used vision-based systems to detect and harvesting the fruits [11–14]. However, these processes are expensive in terms of computational processes handling with low capability processors in practical environments. In this paper, we propose a new methodology for agriculture forming with 6-DOF robot arm. The methodology mainly focusses on checking the conditions of the fruit in the plants, especially on deciding whether the fruit is ripened or still in the raw form, with low latency response time. The structure of this paper is organized as follows: Section 2 presents related work and literature on robotics; Section 3 describes the research methodology proposed in the paper; Section 4 details the implementation of the proposed method, and finally Section 5 concludes paper.

2. Related Work

There is a transformative change in the current society on the agricultural activites with the incorporation of robotics in the forming processes. In addition, the computing techniques such as machine learning, articial intelligence, and deep learning have made the agriculature processes in high accuracy and perfect outcomes. These agricultural processes could include plant recognaitions, fruit couting, soil classfifications, and detection of plan diseases [15–17]. Since, few forming processes are valuable and expensive, it is worth to adopt the robotic systems to the agricultural processes. Moreover, in the next few decades, there is a demand raise for food by 50%, hence the aumoation processes become necesarry, which can avoid the shortag of human workforce and increase the food production [18–21].

There are customized robots designed for different crops. For instance, in support of melon cultivation, specilized robots are developed, named as cartesian robots [22]. The robots for cherry tomots were desgined by addiing the sterio vision to the robot and fruit collector for effectiveness of harvesting, which has success rate of 83%. Some researchers used robotic arams for egg plant and chilly harvesting. However, the success rate was low due to the hard gripper materials. Hence it is signaificant to develop the soft gripper for handling of fruits delicately and safely [23, 24].

Robotic systems now play a crucial role in reducing labor costs, increasing efficiency, and enhancing safety in agricultural tasks. Systems capable of fruit detection using RGB and depth cameras, combined with intelligent motion planning, have been developed for tasks like tomato and green chili harvesting [23, 25]. These robots use AI to identify ripeness produce and plan paths accordingly, although challenges like fruit displacement and occlusion remain. Robots also assist in tasks such as pesticide spraying and greenhouse monitoring.

6-DOF robot arams are popular and they are used in agricultural formings due to their precision and flexibility. Some times, the robot arms are attached to moving devices and it can be used for plucking the fruits, which is important for handling fruits with delicate [9, 10]. In addtion, it also adds some image sensors to the arm. However, it pose some challenges like poor visilbility and object detection. The vision based algorithm YOLOv3 [11, 12] is combined with 6-DOF robot arm that can detect the objects easily in the realtime visions. For example, the tomoto harvesting process, it shows 65% success rate with 92% correctness in the vision. However, there were some problems, especially in the path finding and gripper issues. Some of the aims of the path identification include the indentification efficient peths, safe and secure paths. There were some methods proposed on robot path identification [26–28]. The coordinate geometry is used to find the robot path that can suit the presnted model [26]. By keeping in mind the resource saving during the robot path palnning, it is recommended to use the minimum spanning tree structure in the robot path palnning [27, 28]. Some methods consider the perfronce of the system that depends on the environmental consitions and gripper efficiency [29].

In order to solve the poor visility and accuracy of the object identification, it was suggested YOLOv5/v8, which can be more suitable for greenhouse agricultural conditions. The adoptation of deep learning techniques may solve several problems, which is one of the intitutive of using YOLOv8 [13].

Advanved object identification mechnisms are adopted in YOLOv8 under real time videos. Some methods use the sensor fusion techniques for real time path identification. Multipurpose robots that can perform various tasks like harvesting, spraying, and inspection were proposed [14]. Several works presented the datasets that can provide the realtime agricultural data for the purpose of training and implementation of vision models.

Modern robotic harvesting systems are built by integrating hardware and AI. Key components include: Sensors (RGB cameras, LiDAR, depth sensors) for fruit detection and environmental mapping. Actuators for precise movement and control of the arm. End-effectors such as grippers or cutters tailored to different fruit types. Machine learning models enable real-time fruit recognition and path optimization, improving overall system performance [30].

For motion and trajectory path planning of robot, accurate and secure harvesting operations, trajectory planning algorithms control the robotic arm's movements based on speed control, obstacle avoidance, and route optimization.

The increased need for intelligence and the complexity of industrial and agriculture sector productions is causing the development of dual-arm robots. Increased workspace area with a larger load capacity and increased precision and efficiency through arm coordination are only two of many other remarkable advantages that such a robot offers. Despite the advantages, the dual robot arm poses some of the challenges. One of them is collision avoidance with stationary obstacles in order to guarantee motion synchronization emerged as a major issue in path planning in particular, given the overlap in the dual arms working spaces. In order to ensure that the unmanned system of dual-arm robots can move in a smooth and collision-free manner while remaining safe. The research is of critical importance for pushing forward the application of dual arm robots in industrial production and other fields that call for complex operations in order to increase efficiency, reduce cost, and improve operational safety [31]. Graph search Dijkstra, A*, and sampling approaches (PRM, RRT) are at present the two dominant robot motion planning methods [32]. Although the sampling methods search for paths with high randomness but high planning efficiency and success rate, the graph search approaches are less flexible and computationally efficient. The RRT approach is one of the most widely used in robotic arm path planning since it does not require environment preprocessing and is more adaptable to high dimensional spatial path search. The RRT algorithm was originally presented by LaValle and is enhanced by conducting searches while sampling [33]. The team of some researchers further improved the RRT method by adding a variable sample domain to the 2D RRT algorithm, but the outcomes are no better than those of the traditional technique [34]. By making the step size variable, Li et. Al. improved the RRT algorithm and greatly reduced the node search time [35]. A bidirectional search approach from the start points and the goal point was presented by Q. Y. Guo, which greatly improves the search efficiency of the 3D robotic arm [36].

However, the path is not ideal as a result of the unpredictability of the sample. The A* algorithm resulted in a dual-arm path with chatter that is not smooth [37]. To minimize runtime and maximize precision, a new method is proposed by Zhang et al, which follows a dual-arm cooperation strategy [38]. An improved RRT FN * algorithm is presented in [31], which incorporates robot collision detection to increase the algorithm's effectiveness, employs the adaptive step size strategy to optimize the number of iterations and path length, optimizes the sampling method by introducing the target bias strategy to boost search efficiency, and utilizes Bessel curves to smoothen paths in order to meet the requirements of the robotic arm. The efficiency of the collision avoidance model is verified in three-dimensional simulation to achieve cooperative obstacle avoidance planning for a dual-arm robot, and the algorithm's high search efficiency and convergence rate are verified through two- and three-dimensional scene simulation experiments. In the literature, few general models are provided to use the underlying communication infrastructure that can save energy and resources, which are useful for the robot path planning [39, 40].

In some approach, a vision system placed in between the grippers takes pictures of the fruit. To reduce the likelihood of picking unripe produce, the robot evaluates fruit maturity, size, and placement using image processing techniques. The robot arm gripper's two opposing fingers are made to exert enough force without causing any harm to the fruit.

This ensures controlled gripping pressure to prevent bruising during harvest. Robot arm grippers are among the most critical interfaces in an automated industry since it is the interface with the real world. Robot grippers are end of arm tooling that is also called as "hand" of robot arm which can perform various functions based on the type of gripper installed. Grippers are automated handling devices that mechanically grasp, hold and manipulate objects. Robotic grippers are used in various sectors with applications including robotic agriculture forms, automotive assembly, electronics manufacturing, and many more. As the number of automated processes is increasing, the demand for robotic grippers is also increasing significantly. The technology of grippers has become a major influence on the actual performance of robotic applications. Figure 2 shows the robotic arm gripper in open and closed modes.

Fruit features are identified by a high-resolution camera, and obstacles in the immediate vicinity are detected by ultrasonic sensors positioned on either side of the arm. Real-time 3D environmental awareness is made possible by the integration of these sensors, which is necessary for object interaction and safe navigation. The Robot Operating System (ROS) is used to program the system, taking advantage of its robust libraries like MoveIt for motion planning and its modular design. ROS makes it possible for semi-autonomous and completely autonomous operations to handle data in real-time, abstract hardware, and be extensible. Using encoder feedback and ROS MoveIt data, the actual trajectory of the robotic arm is compared to the intended path in order to assess the motion accuracy of the arm. Deviations are noted and examined.

The ability to recognize objects and ripeness is assessed in a variety of environmental settings. Detection accuracy, processing speed, and false positive/negative rates utilizing various fruit varieties at various maturity levels are examples of performance measures. Dynamic scenarios are used to test the robot's obstacle detection and avoidance skills. The number of collision-free maneuvers and the efficiency of recovery techniques in the face of unforeseen obstacles are used to gauge success.

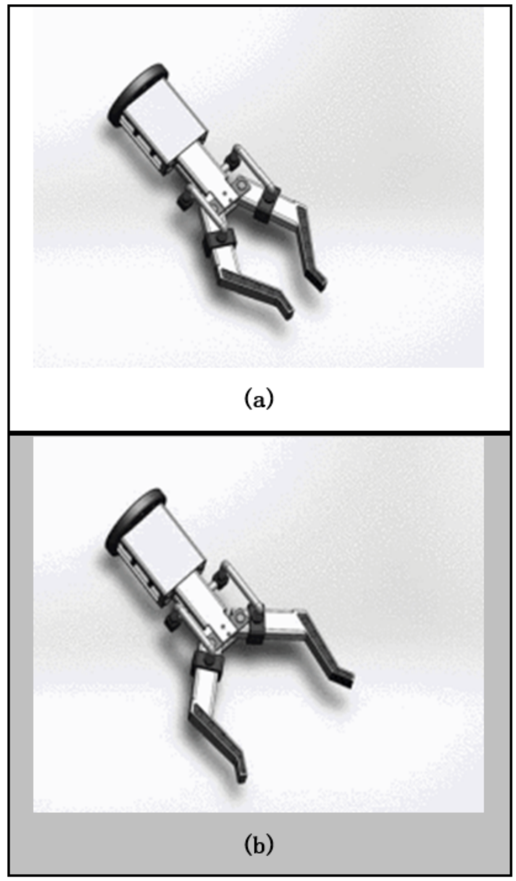

Figure 2. Robot Arm Gripper (a) Open (b) Closed

Overall system performance is assessed based on harvesting cycle duration, energy consumption, and user interface usability. The robot must consistently harvest multiple fruits within a defined time period.

The discussed robotic approach seeks to lower labor demands while increasing agricultural productivity in a sustainable manner, particularly in dangerous or remote farming locations. Significant speed and efficiency benefits can be achieved by replacing 20 to 50 manual laborers with a single robotic arm in well-managed farms. In precision agriculture, robotic arms are a significant technological advancement, especially in controlled settings like greenhouses.

3. Contributions

The paper presents a practical solution for automated fruit harvesting using a six-degree-of-freedom (6-DOF) robotic arm designed for agricultural forms. The methodology follows study of combining robot arm structure with sensors, programming with special hardware, and rotating arms with servo motors. The design structure for the 6-DOF robot arm for the proposed method is shown in Figure 3.

The 6-DOF robot arm is connected with 6-servo motors, and a microcontroller connects all the six servo motors. The microcontroller needs to be programmed in such way that the robot arm trajectory motion plan needs to be smooth enough to reach the place, from where the sensor can able to get enough information about the fruit. The structure attaches a color sensor that can detect the color of the fruit, which is the main task on detecting fruit's ripeness. The bottom most Hinz of the 6-DOF robot arm can make the entire structure rotate around vertical axis.

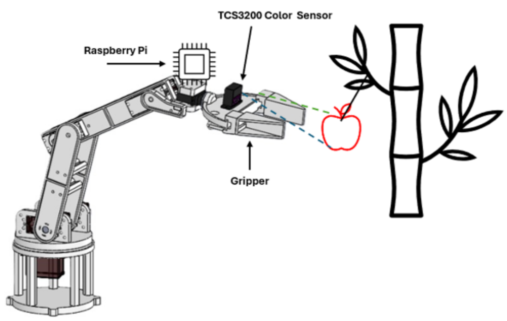

Figure 3. Prototype Design

The research methodology is described in Figure 4.

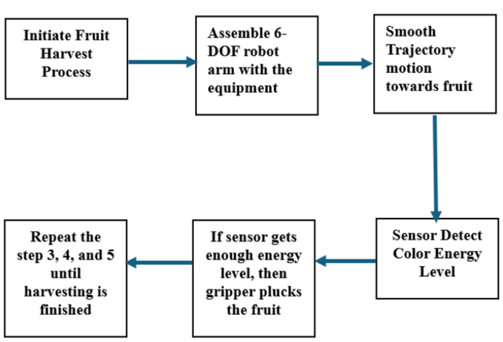

Figure 4. Research Methodology

The research methodology describes that it initially assembles all the required equipment, for instance attaching sensors to detect the fruit color, and servomotors connected to the joints of the 6-DOF robot arm, which in turn connected to microcontroller. The microcontroller controls all parts in the structure to do the defined tasks. Once the harvesting process is initiated by the robot arm, the servo motors take smooth movement on the robot arm to reach the specific direction and speed. Once the trajectory motion is performed then the sensor collects the fruit color in terms of energy level of the color. Upon obtaining the energy level of the color by sensing the fruit surface, it confirms the fruit ripeness if it is red, or it affirms the fruit is in the raw form if it is in the green color. The algorithm of the proposed method is given in Algorithm 1.

Algorithm 1 Fruit Harvesting Process with 6-DOF Robot Arm

1: Initiate the sensor and servomotors with the microcontroller
2: Perform the trajectory motion of 6-DOF robot arm such that sensor is facing the fruit
3: Sensor collects the color energy levels after sensing the fruit
4: If the sensor's color match with the green, then fruit is considered raw
5: If the energy level indicates red color, then the fruit is considered ripen and gripper of the 6-DOF arm plucks the fruit and puts it in the bag
6: Repeat the steps from 2 to 5 until the harvesting process is completed

In the algorithm, it is mentioned that 6-DOF robot arm has color sensor to sense the color of the fruit. In the methodology, it is mentioned the generalization of color sensor. The sensor could be from specific vendors, such as Grove IC2 Color Sensor (Farb sensor) works by taking the color chromaticity of ambient light or color of the object, see Figure 5. The sensor can work in the temperature from -42 Co to 85 Co temperature. The other type of sensor could be TCS2300 Color sensor, see Figure 6. Step 4 and step 5 of the algorithm mentioned that the fruit could be either green if it is on the raw state or could be in the red color if fruit is ripened. The red color of the fruit makes the robot arm pluck the fruit and keep the fruit in the bag. However, algorithm represents as an example fruits like tomato, which has two colors to decide the ripeness. The algorithm could be customized for different harvesting process of various corps with different colors. The methodology could be customized even for multiple color detections at different stages of the fruit condition. The algorithm makes the 6-DOF robot pluck the fruit upon the color of the fruit become red and place it in the bag.

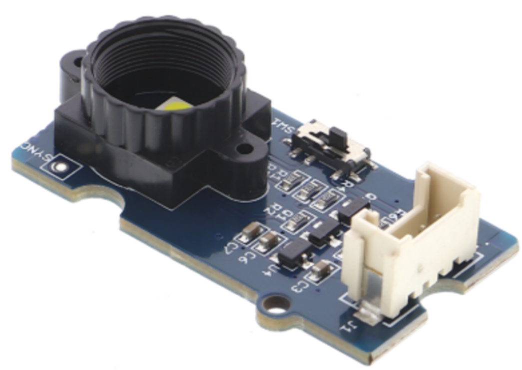

Figure 5. Grove IC2 Color Sensor

The methodology follows a hybrid structure combining analysis and iterative prototype development, divided into clearly defined structure to support technical implementation and evaluation. The proposed method benefits with low latency response time as the microcontroller directly deals with the energy value of color sensor, where the vision-based methodologies such as YOLOv3/v5/v8 deal with lot of computational processes, which may lead to high latency.

Figure 6. TCS3200 Color Sensor

4. Simulations

Prototype design and development have been carried out to analyze the performance of the proposed approach. For the 6-DOF robot arm, it was taken the model from vendor Yahoom DOFBOT robot arm. Figure 7 shows the robot arm.

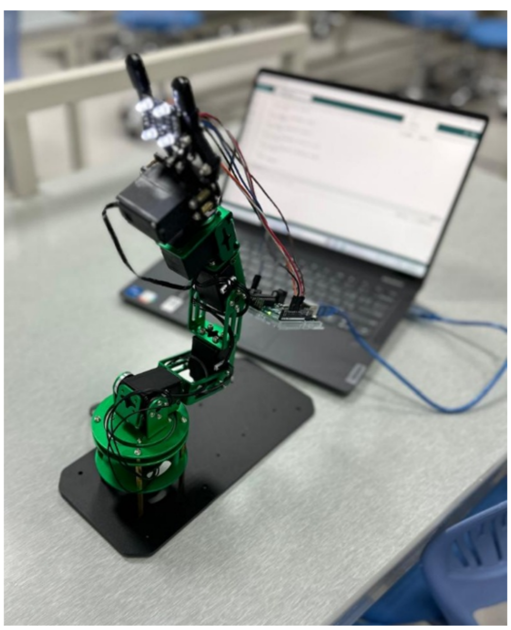

Figure 7. DOFBOT arm

The color sensor considered for the experiment is from the REES52 GY-31 TCS230 TCS3200 Color Sensor Module compatible with both raspberry pi and Arduino. The input voltage for the sensor is 3.3v to 5v. The response time for the sensor typically be 2 milliseconds. For the experiment, raspberry pi 4 microcontroller is used to control both the sensor and servomotors of 6-DOF robot arm.

The program code is written to identify the color of the object. In the first experiment, the red color cube is kept in front of the sensor, see the Figure 8. The energy levels detected by the sensor are plotted. The object is kept at different distances between object and sensor, i.e 1 cm, 3 cm, 7 cm, 11 cm, and 15 cm. After keeping the object, the python code is written to detect the energy level at every 0.5 second. The graphs are plotted after taking 10 samples at different distances.

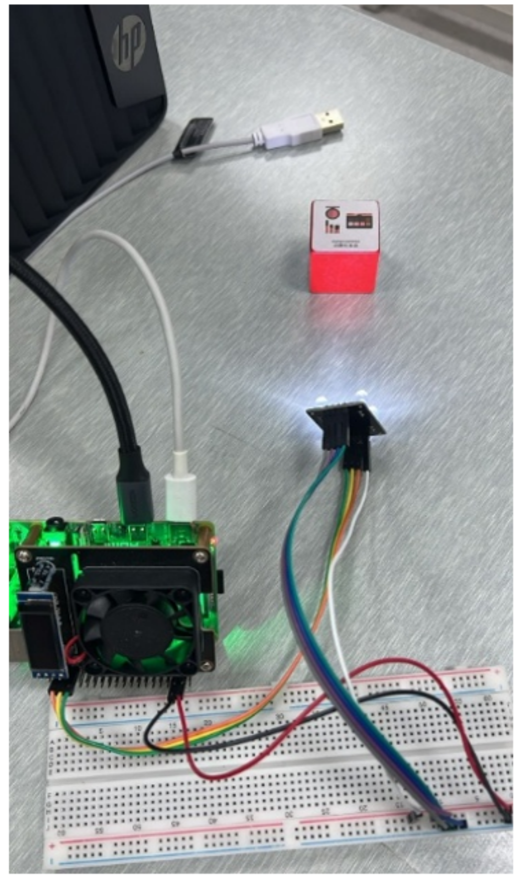

Figure 8. Color Detection Testbed

Figure 9, Figure 10, Figure 11, Figure 12, and Figure 13 show the plotting of the red color energy levels for the distances 1cm, 3cm, 7cm, 11cm, and 15cm respectively. For the second experiment, we collect the energy levels for the green color object. Figure 14, Figure 15, Figure 16, Figure 17, and Figure 18 show the plotting of green color energy level for the distances 1cm, 3cm, 7cm, 11cm, and 15 cm, respectively. The experiments show that the sensor collects data about the color of object successfully.

5. Conclusions

The modern agriculture techniques use the robotic technology for various agricultural processes. The literature review was presented in the paper on the use of robotic technology for agricultural forms. In this paper, we propose a new methodology for modern agriculture forms. Precisely, the proposed approach provides the robotic design prototype that can be used for fruit agriculture harvesting process. The

Figure 9. Red Color with 1 cm

Figure 10. Red Color with 3 cm

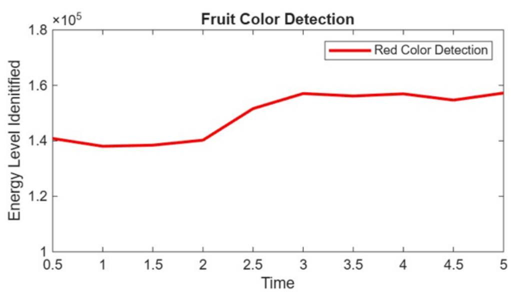

Figure 11. Red Color with 7 cm

Figure 12. Red Color with 11 cm

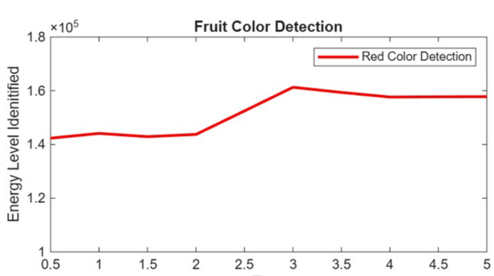

Figure 13. Red Color with 15 cmd

Figure 14. Green Color with 1 cm

Figure 15. Green Color with 3 cm

Figure 16. Green Color with 7 cm

Figure 17. Green Color with 11 cm

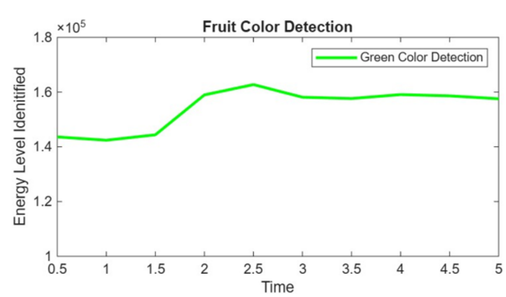

Figure 18. Green Color with 15 cm

method identifies the ripeness of the fruit in the plant forming, and pluck the fruit if it is ripen. The simulation of the proposed design structure is tested and presented in the paper. On summary, the proposed robotic technology is useful for harvesting of fruits in the agricultural forms with low computational processes compared to the vision based sensing process, hence increase with fast response.

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