Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 8, No. 3, August, Pp. 623-632

Neural network-based image processing for tomato harvesting robot

Yurni Oktarina*[1,2], Ronald Sukwadi[1,3], Marsellinus Bachtiar Wahju[1,3]
Program Studi Program Profesi Insinyur, Universitas Katolik Indonesia Atma Jaya, Indonesia
Department of Electrical Engineering, Politeknik Negeri Sriwijaya, Palembang, Indonesia
Program Studi Teknik Industri, Universitas Katolik Indonesia Atma Jaya, , Indonesia

Article Info

Keywords:
Arm Robot Manipulator, Harvesting Robot, Agriculture Robot, Neural Network

Article history:
Received: May 02, 2023
Accepted: July 01, 2023
Published: August 31, 2023

Cite:
Y. Oktarina, R. Sukwadi, and M. B. Wahju, "Neural Network-Based Image Processing for Tomato Harvesting Robot ", KINETIK, vol. 8, no. 3, Aug. 2023. https://doi.org/10.22219/kinetik.v8i3.1723

*Corresponding author.
Yurni Oktarina
E-mail address:
yurni_oktarina@polsri.ac.id

Abstract
Agriculture is one of the areas that can benefit from robotics technology, as it faces issues such as a shortage of human labor and access to less arid terrain. Harvesting is an important step in agriculture since workers are required to work around the clock. The red ripe tomatoes should go to the nearest market, while the greenest should go to the farthest market. Harvesting robots can benefit from Neural Network-based image processing to ensure robust detection. The vision system should assist the mobility system in moving precisely and at the appropriate speed. The design and implementation of a harvesting robot are described in this study. The efficiency of the proposed strategy is tested by picking red-ripened tomatoes while leaving the yellowish ones out of the experimental test bed. The experiment results demonstrate that the effectiveness of the proposed method in harvesting the right tomatoes is 80%.

1. Introduction

Robotics technology is one of the most advanced electronics technologies that may be used in various industrial and residential applications. It can make work and life more manageable, giving people more time to accomplish other things. Agriculture is one of the industries that can benefit from this technology. Agriculture faces challenges such as a lack of human labor and less arid land accessible. The application of robotics technology in agriculture is called digital farming [1][2][3], with Stoelen et al. in 2015 proposing low-cost robotics for agriculture.

Any sort of robotics is relevant in agriculture for any stage of the agricultural process, such as mobile robots for autonomous spraying and static robots for harvesting. An arm robot manipulator is the most likely harvesting robot type, which can replace a human arm in picking up stems [4][5][6][7][8]. Human eyes can be easily replaced by cameras already widely accessible on the market, such as those proposed by Dewi et al. in 2018 for visual servoing design and control for agriculture robots [9].

Harvesting is a crucial stage in agriculture since it is expected to last 24 hours because some crops, such as tomatoes, ripen quickly [10]-[15]. It can quickly change hues, and harvesting should be divided according to the market's distance. The red ripe tomatoes should be selected for the closest market, while the greenest should be selected for the farthest market [16]. A robot can pick and put objects for 24 hours and select colors based on instructions.

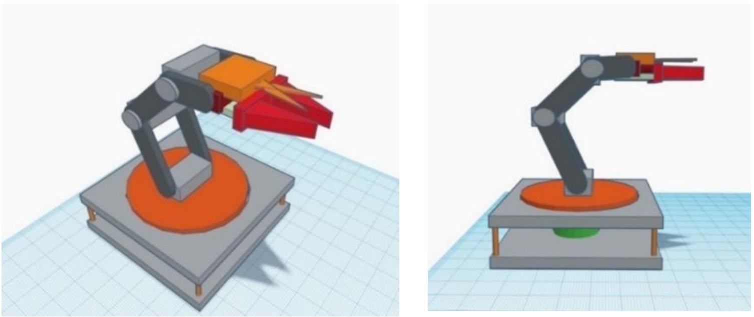
The robot system can be divided into two things, namely the motion and the vision system. The harvesting robot relies heavily on object detection, how the robot detects the fruit and recognizes which one to pick, as Tan et al., 2018 used image processing for blueberry maturity detection [23], Malik et al., 2018 used improved HSV technique for predicting mature tomato [25], and Pereira et al., in 2018 predicts the papaya ripeness with digital imaging and random forest [26]. The vision system should support the motion system to move accurately at a proper speed. The robustness of target detection relates to the robustness of the robot system. Hence, it is essential to implement artificial intelligence to give the robot ability to think about which one to pick [17]-[26].

Artificial intelligence has numerous forms, including fuzzy logic controllers, neural networks, and genetic algorithms. There are infinite variations and developments for each AI and each AI that can be merged to enable improved efficacy, such as ANFIS. However, in agriculture robots, roboticists should consider a robot that is not only functional but also easily reproducible, and even better, one that is cost-effective because the major consumer would be farmers who are unfamiliar with electronic technology. The neural network (NN) allows a robot to digest information to choose the optimal alternative based on pattern recognition, as proposed by Nasiri et al. in 2019. Therefore, NN is very suitable for image processing for only detecting targeted fruit [27][28][29][30] or up to harvesting the fruit with the right ripeness [31].

This paper describes the design and implementation of a harvesting robot. The backpropagation neural network is presented as an image processing tool due to its capacity to discern patterns, allowing the robot to select the appropriate fruit. The tomato is the fruit studied in this study. Tomato ripeness colors range from yellowish to dark red, and this condition is especially crucial given the short harvesting season. Tomatoes can rapidly change color from green to yellowish, orange, red, and dark red. The image processing technique used in this study established the red color to represent ripe tomatoes. The effectiveness of the proposed method is examined by utilizing the experimental test bed and harvesting red-ripened tomatoes while leaving the yellowish ones out. The image processing conducted in this study is to recognize tomatoes and leave other objects such as leaves as the background. The kinematics and dynamics of 5 DOF arm robot manipulator considered in this study are not included since this study emphasized more on how the robot detect the object with NN.

2. Research Method

This paper proposes a backpropagation Neural Network to detect ripe tomatoes. Figure 1 and Figure 2 depict the proposed method. The harvesting robot investigated in this work is a DOF arm robot manipulator equipped with a camera and proximity sensor positioned at the end effector depicted in Figure 1. A scissor is used as the end effector to cut the tomato stem. The design began by dividing the robot into three components, as shown in Figure 2, inputs, processes, and output. Sensor input consists of a camera as the eye and a proximity sensor to guarantee the robot understands the distance between the gripper and the tomato. The raw image acquired by the camera is processed by Neural Network coded in the Raspberry Pi. Image detection is provided to the microcontroller, which processes the input and moves the robot's end effector toward the recognized tomato. The outputs are the robot motions, which are controlled by servo motors mounted on the joints and end-effectors. The robot design was kept as simple as possible to ensure the farmer could reproduce.



(a) (b)

Figure 1. Mechanical design of the 5 DOF harvesting robot

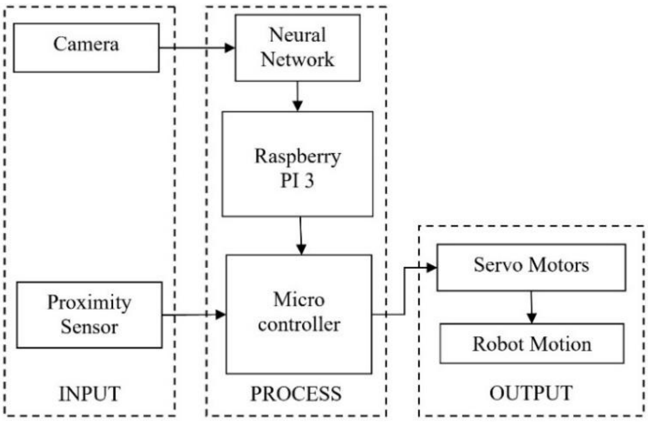


Figure 2. Block diagram design of tomatoes harvesting robot considered in this study

The main objective of this research is to determine methods to ensure that the robot detects the designated target. Figure 3 depicts the picture processing phases; all of these procedures are carried out by a Neural Network (NN). The supervised training algorithm of the input, hidden, and output layers is the backpropagation NN depicted in Figure 3, Figure 4, Figure 5, and Figure 6, where the error is transported back to the hidden layer and how weights change synapses leading to the layer.

Figure 3 depicts the preprocessing stage, which includes the removal of background and noise, feature extraction, and selection. This stage is carried out before the data is fed into the NN. The result of the preprocessing stage is the position of the tomato that needs to be processed further to determine ripeness. Tomato ripeness is determined by its color, which might be red, yellowish, or red-yellow-orange. The first step in preprocessing is to take the raw image from the camera, transform it to grayscale, then flatten it to create a binary image. The image is then converted to HSV before being color segmented depending on portions of red, green, and orange as the primary colors of tomatoes.

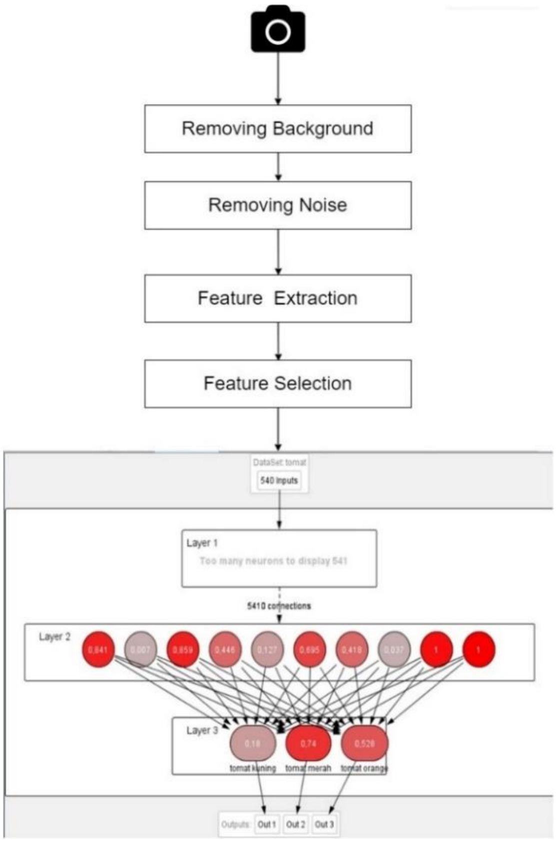


Figure 3. Preprocessing stage input to NN

Since the neural network approach is used to determine which fruits to pick, the procedure carried out by this neural network significantly impacts the robot arm's movement when gathering fruit. In the neural network approach, the input layer is the picture value received by the camera sensor (HSV value), followed by hidden layer 1, where the first training process occurs, and the color sorting is gathered from the input layer. The hidden layer 2 is where the second training process is carried out to identify the color values that fulfill the requirements to be output. The output layer is the outcome of the training process to determine whether the tomatoes are reddish, reddish-orange, or yellowish.

The output of this neural network will then be processed by Arduino to operate the servo motor, allowing the robotic arm to move toward the target fruit depending on the coordinates determined by the camera. There are three methods for determining tomato color in order to evaluate ripeness:

2.1 Yellow Tomato

To assess tomatoes' yellowness, the camera sensor's picture values provide a total of 540 HSV color model values as input data set to the neural network. The hidden layer utilized for training outcomes comprises 9 neurons with a learning rate of 0.2 and momentum of 0.7.

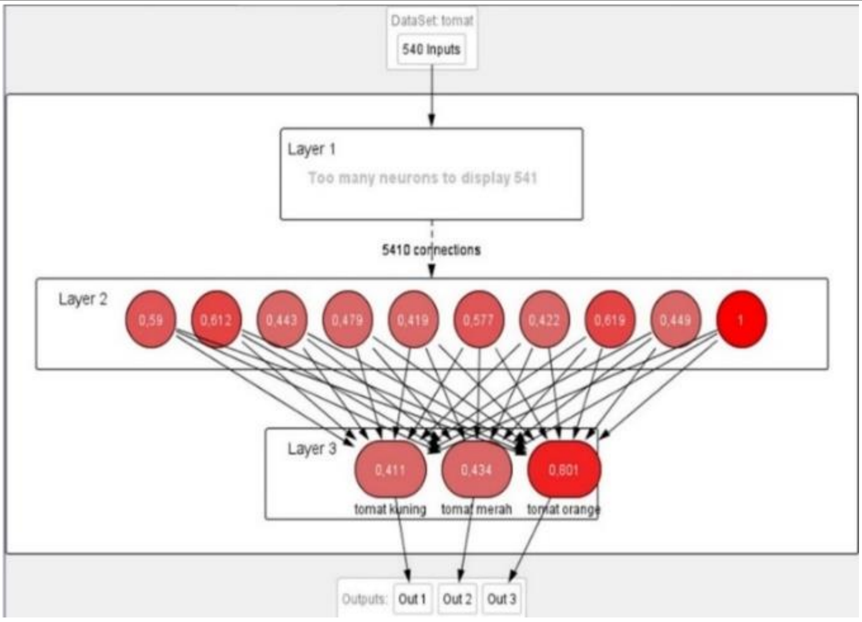


Figure 4. NN architecture design for yellowish tomatoes

The neural network approach used to identify yellowish tomatoes is shown in Figure 6. Layer 3 (the results of determining the output color) shows that for yellowish tomatoes, the weight in the first neuron is 0.88; for reddish-orange tomatoes, 0.014; and reddish tomatoes, 0.103. Yellowish tomatoes have a more significant weight value than reddish and reddish orange tomatoes because yellow has a much more comprehensive range than orange and red.

2.2 Red Tomato

To determine the reddish hue of tomatoes, the picture values from the camera sensor provide a total of 540 HSV color model values as input data set to the neural network. The hidden layer used for training outcomes is made up of 9 neurons with a learning rate of 0.2 and momentum of 0.3.

The neural network approach for identifying the reddish color of tomatoes is shown in Figure 4. The picture depicts 9 hidden layer neurons in layer 2, each with its own number. This picture depicts the weight value of each color value as it appears in layer 3 (the result of picking the output color). The second neuron weighs 0.74 in reddish tomatoes, 0.18 in yellowish tomatoes, and 0.52 in reddish-orange tomatoes. Because the color ranges for each tomato are close together, the weight values for reddish tomatoes and reddish orange tomatoes are not too far away.

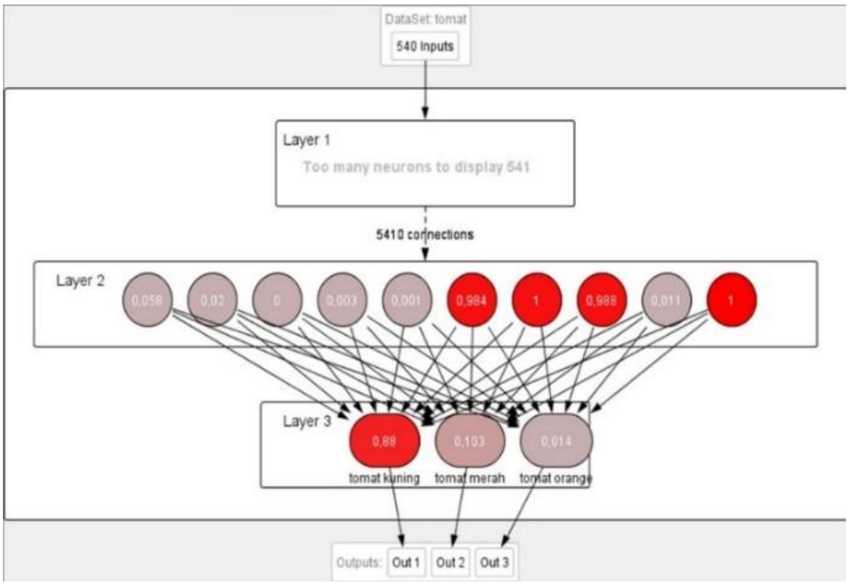


Figure 5. NN architecture for red tomato

2.3 Orange Reddish Tomato

To determine the reddish hue of tomatoes, the picture values from the camera sensor provide a total of 540 HSV color model values as input data set to the neural network. The hidden layer used for training outcomes is made up of 9 neurons with a learning rate of 0.2 and momentum of 0.3.

Figure 5 depicts the neural network procedure for identifying reddish-orange tomatoes. Layer 3 (the outcome of determining the output color) shows that the weight in the third neuron for reddish-orange tomatoes is 0.801, while it is 0.411 for yellowish tomatoes and 0.434 for reddish tomatoes. The weight value for reddish-orange tomatoes is twice that of reddish and yellowish tomatoes. This is due to the fact that orange is the midpoint of the three hues.

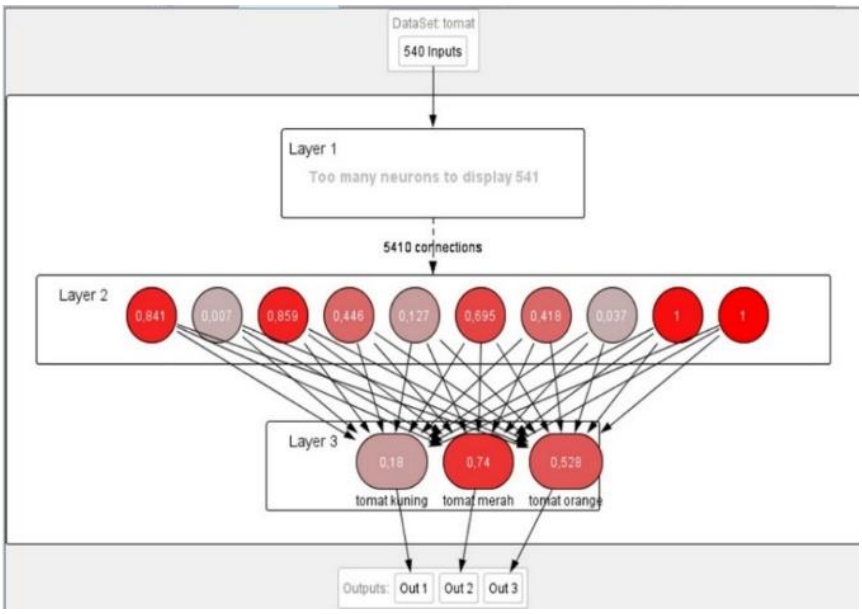


Figure 6. NN architecture for reddish tomato

3. Results and Discussion

This study proposed designing and controlling an arm robot to harvest tomatoes using Neural Network (NN)-based image processing to determine tomato location. Based on backpropagation NN, three layers are designed: input, hidden, and output. The robot is programmed to select the largest tomato first, followed by the second largest, and ultimately the smallest. Figures 7 and 8 demonstrate target detection results; the upper figures are camera images, and the lower figures are image processing results. The image processing output reveals how the robot perceives the tomatoes.

The images obtained by human eyes and cameras differ slightly. Figure 7 depicts the detection of one tomato on the plant, two tomatoes, and three tomatoes, as well as the outcome of the image processing process. Figure 7a shows one tomato, and the robot detects it; Figure 7b shows two tomatoes, and the robot detects the largest of those two tomatoes; and Figure 7c shows three tomatoes on the plant, and the robot detects the largest of those three tomatoes. The yellowish tomatoes in Figure 7 are the same color as those in Figure 4, and this detection is based on the NN design in Figure 4.

The disadvantage of image processing-based detection is that it is heavily influenced by lighting. The size of tomatoes can be considerably influenced by how they are photographed. Figure 8 depicts three tomatoes in a plant of varying hues, indicating ripeness. In Figures 8a and 8b, the robot correctly detects the largest tomato; however, in Figure 8c, the robot sees the largest tomato in the middle. The yellow tomato appeared smaller to the human eye than the two red tomatoes; yet, as seen in the target detection result, the yellow tomato is the largest detected tomato. Due to lighting or illumination, the other two red tomatoes appear small.

The robot is then assigned to harvest tomatoes. The video capture results are presented in Figure 9, where the robot chooses the largest tomato that appears to be the nearest one first. The experiment was carried out on 20 tomatoes. The successful hit rate is displayed in Table 1, indicating the robot can harvest the tomatoes and when the robot fails to harvest. Based on the position of the tomatoes in the image plane (left, center, and right), robot success is 80% for tomatoes on the left, 85% for tomatoes in the middle, and 85% for tomatoes on the right.

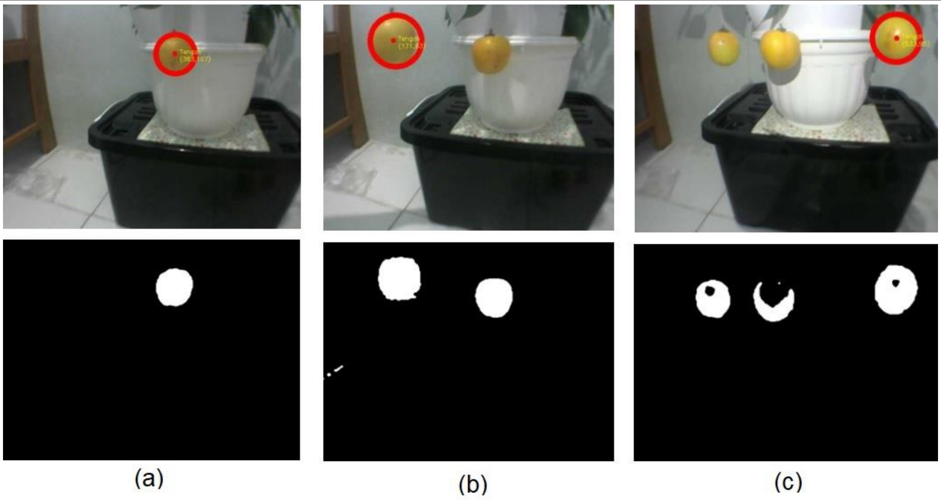


Figure 7. Detection of three same color tomatoes

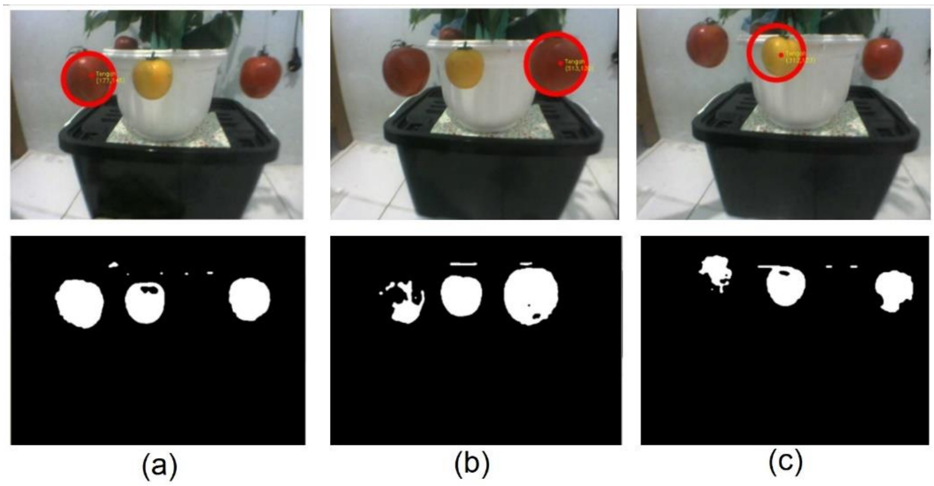


Figure 8. Detection of 3 colors tomatoes with varying hues

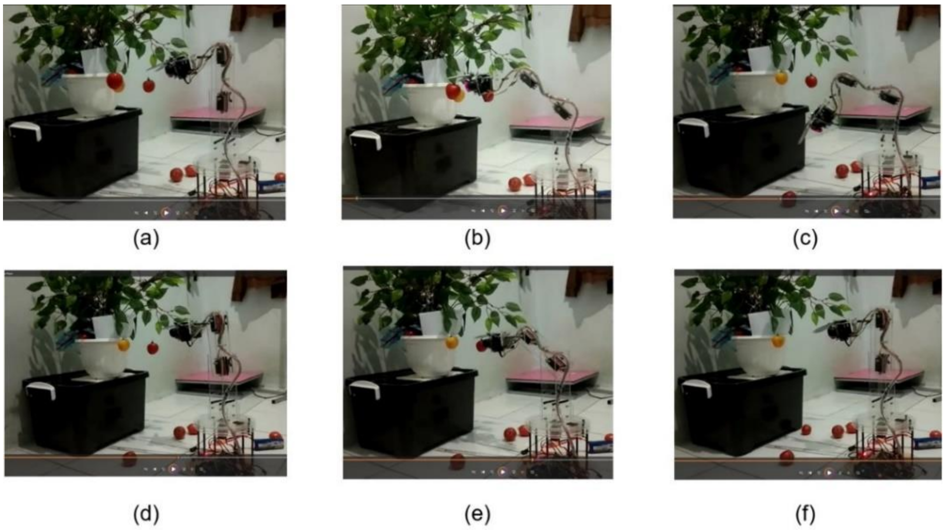


Figure 9. Video captures during tomatoes picking

Based on testing the proposed method on the experimental testbed depicted in Figure 9, the harvesting time is as follows:

- When the fruit on the left is detected, the average time for the robot arm to discover reddish tomatoes before picking them is 7.7 seconds. In comparison, the time for the robot arm to detect reddish orange tomatoes before picking them is 8.84 seconds.
- When the fruit is in the middle, the average time it takes the robot arm to identify reddish tomatoes until they are picked is 6.204 s, whereas the time it takes the robot arm to detect reddish orange tomatoes until they are picked is 5.04 s.
- When the fruit is on the right, the robot arm's average time to identify reddish tomatoes before picking them is 6.168 s. In comparison, the robot arm's time to detect reddish orange tomatoes before picking them is 8.854 s.
- The average time for the robot arm to detect reddish orange tomatoes, pick them up, and return to their initial position while the fruit is on the left is 12.95 seconds. In comparison, it takes 12.95 seconds for the robot arm to detect reddish orange tomatoes and pick them.
- The robot arm's average time to detect reddish orange tomatoes and pick them up until they return to their initial location while the fruit is in the middle position is 10.476 seconds. In comparison, the robot arm detects reddish orange tomatoes and picks them up in 11.33 seconds.
- When the fruit is on the right, the average time for the robot arm to detect reddish-orange tomatoes, pick them, and return to their initial location is 15.186 seconds. In comparison, it takes 13.812 seconds for the robot arm to recognize reddish-orange tomatoes and pick them.

Table 1. Experimental results of tomatoes harvesting robot

Exp. No	Tomatoes Location		
	Left	Middle	Right
1	√	√	√
2	√	×	√
3	×	√	√
4	√	√	√
5	√	√	√
6	√	×	×
7	×	√	√
8	√	√	√
9	×	√	√
10	√	√	√
11	√	×	×
12	√	√	√
13	√	√	√
14	√	√	×
15	√	√	√
16	×	√	√
17	√	√	√
18	√	√	√
19	√	√	√
20	√	√	√
Total Hit	16	17	17
Rate	80%	85%	85%

Table 2 shows the servo motor angle during harvesting; these angles during robot motion are affected by the position of the tomatoes. The cartesian coordinate (x,y) represents the position of the tomato on the image plane, as well as the left, middle, and right positions.

Table 2. Servo motor angles during robot position

Exp. No	Tomato Position	X (pixel)	Y (pixel)	Servo Base	Joint 1 Angles	Joint 2 Angles
1	Left	17	45	115^0	90^0	100^0
2	Middle	232	75	60^0	98^0	94^0
3	Right	311	98	55^0	105^0	85^0
4	Left	37	52	115^0	90^0	100^0
5	Middle	164	79	88^0	102^0	92^0
6	Right	290	92	60^0	100^0	86^0

7	Left	42	56	115^0	104^0	100^0
8	Middle	166	75	90^0	90^0	93^0
9	Right	265	110	55^0	98^0	85^0

This research proposes an image-processing-based tomato harvesting robot. The image processing is divided into two stages: preprocessing and neural network. The experimental results suggest that the proposed strategy effectively operates the tomato harvesting robot.

4. Conclusion

The autonomous harvesting robot is one of modern agriculture's most important artificial intelligence (AI) robots for fruit and vegetable harvesting. A compelling vision system can significantly improve the harvesting robot's ambient sensing capabilities. This study's tomato harvester robot can recognize ripe tomatoes based on their hue. To guarantee that the right tomatoes are delivered to the right market, the ripeness of these tomatoes must be carefully picked. The tomato swiftly changes color, from ripe green to yellow and then red. A Neural Network-based image-processing method for picking ripe tomatoes is presented in this paper. The experiment was repeated 20 times, and the data showed that the possibility of the robot to pick the right tomatoes is 80%; hence, the proposed method was effective for controlling the tomato harvester robot.

References

[1] M. Stoelen et al., "Low-Cost Robotics for Horticulture: A Case Study on Automated Sugar Pea Harvesting," 10th European Conference on Precision Agriculture (ECPA), 2015. https://doi.org/10.3920/978-90-8686-814-8
[2] T. Dewi, S. Nurmaini, P., Risma, and Y. Oktarina, Y., "Inverse Kinematic Analysis of 4 DOF Pick and Place Arm Robot Manipulator using Fuzzy Logic Controller," International Journal of Electrical and Computer Engineering (IJECE), Vol. 10, No 2, pp. 1376-1386, 2020. http://doi.org/10.11591/ijece.v10i2.pp1376-1386
[3] T. Dewi, C. Anggraini, P. Risma, Y. Oktarina, and Muslikhin, "Motion Control Analysis of Two Collaborative Arm Robots in Fruit Packaging System," SINERGIA Vol. 25, No. 2, pp. 217-226, 2021. http://doi.org/10.22441/sinergi.2021.2.013
[4] T. Dewi, Z. Mulya, P. Risma, and Y. Oktarina, "BLOB Analysis of an Automatic Vision Guided System for a Fruit Picking and Placing Robot," International Journal of Computational Vision and Robotics, Vol. 11, No 3, pp. 315-326, 2021. https://doi.org/10.1504/IJCVR.2021.115161
[5] C. Wang, Y. Tang, X. Zou, W. SiTu, and W. Feng, "A robust fruit image segmentation algorithm against varying illumination for vision system of fruit harvesting robot," Optik, Vol. 131, pp. 626-631, 2017. https://doi.org/10.1016/j.ijleo.2016.11.177.
[6] C.W. Bac, J. Hemming, and E.J. Van Henten, "Robust pixel-based classification of obstacles for robotic harvesting of sweet-pepper," Computers and Electronics in Agriculture, Vol. 96, pp. 148-162, 2013. https://doi.org/10.1016/j.compag.2013.05.004
[7] N. M. Syahrian, P. Risma, and T. Dewi, "Vision-Based Pipe Monitoring Robot for Crack Detection using Canny Edge Detection Method as an Image Processing Technique," Kinetik: Game Technology, Information System, Computer Network, Computing Electronics, and Control, Vol. 2, No. 4, pp. 243-250, 2017. https://doi.org/10.22219/kinetik.v2i4.243
[8] M.D. Yusuf, RD. Kusumanto, Y. Oktarina, T. Dewi, and P. Risma, "Blob Analysis for Fruit Recognition and Detection," Computer Engineering and Applications, Vol 7 No 1 pp. 23-32, 2018. https://doi.org/10.18495/comengapp.v7i1.237
[9] T. Dewi, P. Risma, Y. Oktarina and S. Muslimin, "Visual Servoing Design and Control for Agriculture Robot; a Review," 2018 International Conference on Electrical Engineering and Computer Science (ICECOS), Pangkal, Indonesia, 2018, pp. 57-62. https://doi.org/10.1109/ICECOS.2018.8605209
[10] H. Gharakhani, J. A. Thomasson, and Y. Lu, "An end-effector for robotic cotton harvesting," Smart Agricultural Technology, Vol. 2, p. 100043, 2022. https://doi.org/10.1016/j.atech.2022.100043.
[11] T. Dewi, P. Risma, Y. Oktarina, and M. Nawawi, "Tomato Harvesting Arm Robot Manipulator; a Pilot Project," Journal of Physics: Conference Series, 1500, p 012003, Proc. 3rd FIRST, Palembang: Indonesia, 2020. https://doi.org/10.1088/1742-6596/1500/1/012003
[12] Z. Hou, Z. Li, T. Fadiji, and J. Fu,Soft, "Grasping Mechanism of Human Fingers for Tomato-picking Bionic Robots," Computers and Electronics in Agriculture, Vol 182, 106010, 2021. https://doi.org/10.1016/j.compag.2021.106010
[13] J. Chen, H. Qiang, J. Wu, G. Xu, and Z. Wang, "Navigation Path Extraction for Greenhouse Cucumber-picking Robots Using the Prediction-point Hough Transform, Computers and Electronics in Agriculture," Vol. 180, 105911, 2021. https://doi.org/10.1016/j.compag.2020.105911
[14] L. van Herck, P. Kurtser, L. Wittemans, and Y. Edan, "Crop Design for Improved Robotic Harvesting: a Case Study of Sweet Pepper Harvesting, Biosystems Engineering," Vol 192, pp. 294-308, 2020. https://doi.org/10.1016/j.biosystemseng.2020.01.021
[15] Y. Zhao, L. Gong, C. Liu, and Y. Huang, "Dual-arm Robot Design and Testing for Harvesting Tomato in Greenhouse," IFAC-PapersOnLine, Vol. 49, No 16, pp. 161-165, 2016. https://doi.org/10.1016/j.ifacol.2016.10.030
[16] T. Dewi, P. Risma, and Y. Oktarina, "Fruit Sorting Robot based on Color and Size for an Agricultural Product Packaging System," Bulletin of Electrical Engineering, and Informatics (BEEI), vol. 9, no. 4, pp. 1438-1445, 2020. https://doi.org/10.11591/eei.v9i4.2353
[17] A. Nasiri, A. Taheri-Garavand, and Y. Zhang Image-based deep learning automated sorting of date fruit, Postharvest Biology and Technology, Vol. 153, pp. 133-141, 2019. https://doi.org/10.1016/j.postharvbio.2019.04.003.
[18] M. Fashi, L. Naderloo, and H. Javadikia, The relationship between the appearance of pomegranate fruit and color and size of arils based on image processing, Postharvest Biology and Technology, Vol. 154, pp. 52-57, 2019. https://doi.org/10.1016/j.postharvbio.2019.04.017.
[19] J. Jhawar, "Orange Sorting by Applying Pattern Recognition on Colour Image," Procedia Computer Science, vol. 78, pp. 691–697, December 2016. https://doi.org/10.1016/j.procs.2016.02.118
[20] L. Fu, J. Duan, X. Zou, G. Lin, S. Song, B. Ji, and Z. Yang, Banana detection based on color and texture features in the natural environment, Computers and Electronics in Agriculture, Vol. 167, p. 105057, 2019. https://doi.org/10.1016/j.compag.2019.105057.
[21] U. Dorj, M. Lee, and S. Yun, An yield estimation in citrus orchards via fruit detection and counting using image processing, Computers and Electronics in Agriculture, Vol. 140, pp. 103-112, 2017. https://doi.org/10.1016/j.compag.2017.05.019.
[22] L. Fu, Z. Liu, Y. Majeed, and Y. Cui, "Kiwifruit Yield Estimation using Processing by an Android Mobile Phone," IFAC Conference Paper Archive, vol. 51, pp. 185–190, 2018. https://doi.org/10.1016/j.ifacol.2018.08.137
[23] K. Tan, W. Suk, H. Gan, and S. Wang, "Recognising Blueberry Fruit of Different Maturity Using Histogram Oriented Gradients and Colour Features in Outdoor Scenes," Biosystems Engineering, vol. 176, pp. 59–72, 2018. https://doi.org/10.1016/j.biosystemseng.2018.08.011

[24] A. Septiarini, H. Hamdani, H. R. Hatta, and K. Anwar, "Automatic Image Segmentation of Oil Palm Fruits by Applying the Contour-Based Approach," Scientia Horticulturae, 2019. https://doi.org/10.1016/j.scienta.2019.108939.
[25] M. H. Malik, T. Zhang, H. Li, M. Zhang, S. Shabbir, and A. Saeed, "Mature Tomato Fruit Detection Algorithm Based on improved HSV and Watershed Algorithm," IFAC-PapersOnLine, Vol. 51, No. 17, pp. 431-436, 2018. https://doi.org/10.1016/j.ifacol.2018.08.183.
[26] L. F. S. Pereira, S. Barbon, N. A. Valous, and D. F. Barbin, Predicting the ripening of papaya fruit with digital imaging and random forests, Computers and Electronics in Agriculture, Vol. 145, pp. 76-82, 2018. https://doi.org/10.1016/j.compag.2017.12.029.
[27] T. Anandhakrishnan, S.M. Jaisakthi, Deep Convolutional Neural Networks for image based tomato leaf disease detection, Sustainable Chemistry and Pharmacy, Vol. 30, p. 100793, 2022. https://doi.org/10.1016/j.scp.2022.100793.
[28] M. Zaborowicz, P. Boniecki, K. Koszela, A. Przybylak, and J. Przybył, Application of neural image analysis in evaluating the quality of greenhouse tomatoes, Scientia Horticulturae, Vol. 218, pp. 222-229, 2017, https://doi.org/10.1016/j.scienta.2017.02.001.
[29] T. Zeng, S. Li, Q. Song, F. Zhong, and X. Wei, Lightweight tomato real-time detection method based on improved YOLO and mobile deployment, Computers and Electronics in Agriculture, Vol. 205, p. 107625, 2023. https://doi.org/10.1016/j.compag.2023.107625.
[30] J. Qi, X. Liu, K. Liu, F. Xu, H. Guo, X. Tian, M. Li, Z. Bao, Y. Li, An improved YOLOv5 model based on visual attention mechanism: Application to recognition of tomato virus disease, Computers and Electronics in Agriculture, Vol. 194, p. 106780, 2022. https://doi.org/10.1016/j.compag.2022.106780.
[31] Q. Rong, C. Hu, X. Hu, M. Xu, Picking point recognition for ripe tomatoes using semantic segmentation and morphological processing, Computers and Electronics in Agriculture, Vol. 210, p. 107923, 2023. https://doi.org/10.1016/j.compag.2023.107923.