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Automatic Tomato Harvesting System using Image Processing Techniques

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Abstract: The efficiency of farming is increasingly dependent on precision farming. This is due to significant competition, the emergence of new pests and bacteria that spoil the crop, environmental problems, and many other factors from which products lose their value. One of such factors is the timeliness of harvesting. This is especially true in greenhouse complexes, where harvesting occurs regardless of the season, regularly after the ripening of products. The ripening of tomatoes is quite unpredictable, so it is necessary to identify the ripening process to harvest in time. Machine vision can solve this problem by highlighting a separate spectrum of color, which is characteristic of already-ripe tomatoes. Therefore, the article proposes a method for identifying the processes of tomato ripening using image processing methods based on color detectors. The OpenCV library was used for software implementation. A Rasbberry Pi unicameral computer was used to solve this problem.

Keywords*:* Harvesting, Image processing, Tomato

I. INTRODUCTION

The declining and aging population of farmers has become a serious problem. In particular, the number of farmers is annually declining. It is predicted that the num ber of farmers will decrease by half of the present number by 2030. This might affect the food supply in the country. In recent years, smart agriculture has been promoted to solve these problems. Smart agriculture is a type of agriculture that uses robotics, and information and communication technology to promote labor saving, precision, and realization of high-quality production. It is attracting attention as a solution to problems such as aging and decline in the number of farmers.

In this research, we focused on robots that can harvest tomatoes. The yield of tomatoes is relatively large. The skin is thin, and the fruits are bell-shaped. Therefore, it is difficult to harvest tomatoes without damaging them. Additionally, it is a delicate fruit which has a short suitable harvest period and the state of the fruit changes daily. Automatic harvesting of tomatoes might overcome the abovementioned problems. In addition, since tomatoes are mainly cultivated in a plastic greenhouse, they are unaffected by external factors such as wind and rain, and robots can be easily introduced in these enclosures.

During automatic harvesting of tomatoes, to ensure the operation of the harvesting arm, an input by image processing is crucial to determine the color of the tomatoes at the time of harvesting. Research on robot image processing technology is indispensable to ensure accurate operation of the arm. In a previous study, a tomato- harvesting robot was proposed that could detect a single tomato. As its application, we have been working on individual detection of adjacent tomatoes and tomatoes in the foreground. In addition, research has been con- ducted on arms and image processing for accurate harvesting of tomatoes and to detect the posture of tufted tomatoes by three-dimensional analysis and simulation.

As a preparation for harvesting, a study was conducted in which image processing was performed to estimate the harvesting time . Additionally, a study was performed to determine the cutting position using a point cloud for harvesting task. Point cloud was used for fruit detection using three-dimensional point cloud. Furthermore, research was conducted on the application of cameras and laser range sensors in agricultural robots, and on development of fruit harvesting robots. A 3D vision system was developed for asparagus harvesting. Grippers and cutting systems for harvesting have been developed.

These studies focus on harvest time estimation and mechanism development. However, in an environment where tomatoes are harvested, obstacles encountered dur ing harvesting of tomatoes such as leaves, stems, and un- ripe tomatoes should be taken into consideration. Therefore, in this study, it is not imperative to recognize all the tomatoes in the image. In contrast, it is crucial to instruct the harvesting mechanism to target the tomatoes that are easily harvested by the robot arm. However, it is difficult to define the best target.

Therefore, we excluded tomatoes that are difficult to harvest and narrowed down a few tomatoes in the range that can be harvested. We have developed a strategy to ensure that one of them is harvested. In addition, since the environment changes after harvesting of each tomato, it is assumed that the harvest candidates will be continuously narrowed down.

Furthermore, since the tomatoes are repeatedly processed by a micro- computer, the tomatoes that can be distinguished by simple processing based on color and shape are considered as tomatoes that are in a position where they can be easily harvested. Therefore, we propose an image processing technique to determine a route that the robot arm can easily use to harvest tomatoes, considering the surrounding environment.

II. LITERATURE ANALYSIS AND PROBLEM STATEMENT

Spectral analysis of images during the identification of different fruits is widely used in many areas. Thus, a significant part of the work is aimed at identifying the individual contours of the fruit and their shape. However, it is not always possible to record the shape of a tomato fruit due to its accumulation, so you should pay attention to works that use spectral analysis of images to identify objects. It was proposed to collect fruits from fruit trees based on a color detector using a special device, the approbation of which showed an accuracy of 90%. Methods of face identification by spectral features have become widely popular. For example, in the article. It is offered to consider new spectral features created on the Sonic Wavelet transformations, which allow recognizing the texture of the face. An algorithm for recognizing fruits to determine further their weight was implemented.

However, although the identification of fruits by color has several advantages, compared with, for example, methods of identifying fruits by specific points, or by contours, there are certain problems associated with the noise formed because of shadows or changes in the light. Therefore, a number of filters are used to solve such problems, such as the Otsu method, which is often used to reduce noise by low-pass filters. These problems are solved by smoothing and blurring, for example using median filters. Due to the wide popularity of methods of spectral analysis of images, many works are devoted to combined identification methods, both in shape and color.

For example, scientists from Oklahoma in a study of hyper-spectral image analysis methods have identified the most effective approaches to estimating the color spectrum in the image. To highlight the color saturation, you often use the RGB model for identification purposes. This model contains pixels of at least 3 colors with different wavelengths. Such as red, blue, and green (Fig. 1), but for the convenience of working with the color spectrum, usually use the HSV model, where the characteristics of the spectrum also reflect the saturation, which is more in line with human perception of color.

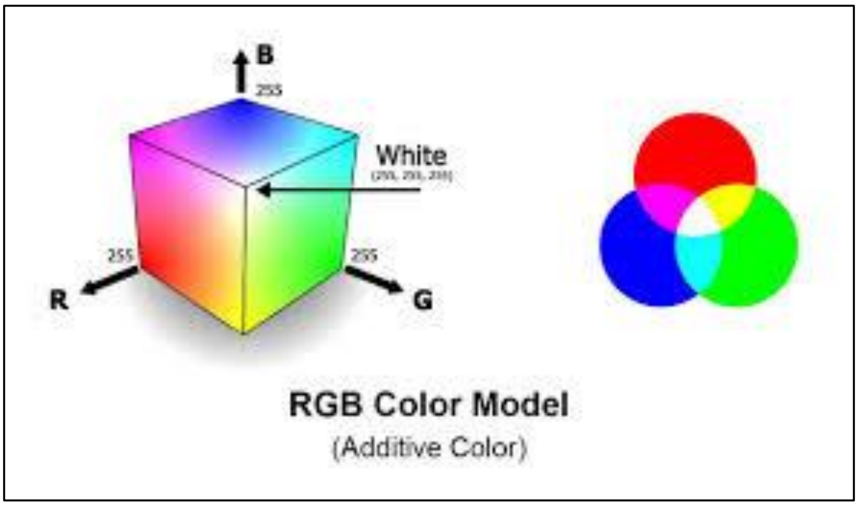

Fig 1. RGB model

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Thus, HSV (English Hue, Saturation, Value - tone, saturation, value in fig 2.) is a color model in which the color coordinates are:

- Hue – color tone in the range of 0-360;
- Saturation – saturation, in the range of 0-100 or 0-1;
- Value – the value of color (brightness). Set from 0-100

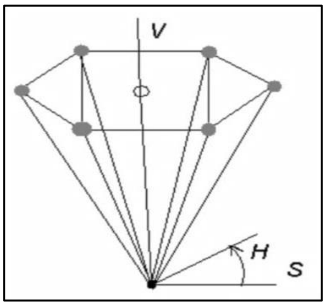

Fig 2. HSV model

The selection of individual color spectra of the image can be done using the library for pattern recognition OpenCv, which includes the possibilities of software implementation of both models. For HSV, the range of shades in this library will be [0,179], the range of saturation - [0,255], and the range of values - [0,255]. If you convert the image of a tomato bush from the format RGB y HSV, we obtain the following images (Fig. 3).

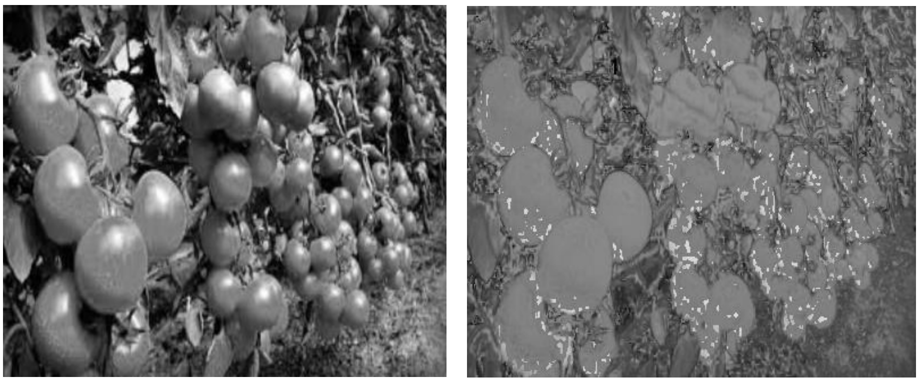

Fig 3. Convert RGB to HSV

Such, you can use image saturation elements. To identify the fruit of the tomato, you can select the cream pixels by color using this library. Creating a mask that characterizes only the fruit. To reduce noise, you can use a Gaussian filter . To determine the spectrum that corresponds to the color of the tomato, you can select its range, but the surface of this fruit has a glossy base, so there is a reflection, which is the cause of certain errors. For example, the image of a tomato was taken, the range of its characteristics by color was established and as a result, incomplete identification was obtained. Fig. 4 shows the following inaccuracies. But despite some error, you can count the pixel IDs of the selected color and set the criteria for the growth of tomatoes by calculating the selected color spectrum at different times, following certain requirements for lighting and angle of the photo-recorder.

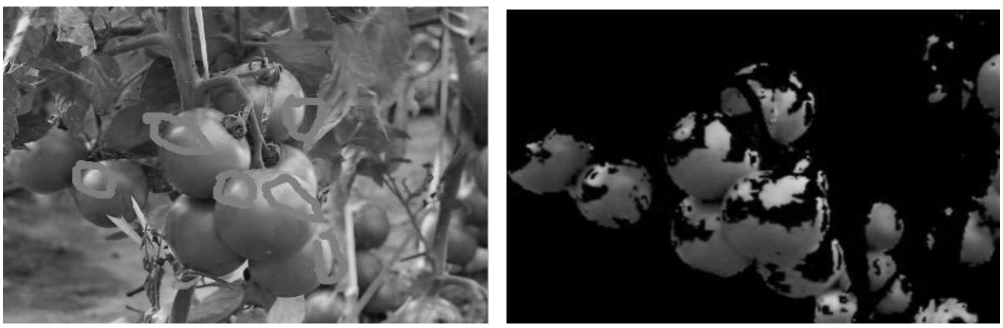

Fig 4. Selecting individual points in each color range

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III. RECOGNITION OF TOMATO

3.1 Feature of Color and Shape

As mentioned above, to ensure automatic harvesting of tomatoes, it is necessary to consider obstacles such as leaves and stems. There is a possibility that the tomatoes at the time of harvest might remain hidden and they can- not be detected or harvested due to the obstacles present around them. In this research, a method was proposed to distinguish between hidden tomatoes and visible tomatoes.

The tomatoes that are visible can be harvested from the front by instructing the robot arm. The hidden tomato directs the path of the robot arm considering the positional relationship with the obstacle. Subsequently, whether it is hidden or not is determined by detecting a circle with "Hough circles" of OpenCV. It was assumed that the tomato is circular, and if a circular shape can be detected, it was a visible tomato, and if the circular shape cannot be detected, it was a hidden tomato.

During recognition of tomatoes in the image, it be- comes easier to recognize tomatoes if other objects are ex- cluded. Therefore, we distinguish between tomatoes and other color elements. Color extraction was used to per- form this action. Color extraction is possible by setting a threshold, but the axis of value differs depending upon the color space used. HSV (hue, saturation, and value) was used in this study because it is crucial for the user to set the color of tomatoes according to the variety and the required yield. Additionally, HSV is closer to human color perception.

Subsequently, a color image from a camera or an image extracted from a specific color has only color information for each pixel for a computer. To ensure that the system is aware of an object in an image like a human being, it is necessary to treat the connection of pixels as an "area." Therefore, we used the labeling function. First, the im- age is binarized. In this binarized image, the process of assigning the same number to pixels in which the white part (or black part) is considered continuous is called labeling.

For labeling, we considered four concatenations (near 4) that treat the continuation of the binarized image only in the vertical and horizontal directions as the same label, and 8 concatenations (near 8) that treat the continu ity in the vertical, horizontal, and diagonal directions as the same label. However, in this study, we focused on the recognition of a tomato divided by obstacles in the image areas as one tomato and adopted the vicinity of eight. While searching for tomatoes in the harvest season from an image, red color is extracted and labeled. How- ever, the redness of the tomatoes might be reflected on the leaves and small red areas might be formed. To reduce such a false detection of tomatoes due to noise not related to harvesting operation, it is necessary to blur and smooth the image. Therefore, a smoothing filter was used to blur the image.

In this research, we adopted the Gaussian filter and median filter implemented in OpenCV. The Gaussian filter performs natural smoothing by weighted averaging in the kernel, and the median filter smoothes the kernel center to the median value in the kernel to remove noise while leaving edges. When green was extracted and information on detailed areas such as vines and stems was required, a median filter was used. In the experiment, the size of Gaussian was set to (15, 15) and the size of median was set to 25.

3.2 Instruction to Robot Arm

In this study, it was assumed that the articulated robot arm is equipped with a cup-shaped end effector, which can grip to wrap around the tomato to pluck it. In addition, since the basic size is determined by the tomato variety, it is possible to cope with a few size variations by preparing a slightly large cup. From the geometrical relationship between the installation position of the camera and fixed position of the robot arm, the target position was harvested using inverse kinematics calcula- tion to ensure that it is within the cup of the end effector. Figure 2 shows the tomato sapling in the tomato robot competition. In this research, it was assumed that the tomatoes are recognized in such an environment.

The following situations can be considered for the recognition of tomatoes by the input from the camera.

(1) Tomatoes are not shown in the image.
(2) There are mature tomatoes that are visible.
(3) There are hidden mature tomatoes.

In case of (1), the program is terminated, and in case of (2), the harvesting operation is performed from the front (details are shown in Section 2.4).

In case of (3), there are several possible patterns for hiding tomatoes, but with the upper left of the screen as (0, 0), x on the horizontal axis and y on the vertical axis, and the coordinates of the centroid of the tomato and the obstacle. Subsequently, a safer route is provided as output by comparing x and y positions.

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For example, consider the state shown in Fig. 3. In this case, the coordinates of the center of gravity of the tomato in the center were (x_1, y_1) = (321, 285) and the coordinates of the center of gravity of the upper right leaf were (x_2, y_2) = (371, 194). In such a positional relation- ship ($x_1 < x_2, y_1 > y_2$), since an obstacle was presented in the upper right portion for tomatoes, the system was instructed to perform the harvesting operation from the lower left. Similarly, as shown in Fig. 4, the output is ob tained using four directions. Additionally, when multiple stems (straight lines) are detected on the screen, there is a high possibility that the arm will come in contact with the stems during the harvesting operation. Therefore, an output will be displayed that states that the tomato will be "difficult to harvest."

3.3 Tomato Detection Algorithm

Using the above image processing technology, we considered the following model. Following shows the flowchart of the program used in this experiment.

1. Input the image from the camera.
2. Extract red color to determine mature tomatoes using the color image of the camera.
3. The area where the red pixels are connected is regarded as an area, and the number of areas is counted.
4. If an area is observed, the coordinates of the center of gravity can be obtained.
5. If the area is not observed, proceed to the end of the program.
6. Obtain the centroid coordinates of the red area.
7. Assuming that the tomatoes are circular, if the circular shape can be detected, the whole picture can be observed and the harvesting operation can be per formed from the front.
8. Obtain the center coordinates of the circle.
9. Considering the center coordinates of the circle as the target value, instruct to the arm to ensure that it is harvested from the front.
10. Exit the program.
11. To identify the position of objects that hide tomatoes (leaves, stems, immature tomatoes). Extract green color.
12. Consider the area where green pixels are connected as an area.
13. Obtain the centroid coordinates of the green area.
14. Perform straight line detection to determine the pres ence or absence of stem in the proximity.
15. Compare the centroid coordinates of the red area and the green area, and select the route from the result.
16. Output the harvest route including coordinate infor- mation to the arm.

IV. ALGORITHM

4.1 Detection of Visible Tomatoes

First, the image obtained by extracting red from the original image was gray-scaled and then binarized. This ensure that the information for each pixel of the image was defined by the binary values of "0" and "1." Therefore, the computer can easily process the information in the image and allows labeling. Subsequently, area (labeling) and surrounded by a rectangle. Finally, for tomatoes that were visible, it was assumed that circular detection can be performed by Hough circles of OpenCV. Additionally, circular detection and center coordinates were acquired. If a circle can be detected, it was ensured that it was not hidden by an obstacle, and the output was provided to the arm to per- form the harvesting operation from the front of the camera.

4.2 Experiment of Tomato Recognition

In this research, a color image was input as described above, image processing was performed, and a sentence was provided as output. First, to read the color image, the RGB-D sensor RealSense D435 (Intel) was used. RealSense D435 is connected to a PC via USB 3.0 Type-C, and it transmitted image information and sup- plied power using a single cable. The image input from the camera is processed by the image processing software OpenCV 4.1.1.

4.3 Experiment 1: Detection of Mature Tomatoes

At the actual harvesting site, it is possible that the mature tomatoes are not visible on the camera screen. Therefore, an experiment was conducted to determine the presence or absence of mature tomatoes in the image. First, 10 images were randomly prepared, which show images with and without mature tomatoes. For each image, the output was provided in characters if the presence or absence of mature tomatoes can be correctly determined. even though the tomatoes that can be harvested are not shown as in Observing the output images that extracted the red color of those images, it was observed that the red color of the tomatoes in the other ridges reflected in the back was extracted. In addition, red extractions other than that of tomatoes, such as soil color, were also observed. For the above reasons, it is probable that "Mature tomatoes are shown" was displayed even when the tomatoes that could be harvested were not shown. As a solution, by per- forming measures such as extracting the foreground (seg- mentation), it is possible to discuss only the situation in the foreground without reflecting the background.

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4.4 Development of tomato ripening monitoring system

Detection of changes in the images of tomatoes can be implemented because of a movable mechanism, which is controlled by a single-board computer RaspberryPi. To establish the places of photography, on such a device you can install an infrared sensor that will respond to specially selected places. Standard infrared distance sensors allow you to respond to approximations at a distance of up to 30 cm. This is sufficient to identify the stopping point of a moving device. The implementation of the software algorithm can be performed based on Python interpreter and libraries: sqlite3, for database operation, OpenCv, for image processing, RPi, for work with RaspberryPi COM port, which will be used to provide control signal to drive the transport platform.

In this case, the start, stop and input functions can be implemented using a single-chamber RspberryPi computer. Approbation of this algorithm can be implemented with the following sample of photographs, where there is a moderate increase in the number of red tomatoes. After receiving data on the number of color-defined points and storing them in a database, you can work with them. Thus, the growth is identified by increasing the red color in the images, which can be visualized as the ratio of the obtained points to their total number.

4.5 Python Code for execution

```
#python code
import cv2
import numpy as np
# Load the image
image = cv2.imread('tomatoes.jpg')
# Convert the image to grayscale
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
# Apply Gaussian blur to reduce noise and improve contour detection
blurred = cv2.GaussianBlur(gray, (15, 15), 0)
# Perform edge detection using Canny
edges = cv2.Canny(blurred, 50, 150)
# Find contours in the edge-detected image
contours, _ = cv2.findContours(edges.copy(), cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
# Initialize a list to store detected tomatoes
detected_tomatoes = []
# Define the minimum area for a region to be considered a tomato (you can adjust this)
min_tomato_area = 1000
# Loop through the contours and filter out small ones (noise)
for contour in contours:
    area = cv2.contourArea(contour)
    if area > min_tomato_area:
        detected_tomatoes.append(contour)
# Draw bounding boxes around detected tomatoes
for tomato_contour in detected_tomatoes:
    x, y, w, h = cv2.boundingRect(tomato_contour)
    cv2.rectangle(image, (x, y), (x + w, y + h), (0, 255, 0), 2)
# Display the result
cv2.imshow('Tomato Detection', image)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

4.6 Here's a breakdown of the steps

1. Load the image: Load the image in which you want to detect tomatoes.
2. Convert to grayscale: Convert the image to grayscale to simplify further processing.
3. Gaussian blur: Apply Gaussian blur to the grayscale image to reduce noise and enhance the edges.
4. Edge detection: Use the Canny edge detection algorithm to identify edges in the blurred image.
5. Find contours: Find contours in the edge-detected image using the cv2.findContours function. Contours are the boundaries of objects in the image.
6. Filter contours: Loop through the detected contours and filter out small ones (noise) based on their area. Adjust the min tomato area threshold to control the minimum size of a tomato region.
7. Draw bounding boxes: Draw bounding boxes around the detected tomatoes using cv2.rectangle.
8. Display the result: Show the image with the bounding boxes to visualize the detected tomatoes.

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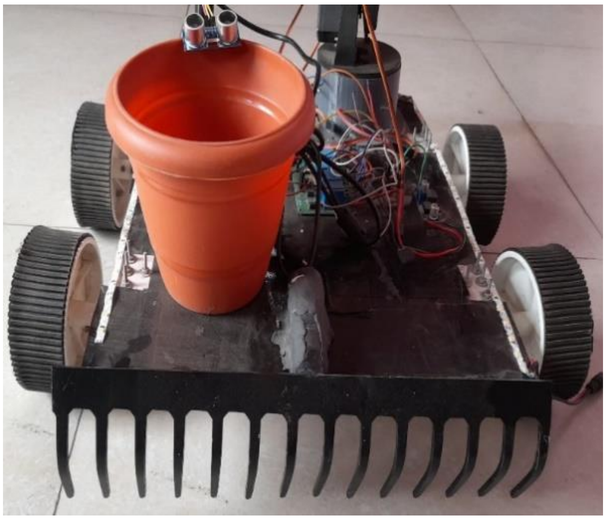

Fig 5. Side View

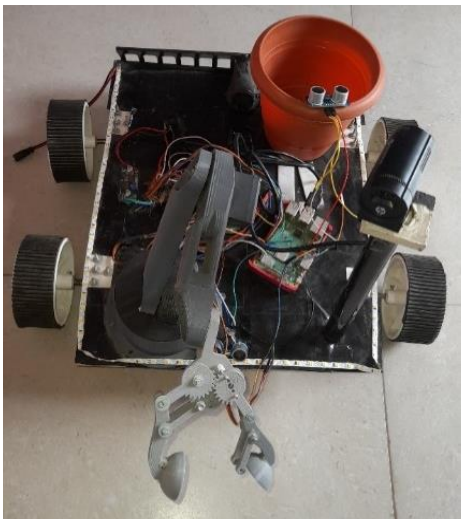

Fig 6 Top view

4.7 Main Features

A. Level Sensor:
A level sensor is a device used to detect the level of substances, such as liquids, granular materials, powders, and even gases, within a container or a process. These sensors are crucial in various industries like manufacturing, pharmaceuticals, food and beverage, and water treatment, among others, where accurate monitoring and control of substance levels are necessary for efficient operation and safety.

B. LED Strips:
LED strips, also known as LED tape lights or LED ribbon lights, are flexible circuit boards populated with light-emitting diodes (LEDs). They are commonly used for decorative lighting, accent lighting, and task lighting in various applications, including interior design, architectural lighting, signage, and entertainment. We used LED for the purpose of night vision to robot camera.

C. Weed Remover:
A weed remover is a tool or device designed to remove weeds from gardens, lawns, or other outdoor areas. There are various types of weed removers available, each with its own method of operation. The choice of weed remover depends on factors such as the type and size of weeds, the size of the area to be treated, personal preference, and environmental considerations. It's important to use weed removal methods safely and responsibly to minimize damage to desirable plants and the environment.

D. Ultrasonic Sensor:
An ultrasonic sensor is an instrument that measures the distance to an object using ultrasonic sound waves. An ultrasonic sensor uses a transducer to send and receive ultrasonic pulses that relay back information about an object's proximity. In this project, this sensor is used for the purpose of obstacle detection by measuring prior distance to robot, which enhances the less accidents.

4.8 Advantages of Project:
1. Increased Efficiency: Automation reduces the reliance on manual labor, enabling continuous operation and reducing the time required for harvesting tasks. This results in increased efficiency and productivity in agriculture.
2. Precision and Selectivity: Image processing allows for the precise identification of ripe crops, such as raspberries, and selective harvesting. This not only reduces waste but also improves crop quality.
3. Environmental Sustainability: Automation systems can be designed to minimize environmental impact by reducing soil compaction, minimizing chemical usage, and avoiding damage to non-target plants.
4. Real-time Adaptability: Automation systems equipped with image processing can adapt to changing field conditions, variations in crop maturity, and unexpected events in real time.
5. Safety: Implementing safety features, collision avoidance, and emergency shutdown mechanisms ensures the safety of human workers and the equipment involved in the automation process.

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6. Data-Driven Decision Making: Automation systems collect valuable data on crop health, yield, and system performance. This data can be leveraged for data-driven decision making, further optimizing agricultural practices.
7. Cost Savings: While the initial investment in automation technology may be significant, it can lead to long-term cost savings through reduced labor costs and improved crop yield.
8. Technological Advancements: Advances in computer vision, machine learning, robotics, and sensor technologies have made the development of such automation systems increasingly feasible and reliable.

V. CONCLUSION

In conclusion, the development of an automation harvesting arm system using image processing represents a promising and innovative approach to address challenges in agriculture, particularly in the context of crop harvesting. This system leverages advanced technology to enhance efficiency, precision, and sustainability in agricultural practices. Ultimately, automation harvesting arms using image processing hold great potential to revolutionize and modernize agriculture. By optimizing crop harvesting processes, these systems contribute to addressing labor shortages, increasing food production, and promoting sustainable farming practices.

As technology continues to advance, we can expect further innovations and improvements in these automation systems, making them an asset for the agriculture industry. Incorporating elements such as ultrasonic sensors, servo motors, a robust chassis and frame, and an efficient power supply enhances the overall performance and reliability of the automation harvesting arm. It's important to emphasize that the success of such systems depends on careful planning, design, and integration to meet the specific needs and conditions of the agricultural setting.

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