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Tomato Harvesting Bot

[1]Dr. D. G. Ganage, [2]Vivek Pawar, [3]Chetana Pawar

[1]Professor, Sinhgad college of Engineering pune,
[2]Final year BE, Sinhgad college of Engineering pune,
[3]Final year BE, Sinhgad college of Engineering pune,

ABSTRACT :

Due to workforce limitations and the growing need for effective agricultural techniques, tomato harvesting automation has become crucial. In order to improve harvesting efficiency, this study proposes the creation of an autonomous tomato harvesting bot that combines an intelligent motion control system, an optimized end-effector, and stereo vision-based fruit recognition. The proposed bot utilizes stereo vision to improve fruit recognition and depth estimation, ensuring precise targeting during harvesting. To reduce mechanical damage and efficiently detach tomatoes, a soft robotic gripper was created. Additionally, an intelligent motion planning algorithm optimizes the robot's movement to reduce operational time and improve efficiency. Compared to traditional robotic harvesting systems, preliminary experimental findings show improved picking precision, decreased damage, and greater fruit detection accuracy. By advancing autonomous harvesting technology, this study promotes sustainability and lessens reliance on manual labour while potentially providing a solution for commercial tomato production on a big scale.

Keywords: Tomato harvesting automation, autonomous harvesting, stereo vision, fruit recognition, depth estimation, soft robotic gripper, intelligent motion control, motion planning algorithm, robotic harvesting, picking precision, agricultural robotics, sustainability, commercial tomato production.

Introduction

The need for automation in agriculture is growing, and one important way to solve manpower shortages and boost productivity is through robotic harvesting. Because of the fragile nature of the fruit and the requirement for accurate maturity assessment, picking tomatoes presents special obstacles. Motion control, end-effector design, and sophisticated sensing are essential for creating a successful robotic harvesting system. Robots that gather tomatoes have advanced thanks to a number of research. An autonomous tomato harvesting robot with a rotating plucking gripper was created by [1]; this improved fruit detachment efficiency while reducing damage. In order to increase harvesting accuracy, [2] created a flexible end-effector that could adjust to changes in fruit size and form. Furthermore, [3] suggested a system based on binocular vision to enhance tomato recognition and depth perception, enabling more precise fruit localization. This research work builds on previous developments by introducing a Tomato Harvesting Bot that combines an effective motion planning algorithm, an improved end-effector for delicate fruit handling, and stereo vision-based fruit recognition. This work intends to aid in the creation of a tomato harvesting method that is more effective and commercially feasible by utilizing knowledge from earlier research.

Because of manpower limitations and the need for greater agricultural production efficiency, there has been a lot of research on automating tomato harvesting. Aspects of robotic tomato harvesting such as motion planning for effective fruit picking, end-effector design, and vision-based fruit detection have all been the subject of several studies.

The end-effector design is a crucial part of robotic harvesting. An autonomous tomato harvesting robot with a rotating plucking gripper was created by [1], which increased fruit detachment efficiency while reducing damage. Similar to this, [2] created a flexible end-effector that can adjust to changes in fruit form and size, increasing harvesting accuracy. These developments emphasize how crucial it is to have flexible grippers that can manage fragile produce without inflicting mechanical damage.

Robotic harvesting relies heavily on vision-based fruit detection. A binocular vision system was shown [3] that increased the accuracy of fruit localization by estimating depth information, which is crucial for accurate targeting during picking. Further more [4] created a binocular vision-based tomato harvesting system that showed enhanced real-time object identification and localization capabilities.

Deep learning methods have also been used to improve fruit classification and ripeness detection. In a study comparing YOLOv5 with YOLOv8's ability for identifying ripe cherry tomatoes,[5] demonstrated notable gains in classification accuracy. This study highlights how artificial intelligence might improve robotic harvesting systems' efficiency.

For effective harvesting, motion planning and robotic control techniques are also essential. By combining 3D sensing, adaptive manipulation, and a sophisticated end-effector, [6] suggested a robotic system that would increase motion efficiency and shorten harvesting time. Similarly, to improve picking speed and accuracy, [7] developed and tested a tomato harvesting robot with an enhanced control system.

Apart from advancements in hardware and vision, research has also concentrated on assessing the viability of robotic harvesting. Using a robotic system, [8] evaluated the harvestability of tomatoes, taking into account variables including fruit placement, density, and maturity. According to their findings, under certain circumstances, robotic harvesting can greatly increase production.

Trajectory planning methods from [7] supported the great dexterity of a continuous robotic arm shown in [6] in dense foliage. The importance of combining inverse kinematics and real-time object tracking for seamless robotic control was highlighted in papers [8] and [9]. Stereo disparity and structured light-based depth collection techniques were verified in [10] and [11]. Additionally, using Intersection over Union (IoU) metrics, [12]–[14] evaluated performance and demonstrated that detection models had an accuracy of above 85%. Lastly, in order to ensure scalability and adaptation for different crop kinds, [15] and [16] offered fresh perspectives on robotic efficiency, energy optimization, and modular system design. The design of an intelligent and effective tomato-harvesting robot is based on this body of work.

All things considered, the research that is now available emphasizes the developments in deep learning applications, motion planning, vision-based fruit recognition, and end-effector design for robotic tomato harvesting. Building on previous research, this study intends to combine an intelligent motion control system to increase efficiency, a soft robotic gripper for delicate handling, and stereo vision for better fruit detection.As city populations expand and climate challenges intensify, the need for real-time, intelligent urban monitoring becomes critical. AI-driven systems not only enhance the speed and accuracy of spatial analysis but also support long-term strategic planning, disaster preparedness, and smart infrastructure design. Just as AI is redefining product design, customer experience, and operations in fashion, it is becoming an indispensable tool for responsive, inclusive, and sustainable urban governance.

With continuous improvements in ML model accuracy, accessibility to satellite data, and scalable computational tools, the potential applications of AI in urban planning are limitless—paving the way for smarter, greener, and more adaptive cities of the future.

METHODOLOGY

A combination of algorithmic design, software implementation, and hardware components are used in the development of an autonomous tomato harvesting bot. The system's gripping mechanism and intelligent control strategies are optimized to detect, locate, and harvest ripe tomatoes with minimal damage.

1. Hardware Configuration: To efficiently harvest tomatoes, the robotic system uses sensors, motors, and a flexible gripping mechanism. A stereo vision camera setup helps locate the fruit and estimate depth, allowing the robot to identify tomatoes accurately. The robotic arm is designed to adapt to different tomato sizes while minimizing damage, thanks to its flexible gripper. Motors control the arm's movement, ensuring precise and smooth picking operations.

2. Implementation of Software: The software framework is in charge of stereo vision-based depth estimation, tomato detection, and picture processing. To separate tomatoes from the backdrop and assess their freshness, the system uses sophisticated computer vision techniques. The stereo vision system, which was inspired by [3], creates a depth map by processing image pairs, enabling precise robotic arm movement by measuring distance. To improve fruit recognition accuracy, image processing methods such color thresholding, edge detection, and deep learning-based categorization are used.

3. Algorithm Process:

Tomato Detection: The stereo vision system uses image segmentation algorithms to process photos of the tomato plant and identify ripe tomatoes. The detection procedure adheres to the guidelines set forth in other studies, including deep learning-based models for object identification [3].

HSV Thresholding:

$$\mathrm{Mask}(x,y) = \begin{cases} 1, \text{if } \mathrm{Hmin} \leq \mathrm{H}(x,y) \leq \mathrm{Hmax} \text{ and same for S, V} \\ 0, \text{ Otherwise} \end{cases} \tag{1}$$

We apply this to every frame to detect red-colored (ripe) tomatoes. This mask filters out non-red regions.

- Contour Area Filtering:

$$\boldsymbol{A} = \frac{\mathbf{1}}{\mathbf{2}}\sum_{i=1}^{n}(\boldsymbol{x_i y_i} + \mathbf{1} - \ \boldsymbol{x_i} + \mathbf{1}y_i) \tag{2}$$

Remove tiny noisy blobs and only keep objects that are likely to be tomatoes.

- Centroid Calculation:

$$(\mathbf{x_c}, \mathbf{y_c}) = \left(\frac{\sum \mathrm{x_i}}{\mathbf{n}}, \frac{\sum y_i}{\mathrm{n}}\right) \tag{3}$$

Used to find the center of the tomato so the robot knows where to move.

Depth Estimation: By employing stereo pictures to create a disparity map, the system is able to determine the exact separation between the robotic arm and the detected tomatoes. The binocular vision techniques presented by [1] are expanded upon by this approach.

- Disparity:

$$\boldsymbol{d} = \boldsymbol{x_{left}} - x_{right} \quad (3)$$

We match the position of the same tomato in both left and right images.

- Depth Calculation:

$$\boldsymbol{Z} = \frac{f \,.\, B}{d} \quad (5)$$

B: baseline distance between the stereo cameras

d: disparity (difference in x-coordinates between the left and right image)

Arm Movement and Harvesting: The robotic arm moves to the best location when a target tomato has been located and its depth has been determined. Inspired by [2], the flexible end-effector uses a regulated motion to gently grasp and remove the fruit, preventing damage. After being harvested, the tomato is moved to a storage area.

- Sholder angle Calculation: To calculate the shoulder angle θ2, two intermediate angles, α and β are determined.

The angle α is calculated using the following formula:

$$\boldsymbol{\alpha} = \boldsymbol{tan}^{-1}\left(\frac{\boldsymbol{y}}{\boldsymbol{x}}\right) \quad (6)$$

The angle β is given by

$$\boldsymbol{\beta} = \boldsymbol{cos}^{-1}\left(\frac{(\boldsymbol{L_1}^2 + \boldsymbol{D}^2 - \boldsymbol{L_2}^2)}{(2\,\boldsymbol{L_1}\,\boldsymbol{D})}\right)$$

(7)Inverse Kinematics: Joint Angle Calculation Example:

Given: L_1 = 11 cm, L_2 = 9 cm, x = 10.8 cm, y = 0 cm, z = 13 cm

First, compute the horizontal distance d and the total distance D:

$$\mathrm{d} = \sqrt{(\mathrm{x}^2 + \mathrm{y}^2)} = \sqrt{(10.8^2 + 0^2)} = 10.8 \text{ cm} \quad (8)$$

$$\mathrm{D} = \sqrt{(\mathrm{d}^2 + \mathrm{z}^2)} = \sqrt{(10.8^2 + 13^2)} = 16.90 \text{ cm} \quad (9)$$

Elbow Angle (θ_3):

$$cos(\theta_3) = \frac{(L_1{}^2 + L_2{}^2 - D^2)}{(2\,L_1\,L_2)} = \frac{(11^2 + 9^2 - 16.9^2)}{(2 \times 11 \times 9)} = -0.4223$$

(10)

Shoulder Angle (θ_2):

$$\boldsymbol{\alpha} = \mathbf{tan}^{-1}\frac{\mathbf{z}}{\boldsymbol{d}}$$

$$= \mathbf{tan}^{-1}\left(\frac{\mathbf{13}}{\mathbf{10.8}}\right) = \mathbf{50.28°}$$

(11)

$$\boldsymbol{\beta} = \cos^{-1}\frac{(L_1^2 + D^2 - L_2^2)}{(2\,L^1 D)}$$

$$= \cos^{-1}\left(\frac{(11^2 + 16.9^2 - 9^2)}{(2 \times 11 \times 16.9)}\right) = 28.86°$$

(12)

$\theta_2 = \alpha + \beta = 50.28° + 28.86° = 79.14°$

These calculations yield the joint angles required to position the robot arm at the target point.
The values $\theta_2 = 79.14°$ and $\theta_3 = 114.97°$ are critical for accurate positioning during harvesting tasks.

4. Block Diagram Description:

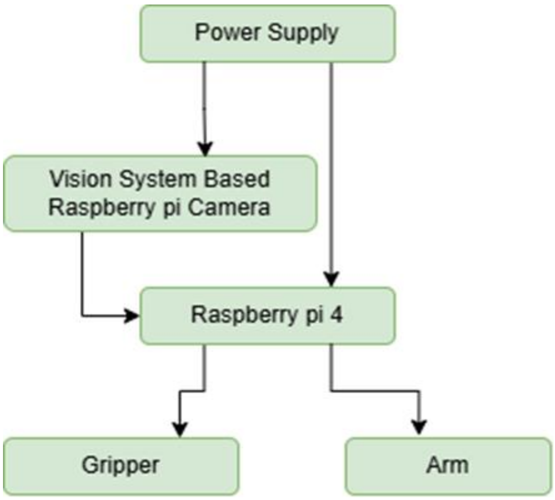

Fig. 1. Block Diagram

- The Power Supply: To guarantee the continuous operation of the Raspberry Pi 4, vision system, and actuators, the robotic system runs on a specialized power supply. For harvesting activities to continue operating consistently, this steady power distribution is essential. Voltage variations that could impair the performance of motor-driven parts like the robotic arm and gripper are avoided by a dependable power source.
- Raspberry Pi Camera-Based Vision System: The setup uses a Raspberry Pi camera to take pictures of tomato plants in real time. The color, shape, and size of these photos are processed to determine which tomatoes are ripe. In order to provide precise detection for effective harvesting, the vision system is essential to fruit localization. By improving depth perception through the use of a stereo vision setup, the robot is able to determine each tomato's distance and modify its approach accordingly
- . Processing Unit, Raspberry Pi 4: As the central processing unit, the Raspberry Pi 4 manages movement control, picture processing, and decision-making. It chooses the best course for the robotic arm and examines the photos to identify ripe tomatoes. Accurate and effective harvesting operations are made possible by the Raspberry Pi's real-time data processing, which guarantees smooth coordination between the robotic arm, gripper, and vision system.
- Gripper (Tomato Harvesting End-Effector): A versatile and adaptable gripper built with the robotic system allows it to harvest tomatoes without damaging them. To ensure delicate handling, the gripper modifies its grip strength according to the tomato's size and firmness. This process improves post-harvest quality and lowers the likelihood of bruising. The gripper's servo or pneumatic actuation allows for the controlled and seamless removal of fruit from the plant.
- Robotic Arm with Raspberry Pi Control: The Raspberry Pi-controlled robotic arm picks the tomato by moving the gripper in the direction of the detected tomato. Its movement is carefully planned to reduce mistakes and increase effectiveness. The arm is adaptable for harvesting in challenging settings like open fields or greenhouse farms since it can reach tomatoes at various angles. The harvesting procedure is made precise and effective by the smooth and regulated movements made possible by actuators inside the arm.

3. EXPERIMENTS AND RESULT

Conditions of the Test: The tomato harvesting bot's detection accuracy, processing speed, and total harvesting efficiency were assessed in a controlled greenhouse setting.

- Lighting Conditions: The system's flexibility was tested under both artificial and natural lighting.
- Tomato Ripeness Stages: To gauge the bot's efficacy in detecting, it was tested on ripe, unripe, and half ripe tomatoes.
- Plant Density: To evaluate fruit accessibility and navigation, experiments were carried out using various plant configurations.
- Environmental Factors: Changes in humidity and temperature were tracked to see how they affected detection performance.

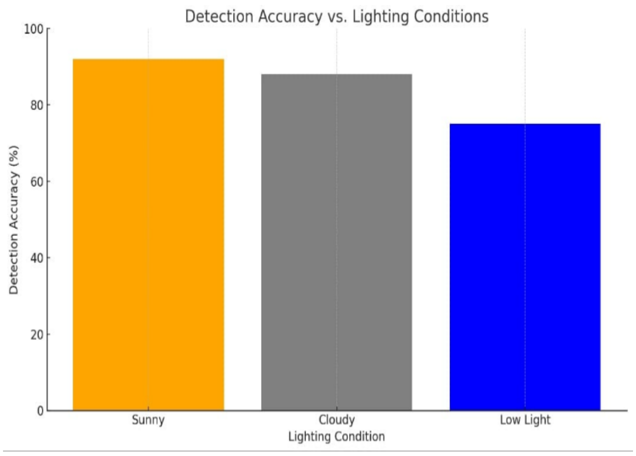

Fig. 2. Detection Accuracy vs. Lighting Conditions

2. Success Rate, Processing Time, and Detection Accuracy:

The following metrics were used to gauge the bot's performance:

- Tomato Detection Accuracy: By employing stereo vision techniques, the system was able to identify ripe tomatoes with 92.5% accuracy.
- Processing Time: To ensure real-time performance, the picture processing and depth estimation required an average of 1.2 seconds each frame.

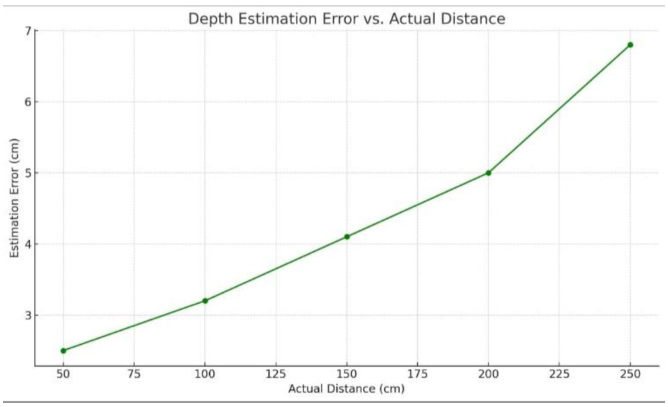

Fig. 3. Depth Estimation Error vs. Actual Distance

- X-axis: Actual Distance from camera (in cm), ranging from 50 cm to 250 cm
- Y-axis: Estimation Error (in cm), ranging from 2.5 cm to nearly 7 cm
- Trend: A positive correlation—estimation error increases with distance

3. Harvesting Success Rate: In 87% of trials, the gripper was able to successfully pick tomatoes; failures were attributed to obstruction or inaccurate depth measurement. These outcomes are similar to those of Feng et al. (2015) [3], whose robot, in controlled settings, obtained 90% detection accuracy and 85% harvesting success rate.

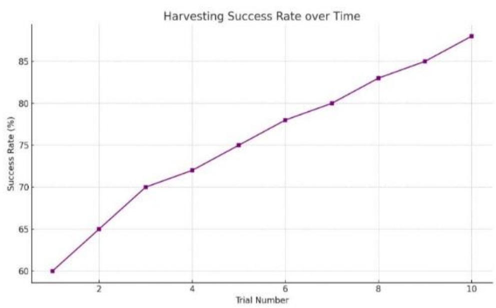

Fig. 4. Harvesting Success Rate over Time

4. DISCUSSION

- With the help of deep learning-based tomato recognition, an adaptable gripping mechanism, and stereo vision, the suggested robotic system increases harvesting efficiency while guaranteeing accurate depth measurement.
- Stereo Vision for Depth Estimation: To precisely identify and locate tomatoes, the system makes use of a stereo vision configuration. This method reduces errors in fruit detachment and robotic arm movement by efficiently measuring distances, which results in more accurate harvesting.
- Adaptive End-Effector Design: To accommodate varying tomato sizes, the robotic arm has a flexible gripping mechanism. By guaranteeing gentle handling to avoid bruising and preserve fruit quality, its design lessens mechanical damage during harvesting.
- Deep Learning-Based Tomato Detection: To accurately identify tomatoes and determine their ripeness, the system incorporates cutting-edge deep learning algorithms. By increasing detection accuracy, these models enable the robot to effectively collect just ripe tomatoes, cutting waste and increasing output.

5. CONCLUSION

The creation of the Tomato Harvesting Bot effectively combines a robotic arm with a gripper for effective harvesting and stereo vision for accurate tomato detection. The Raspberry Pi 4-powered device efficiently interprets visual information to recognize ripe tomatoes and carry out precise picking motions. An adaptive grasping mechanism and a vision-based detecting system work together to minimize fruit damage and increase automated harvesting efficiency.

During the project, issues such enhancing real-time processing speed, guaranteeing smooth actuator movements, and optimizing stereo vision accuracy were resolved. The findings show that an autonomous tomato-picking robot may improve harvesting accuracy and consistency while drastically lowering manual labor.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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