Original Article

AUTOMATED SYSTEMS AS A FACTOR AFFECTING ON FLOWERS PLANT HARVESTING

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Abstract

In the last decade, the adoption of fully automated systems in agricultural operations has become an urgent need due to high labor costs and low efficiency. The harvesting process is one of those agricultural activities that require a lot of work in addition to high costs. The study investigates different fully automated harvesting systems for one of the most important crops, medicinal and aromatic plants, especially flowers which are involved in many industries and characterized by high economic importance in the global trade balance of crops. Process technologies that include harvest automation and standardization of the automated system detection problems and accuracy were analyzed and compared. Finally, to solve the various problems that facing the cutting flowers production, it is necessary to accelerate the development of mechanized harvesting, realize the mechanization of information acquisition and standardization in order to advance precision agriculture and agricultural wisdom for the future.

Keywords: Robot, Automated, Harvesting, Flowers, Visual selection.

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1. Introduction

Global ornamental plant exports have grown steadily over the past five years, at a compound annual growth rate of 3.9 %. All subcategories (cut flowers, potted plants, bedding/patio plants, bulbs, perennials, shrubs, and trees) experienced growth (Gabellini and Scaramuzzi, 2022). In order of production output, Netherland, Germany, France, Greece, Spain , Italy and United kingdom are the next highest producers (Adebayo et al., 2020). Unavailability of skilled labor for harvesting and post harvesting of floriculture produce is affect the floriculture production (Kalmegh and Sing, 2016). In recent years, floriculture industry lean over on automated harvesting system due to the high cost in labors and efficiency of work. Therefore, many researches and developments have made on harvesting operation in many area. The agricultural robot technology is an unavoidable requirement of agriculture, as its fundamental task is not only to solve the problem of less labor, precision, safety, comfort, and green operation, which is difficult to realize with traditional agricultural machinery and equipment, but also to fill the blank fields that many traditional types of agricultural machinery cannot fill (Jin et al., 2021). Although robots are still not as fast as humans in many cases, agriculture is currently developing robotic systems to work in the field and assist producers with tedious tasks, pushing agricultural systems to the new concept of Agriculture (Saiz and Rovira, 2020). The aim of this article is to discuss the various agricultural robotic systems used in flower harvesting and evaluation criteria of this robots, which have emerged as one of the most promising research areas in the last five years.

2. Automation Systems

Automation makes a work process, process or equipment automatic rather than human action or control. Automation does not simply transfer human functions to machines, but involves a profound reorganization of the work process, in which both human and machine functions are redefined. Early automation was based on mechanical and electromechanical controls; But over the past 40 years, the computer has gradually become the primary automation tool. Modern automation is usually associated with computerization (Gerovitch, S., 2003).

2.1 Automation systems applications in Agricultural

Technological advances make it possible to automate almost every part of agriculture, from planting to harvesting. Most agricultural technologies fall into three categories expected to support the smart farm: autonomous robots, drones or UAVs, sensors and the Internet of Things (IOT) (Kumar et al., 2017 and Amritanshu et al., 2014). IOT focuses on three aspects Communication, automation, and cost savings in the system. IOT enables people to perform routine activities using the Internet, thus saving time and cost and making them more productive. IOT enables the detection and/or remote control of objects through an existing network model. IOT in environmental monitoring helps to know the quality of air and water, temperature and soil conditions. IOT can also play an important role in precision agriculture to improve farm productivity (Sreekantha, and Kavya, 2017). Mobile robots originally built as automated guided vehicles (AGVs). This work deals with a mobile robot as a device that had to perform tasks in a partially known external environment to deal with unpleasant or dangerous tasks that humans actually perform. Automation of control and speed is a challenge that can increase productivity in many agricultural operations (Garcia et al., 2001).

2.2 Harvesting Robots

Harvesting robot consider as automation application in agriculture production. Not only reduce current labor costs, which account for 29% of total production costs (Jukema and Van de Meer 2009), but also harvesting robot enable new functionality by utilizing sensing abilities that humans either lack or cannot achieve with comparable accuracy, consistency, and cost (Bac, 2015). In recent years, research and development in harvesting robots have focused on economically viable crops harvesting robots like harvesting robots that working in greenhouses. Robots, that working in open field are one of the areas that require years of development due to the many variable factors that affect the working environment which making the need for smarter robots that can deal with an unstable work environment more urgent for robots application in open fields.

2.3 Harvesting Robots Subsystems

Most harvesting robots developed today are designed for a specific field and production environment (Montoya-Cavero et al., 2021). Although there are several hardware architectures, there are three main subsystems, which are: (1) a vision subsystem that allows the robot to detect the crop in its environment, its maturity, and then its 3D location by processing data from the vision sensor (2) a mobile delivery subsystem that allows the robot to reach the ripe product at the terminal, and (3) the final reinforcement subsystem that allows the robot to harvest without damaging its crop (Zhang et al., 2021). Another classification of subsystems in harvesting robots to fruit localization module, harvesting arm and gripper-cutter (Ceres et al., 1998). In complex robotics tasks, such as agricultural applications, detection systems (vision subsystem) are a key factor influencing the functionality and efficiency of work. The right choice of sensor system is usually made in light of the functions and requirements defined during the design phase of the robot. In this context, the sensory system based on computer vision has a special place due to its versatility. It can be used in many applications from fruit recognition (including size, color, ripeness, etc.) to object tracking and robot path determination after scene analysis (Hongkun et al., 2020). Obstacle detection systems can include a wide range of sensors and technologies, from ultrasonic sensors and laser to more sophisticated computer vision-based solutions (Mustapha et al., 2012). The navigation system is another important robot subsystem. It takes care of finding the way to the desired destination. It can be divided into three parts: locate where I am; the mission I want to go to; and finally, how to get there (Bayramoglu et al., 2009). Several methods have been presented to control a mobile robot system. They can be divided into two main parts: global planning and local control. The first is based on complete knowledge of the environment and the robot. The second category consists of local control or behavioral strategies. When deciding to move the robot, the current state of the robot and its relationship with the environment is considered (Nefti et al., 2001). Harvesting arm and gripper-cutter or (manipulation and grasping) is the functional operator subsystem of the robot. There are many different definitions of manipulation and grasping, depending on the different situations and applications. However, in general, mechanical manipulation can be defined as the application of force or torque to an object that causes movement or deformation, while holding an object can be called grasping. Each manipulator requires a gripper mounted on the terminal of the manipulator (Samadikhoshkho et al., 2019). There are different classifications of the grippers. Based on the number of fingers and configurations of each gripper, various types of grippers are presented according to Samadikhoshkho et al. (2019): Robot Grippers with 2 Fingers - Robot Grippers with 3 Fingers - Robot Grippers with Flexible Fingers - Multi-Finger and Adaptive Grippers - Grain-Filled Flexible Ball Grippers - Bellows Grippers – O ring Grippers. From the actuation point of view, another type of classification is presented by Robotworks (2022). The actuation method for each gripper is chosen based on the object characteristics. This classification types are: Cable-Driven Grippers - Vacuum Grippers - Pneumatic Grippers - Hydraulic Grippers - Servo-Electric Grippers.

3. Automatic Harvesting Theories

Automatic robotic harvesters that require little or no human intervention are considered a category of harvest theory classification (Li et al., 2011). As a result of the rapid Revolution in robotic solutions for harvesting and the design of new gripping and end effectors in recent years, It became necessary to update the classification of automatic harvesting methods to include these latest technologies (Navas et al., 2021). The updated classification of harvesting methods made by Navas et al.(2021), divide it into three main groups; Indirect harvesting : application of mechanical force or movement indirectly on the whole plant or part of it To make the fruits fall without any contact points. air blasting, limb shaking, trunk shaking and canopy shaking are examples methods of Indirect harvesting; Direct harvesting : harvesting method used in case of Difficulty applying direct harvesting due to the characteristics of the plant structure but require the direct application of a mechanical force on the fruit or its peduncle; these picking techniques also known as picking patterns (e.g., twisting, pulling or bending (Dimeas et al., 2015)), the last group is direct harvest with a driving force applied to plant stem: a method applied to fruits that require a direct mechanical movement or another type of cutting method applied directly to the stem because they are morphologically related to a plant with a hard stem that must be cut, such as eggplants, melons, oranges , cucumbers and harvested peppers. According to this classification, the theories of flowers harvesting automated systems can be considered as falling under the direct harvesting and direct harvest with driving force methods. Brabandt and Ehlert (2011) classified the picking principle of flowers to two basic principles; picking comb and picking rotor. The picking combs can move linearly or rotate. As addition feature, the linearly moved picking combs can be designed with additional cutting of stalks. The rotating picking combs are characterized by central and outside discharge of the flower heads and it could be presented in two forms; the form of pin drums and brush pairs

4. Status of The Flowers Harvesting Automated System

The key technical problems are mainly the lack of picking automated equipment. At present, the mechanization of flowers production is minimal–only a few time-consuming work. However, laboratory studies into some of these technologies are underway. At present, flowers picking relies mainly on manual labor and is flowers harvesting began in recent decades. Rath and Kawollek (2009) invented an autonomous cutting flowers picking robot at Leibniz University Hannover in Germany. The robot possessed a machine vision control system and standing robot with 6 DOF, mounted onto an additional vertical linear axis for the expansion of its work space. Consequently, the robot could carry out additional upward and downward motions that could pick Gerbera jamesonii which was used as model plant to testing the system. A prototype harvesting robot for cutting flowers is shown in Fig. (1). A pneumatic harvest knife was equipped with the robot which was able to cut the Gerbera pedicels and to hold them with a holding fixture. A pneumatic end effector harvester was created that harvests the crop by cutting it (Fig. 2).

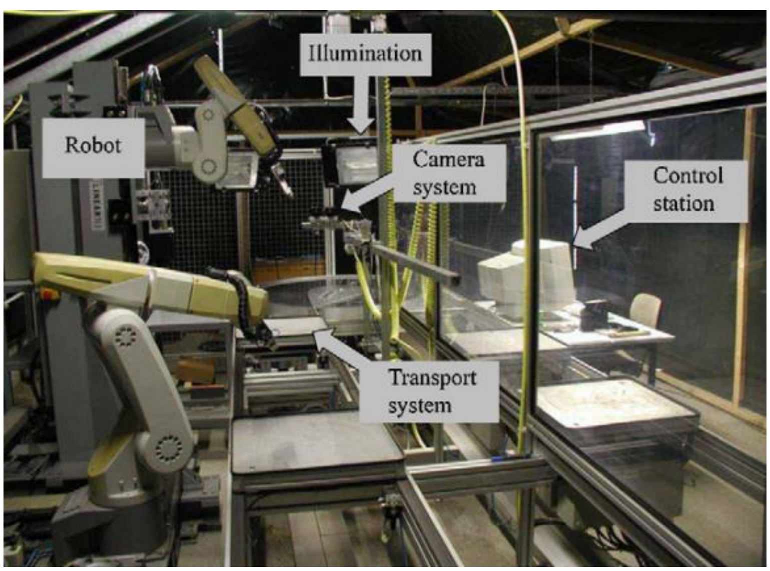

Fig. 1. Test station with robot, camera system, illumination, transport system and control station.

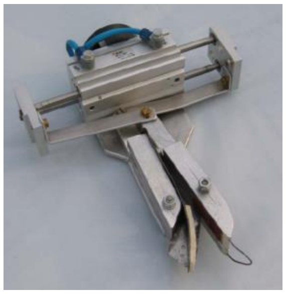

Fig. 2. Pneumatic robot actuator for cutting and holding the gerbera stem (self-development, prototype).

Abarna and Selvakumar (2015) developed a rose harvesting robot at VIT University, Chennai, India, which included a 2DOF model with RR manipulator, end effector, and chassis. The 2-DOF manipulator is mounted on a chassis with two wheels driven by DC motors. Recognizing by color and pattern is the recognition techniques used to detect rose flower. Once a flower is detected, a trigger is given to the PIC controller to activate the robotic arm for harvesting. The picking end effector was designed to hold a knife to cut the stem of a rose (Fig. 3 and Fig. 4)

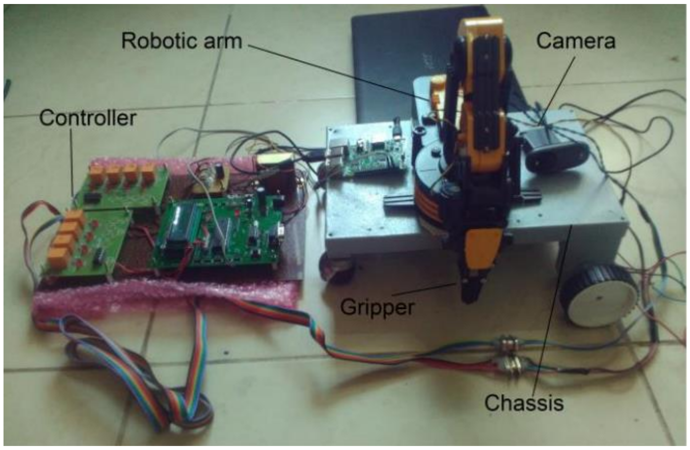

Fig. 3. Rose flower harvesting robot.

Fig. 4. The robotic arm duaring harvesting operation

Shree et al. (2019) invented a new quick and convenient method of automatic harvesting with Deep Convolutional Neural Network recognized system. For accurate object recognition the exact location of the flower along with the flower markings on the plant is requires and this represented a challenge task in computer vision and machine learning (Fig 5.)

Fig. 5. Results of proposed system for flower detection from the color images based on deep convolutional neural network

Vinot Kumar et al., (2019) have invented and implement a fully autonomous system capable of collecting flowers. The flowers can be harvested from the plant in perfect condition with the help of a robotic arm cutter (Fig. 6), which takes less time to harvest than manual harvesting. The developed robot will be suitable for small flowers like roses.

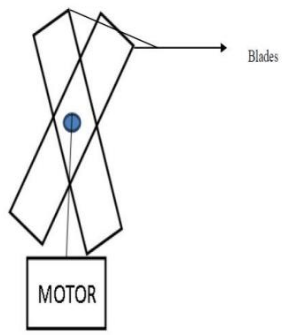

Fig. 6. Robotic cutter arm with motor

Also Bhaskar et al. (2021) invented a real Time Farmer Assistive Flower Harvesting Robot (Fig. 7).the main target of the robot was to reduce the work and risk of the farmers. The main target of the robot was to reduce the work and risk of the farmers. The working theory was based on Image Processing, AI, ML and IOT. Image Processing and LBP (local binary patterns) technique were the detection techniques used to detect the flowers with the help of the raspberry pi camera.

Fig. 7. The AGROBOT in flower harvesting fields

As advanced functions and thanks to AGROBOT's high-resolution camera, it was able to detect plant pests and insects through image processing. AGROBOT has a small tank of pesticides and insecticides. When it comes in contact with pests, it automatically sprays towards those plants. The flow chart of operations sequences in AGROBOT system showed in Fig. (8). The AGROBOT could be successfully detect and picks the flower and places it in the basket using various algorithms, and also detected pests and spray pesticides and insecticides on plants.

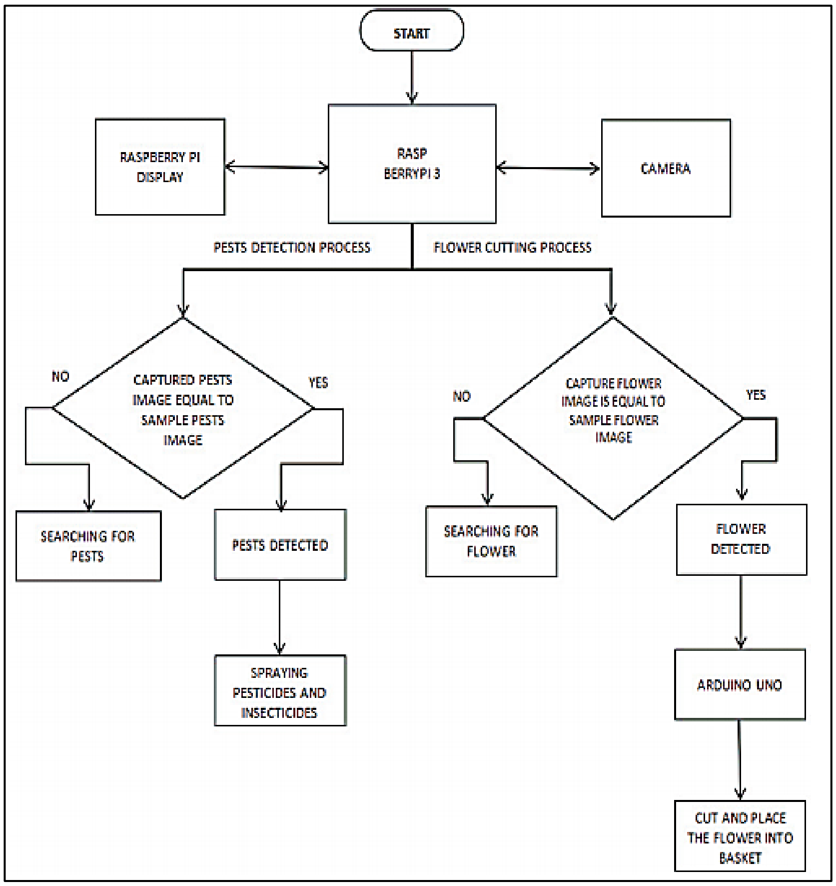

Fig. 8. Flow chart of operations sequences

Guo et al. (2022) invented safflower picking robot based on a parallel manipulator. The robot mainly consists of a walking device, parallel manipulator device, vision device, picking device, filament collection device, control system, and motor drive system (Fig. 9).The robot moves between rows of safflower plants and stops when it reaches a mature safflower area. The upper (host) computer controls the rotation of the motor, where the motor shaft is connected to the active arm of the parallel manipulator, and the motor shaft rotates at a certain angle to drive the parallel manipulator to move to the target position. The safflower arrives at the picker with a flower transport hole, and a cranked slider cutter does the back and forth cutting of the safflower. The filament collection device is energized, the suction fan creates a vacuum, and the filament is sucked into the collection box and passes through the flower transport hose under vacuum while the saffron filaments are collected and collected (Fig. 10).

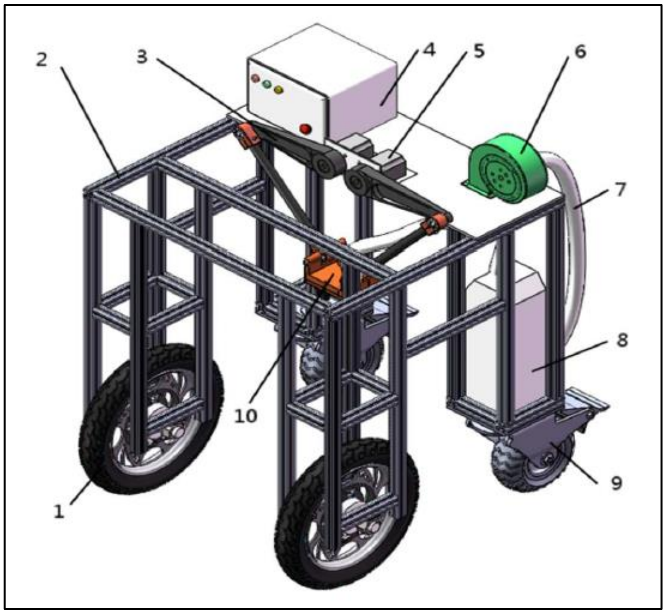

Fig.9. Structure diagram of the safflower picking machine: (1) electric drive wheels, (2) frame, (3) parallel manipulator device, (4) controller, (5) servo motor, (6) negative pressure suction fan, (7) house, (8) filament collection box, and (9) walking wheels.

Fig. 10. The robot picking operation

5. Evaluation and Analysis of Flowers Plant Harvesting Robots

Mechanized harvesting is currently used in cutting flowers production. The focus of the development of mechanization in flower production is to reduce costs and gain the advantage of efficient and inexpensive field operations in flower identification and automatic harvesting. From this researches what has been discussed that the mechanisms and technologies used for flowers harvesting in both the lab and in commercial orchards. In different aspect, related researches are concluded in Tables (1). The scientific paper has been extensively reviewed since these systems are crucial components determining whether or not a flowers harvesting machine can successfully face its performance demands. First, the flower picking technology is designed for laboratory applications such as image processing, manipulation, final effects control, vehicle motion control and control. For fields, mechanized floriculture equipment must be able to sense its surroundings (Mu et al., 2018). Despite of mentioned before, there are many criteria by which robots could be evaluated. In general the flower harvesting robots the success rate of harvesting evaluation test is the most important criterion to evaluate the performance. The visual selection criterion is the second criterion that pays attention in flowers collecting robots which represent the basis on which the harvesting process takes place.

5.1 Visual Selection

Three-dimensional model was making to discover the flowers in picking robot for flowers (Rath and Kawollek, 2009). Before testing of the developed system, a calibration of the entire system was carried out to ensure its efficiency. The calibration was done through a calibration board (with printed marks) and then installed on the robot actuator. Twelve different varieties of Gerbera jamesonii were planted to obtain the image dataset to configure detection and processing algorithms. In the harvesting process, the system used to detect and model the plant stems by using the green color channel that achieved the highest response and then converting the images to gradations of gray to identify the flowers.

The results showed that the detection rate differed according to the number of plant stems(Fig. 11). The robot achieved a detection rate of 94% in the case of one lute, while it was 66% in the case of two and 44 in the case of the three.

Table 1. Different Types Of Flowers Harvesting Robots

Robot type	Visual System Description	Detection Rate (%)	Harvesting Rate (%)	Reference
Gerbera jamesonii Robot	- 3D model based on image processing using (2 high resolution camers	- 94% (one plant stem) - 66% (two plant stem) - 44% (three plant stem)	- 97%(1-2 pedicel) - 89% (3- 4 pedicel) - 50% (≥ 5 pedicel)	**Rath and Kawollek (2009)**
Rose Flower Robot	- Color and pattern detection techniques. - Image processing using Raspberry Pi camera. - PIC module	- 74% (50 mm distance from plant) - 80% (100 mm distance from plant) - 86% (150 mm distance from plant) - 90% (200 mm distance from plant)	- No Result previewed	**Abarna and Selvakumar (2015)**
Marigold Flower Robot	- Detection algorithm based on proposed Deep Convolutional Neural Network	- 87.79 %	- No Result previewed	**Shree et al., (2019)**
Safflower Robot	- Using CCD camera	- No Result previewed	- 87.91 %	**Guo et al., (2022)**

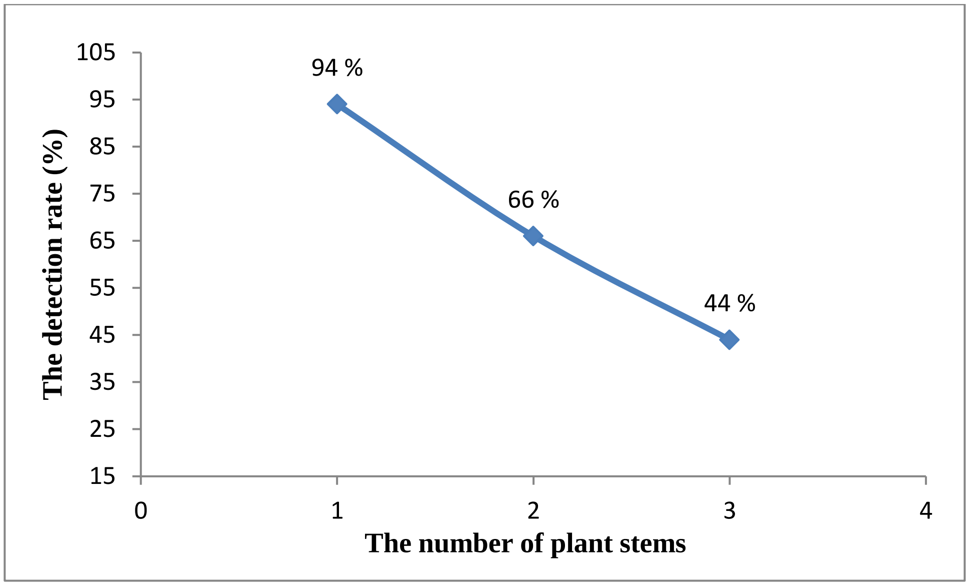

Fig. 11. Relationship between the number of plant stem and detection rate

Rosa harvesting robot was designed based on image processing to select the flowers to be harvested (Abarna and Selvakumar, 2015). The color detection method was used as a basis for AI model, where fire engine red (R-206, G-22, and B-32) color was chosen as reference color for comparison. Pattern matching is done by training the system with positive and negative images using sequential training. The system was tested to determine its success in detecting flowers, where the camera was placed at different distances from the flowers (50, 100, 150, 200, 250, 300) and 10 repetitions were taken for 50 plants in order to study the relationship between detection rate and the distance of the camera to determine the appropriate degree of closeness to the flowers. The evaluation results showed that the detection rate varies according to the distance of the camera from the flowers (Fig. 12), where it is a positive relationship, as the distance increased from 50 mm to 200 mm sequentially, the detection rate increased from 74% to 90%. After reaching the peck of the curve at 200 mm, the detection rate begins to decrease with increasing distance. At 250 mm the detection accuracy was 82% and at 300 mm it was 60%.

Marigold harvesting detection robot was evaluated (Shree et al., 2019). The evaluation results of the proposed flower detection system using color images based on deep neural network showed that the system provides 87.79% accuracy of the flower image captured by the automatic robot system. If the flowers are hidden behind leaves and branches and are not visible properly in the image, the proposed framework cannot detect the flowers.

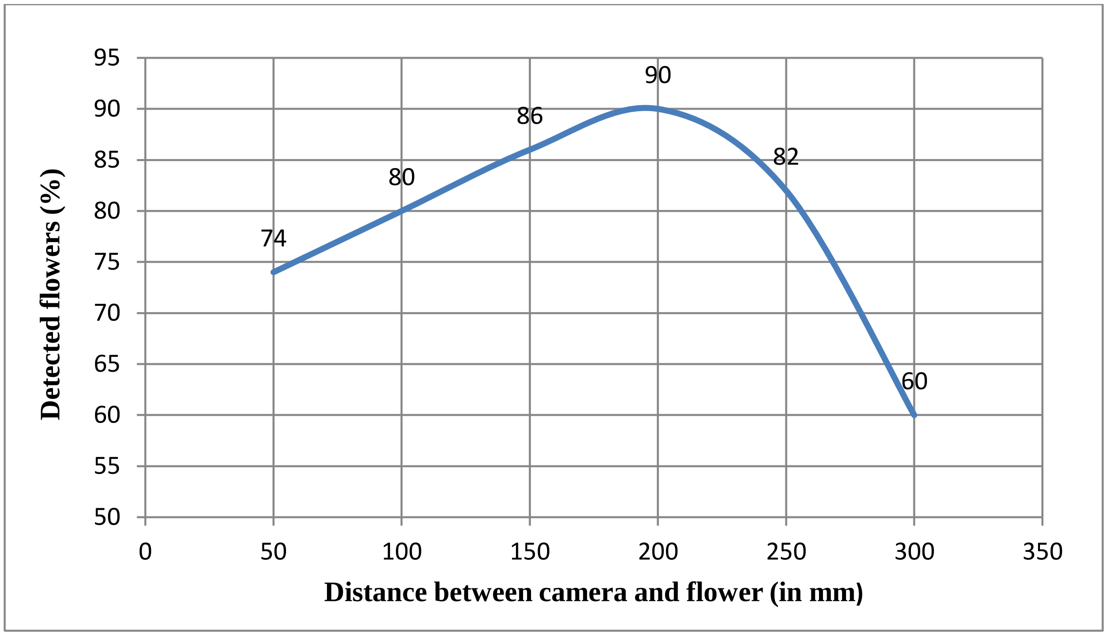

Fig. 12. Relationship between camera distance and detection percentage

5.2 Flowers Harvesting success rate

The success rate of the robot during the harvest was measured (Rath and Kawollek 2009) 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%. Guo et al. (2022) designed picking robot for safflower, and evaluated its performance. 15 pots of plants were equally divided into groups of 3 pots for a total of 5 groups of test samples. The picking test was carried out under laboratory conditions. The test results showed that the average picking cycle of safflower filaments was 16 s/flower ball. The net picking rate of filaments was ranged 85.88% and 89.16% (Fig. 13) with average value of 87.91%, which satisfied the filament picking requirements and verified the feasibility of the safflower picking robot.

6. Discussion and Conclusion

Based on the studies reviewed in this paper, it is clear that the two main criteria for evaluating the performance of flower harvesting robots were Detection Rate and harvesting rate. Where the visual selection testing and evaluation standard, especially the Detection Rate, is the main

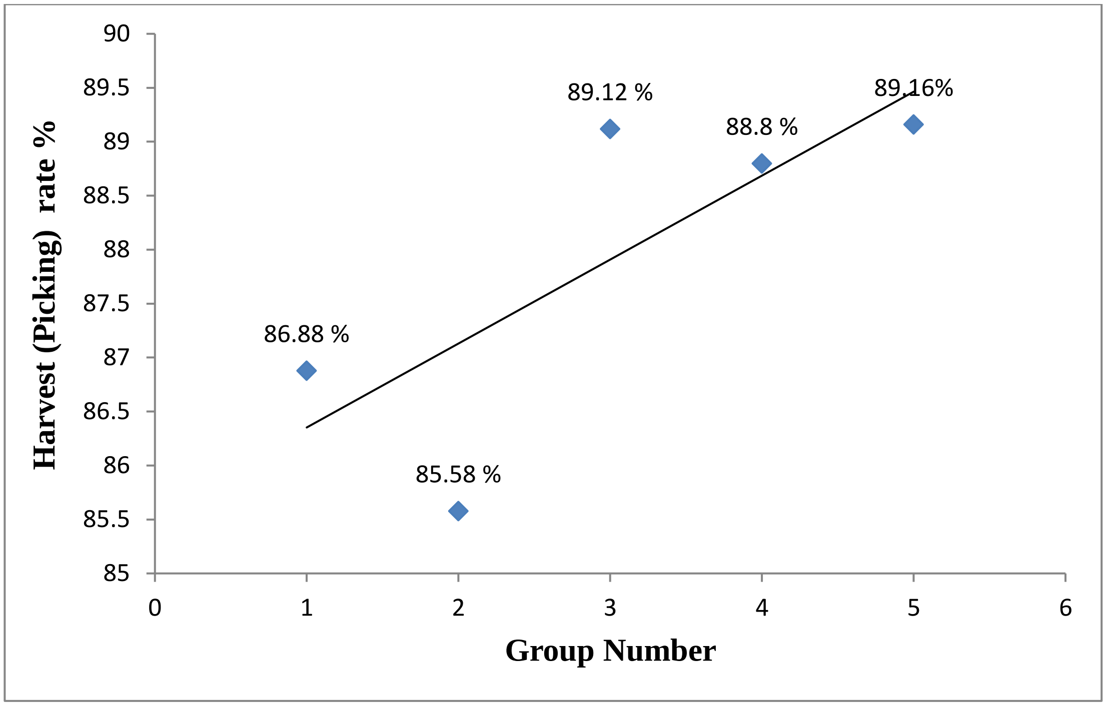

Fig. 13. Results of safflower robot picking rate test

criterion investigated in the flower picking robot research. Visual selection is the basis on which the harvesting process is based. Different results (Table 1) showed that the detection rate generally ranged from 44% to 94%, depending on the type, size and properties of the harvested flowers. The factors affecting this criterion can be concluded and summarized as follows:

- The type of image processing and color tones used in recognition and analysis process.

- The density of flowering plants and the size of the harvested flower.

- Confusion in captured images due to the presence of various elements other than flowers.

- Accuracy and quality of captured image.

In general, detection rate increases as plant density decreases. The presence of flowers individually, without pollution in the image or decreased resolution, lead to increase the accuracy of the robot's detection. The rate of harvesting is the second important criterion, but despite that this criterion has not received much attention in the studies on flower harvesting robots. However, this criterion can be given a relative value across the studies reviewed. The harvest rate of flower harvesting robots varies from 50% to 97%. The accuracy of this percentage cannot be trusted because the lack of available studies on this criterion. Therefore, extensive research is needed to obtain a more accurate percentage of this criterion.

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