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Online Detection of Tomatoes for Robotic Harvesting

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ABSTRACT

To minimize potential damage, it is crucial to carefully harvest greenhouse crops like tomatoes at the optimal time. To improve this process, the use of robotic harvesting methods has been proposed. The robotic harvester consists of important components including a mobile platform with robotics, displacement units that can move linearly or rotationally, a manipulator, a gripper, a camera, an image processing-based fruit detection unit, and a depth sensor. A robotic manipulator with three linear degrees of freedom was created in the Cartesian coordinate system. To enhance its capabilities, a gripper mechanism was incorporated, providing an additional rotational degree of freedom. The primary objective of this robot was to autonomously detect the position of ripe tomatoes. To achieve this, the displacement control of both the robot arms and gripper was executed through commands from the image processing unit. Different channel of some color space was studied. The effectiveness of this channels was assessed by conducting tests in the presence of tomato plants. The accuracy of the system in approaching the crop were thoroughly evaluated. Channels H of HSV color space, Cr of YCrCb color space, and a of Lab color space showed better result. The accuracy of detecting ripe tomatoes in channel H of HSV color space was the highest and 87%.

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INTRODUCTION

By the year 2050, it is projected that the global population will reach approximately 10 billion individuals. Consequently, ensuring food security for this expanding population stands as one of the primary challenges faced by humanity. To enhance agricultural production and meet this demand, several measures must be implemented. These include optimizing water consumption, overcoming climatic constraints, boosting crop yields, adopting vertical agriculture techniques, and implementing automated controlled climates. However, the successful implementation of controlled climate production methods necessitates skilled operators. As the scarcity of labor persists and labor costs continue to rise, the automation of various stages of greenhouse crop production becomes an inevitable solution.

Based on the data concerning the allocation of labor in tomato farming, approximately 25 to 40% of the overall workforce is engaged in repetitive harvesting activities. In the conventional harvesting method, manual labor is predominantly utilized with minimal assistance from mechanical tools such as trolleys and cutting implements. Consequently, the majority of the expenses incurred are attributed to human labor (Abdi-pour & Shamsi, 2023; Benavides et al., 2020).

In recent times, there has been significant attention given to the advancement of robots as potential replacements for fruit workers. However, it is important to note that robots operating in natural settings cannot solely rely on geometric coordinates of their targets to carry out their tasks. Therefore, they must possess the capability to identify unnecessary leaves, apply pesticides, gather and trim fruits and branches, much like a human would, all in accordance with the intended objective.

The process of automatically harvesting tomatoes involves the identification of ripe tomatoes, locating their central points, and then separating them. In a greenhouse setting, ripe tomatoes are often surrounded by the stem, leaves, unripe tomatoes, and the ground. By implementing a comprehensive classification system, we can ensure that the harvesting process occurs at the optimal stages of ripening (Chen, 2015).

The maturity stage of tomatoes can be primarily determined by their color. Additionally, the image processing system is capable of recognizing color as well. In the case of the tomato harvesting robot, the image processing steps involved the identification of target areas, specifically the tomato fruits, within the camera's field of view. Furthermore, the system was able to recognize and position each ripe tomato individually in two dimensions. To ensure efficient tomato harvesting, a secondary sensor was utilized to determine the depth at which the ripe tomatoes should be placed. Finally, the results obtained from the first three steps were integrated and optimized to provide a comprehensive solution (Chen, 2015).

Mohammadi Monvar et al. (2012) employed a color CCD camera to successfully identify tomatoes. The researchers utilized three different color spaces, namely RGB, HSI, and YCbCr, along with three distinct algorithms for edge, curve, and color detection. The findings of their investigation revealed that the YCbCr color space yielded a tomato detection rate exceeding 83.3% (Mohammadi Manour et al., 2013).

Yin et al. (2009) introduced a robotic system designed specifically for the purpose of harvesting tomatoes in a greenhouse setting. The primary objective of their research was to develop a method for effectively detecting ripe tomatoes within the intricate and challenging environment of a greenhouse. To achieve this, the researchers employed the Lab color space and utilized the k-means clustering method to accurately identify ripe tomatoes. Additionally, they employed the mathematical morphological method to address various challenges such as removing noise, resolving overlapping instances, and mitigating shading issues. The effectiveness of the system was evaluated through a validation test involving 20 tomatoes, wherein only one case exhibited an error, highlighting the system's overall accuracy and reliability.

Wei et al. (2014) employed the OHTA color space to identify the location of pixels associated with mature tomatoes within the intricate setting of a greenhouse. To achieve this, they utilized the automatic Etsu method for thresholding. OHTA, which comprises 8 color components, served as the basis for their analysis. The results indicated a commendable extraction accuracy of approximately 95%.

Feng et al. (2015) employed a CCD camera and the HSV color model to carry out image segmentation. To determine the three-dimensional distance to the center of each tomato, a laser sensor was utilized. The researchers achieved a success rate of 83.9% in tomato harvesting, with a time requirement of 24 seconds for a complete harvesting cycle, encompassing tomato location recognition, arm movement, and harvesting.

Malek et al. (2018) employed the HSV transformation technique to successfully identify red tomatoes. To separate tomatoes that were clustered together, they applied the edge algorithm. The results of their analysis revealed that approximately 81.6% of the red tomatoes were accurately detected.

Researchers utilized three-dimensional (3D) images to discern the product. Wang et al. (2017) employed a stereo vision system integrated with Otsu's method to accurately identify ripe tomatoes. The detection of ripe tomatoes achieved an impressive success rate of 99%.

Yoshida et al. (2019) successfully captured three-dimensional images of tomatoes and accurately identified the location of the tomato bunch. The researchers utilized a limited set of six sample images for their analysis, however, the time taken for each image acquisition was not explicitly mentioned. Remarkably, they achieved an impressive accuracy rate of 98.85% in their findings. The primary objective of their work involved detecting and determining the position of ripe tomatoes in the two-dimensional plane (X, Y) using a camera. Subsequently, the precise location of fruit separation from the plant was determined and transmitted to the mechanical system.

Various robotic platforms were utilized to transport the end effectors and execute the task of transferring the position command from the computer to the system, thereby achieving the designated targets. In their study, Feng et al. (2018) made specific modifications to their system to cater to the harvesting of cherry tomatoes. They employed a camera to determine the precise position of the tomatoes, a laser sensor to measure the distance between the tomato and the end arm, and a Cartesian system to manipulate the arms, resulting in the development of a cherry tomato harvester. The results of their experiment revealed that this robotic system successfully harvested 83% of ripe tomatoes. Furthermore, they were able to complete a single withdrawal cycle within a time frame of 8 seconds. It is worth noting that the duration required for the movement of the platform was not included in this measurement.

Lili et al. (2017) constructed a robot consisting of four wheels and a 5-degree-of-freedom arm robot attached to it. The robot was equipped with an Akerman steering wheel and utilized a laser sensor to accurately determine the direction of movement with a precision of 8 cm. To detect ripe tomatoes, the researchers employed the Otsu method and a dual camera. The depth-finding system exhibited an error of 10 mm when the tomatoes were located at a distance of 60 cm. The entire process of detecting and harvesting tomatoes took approximately 15 seconds. The system developed by Lilly et al. achieved an accuracy rate of 86%.

In the researches of Hashimoto et al. (2012) and Menesatti et al. (2012), four types of features were used: color, shape, size and texture. The color characteristics depended on the position of the fruits in the canopy, because the lighting conditions were not completely uniform. Color calibration of the images taken under field conditions was done. For the shape feature, a very simple feature of the area's width to height ratio was used.

Wan et al. (2018) employed a color model and shape analysis in order to identify tomatoes. Nevertheless, these methodologies were incapable of extracting profound features and consequently resulted in the occurrence of detection errors under intricate environmental circumstances. Whittaker et al. (2019) adopted a shape-oriented procedure (known as circular Hough transform) to identify tomatoes and demonstrated that this approach is proficient in ascertaining the location of tomatoes based on their respective shapes in images that possess notable background noise. However, the computational nature of this method necessitates a substantial amount of time for non-tomato processing, thereby rendering its application within real-time robotic harvesting to be quite challenging.

One of the additional challenges encountered in this research pertained to the automatic collection of tomatoes, specifically the presence of hindrances such as leaves and stems. Tomatoes that are clearly visible to the detection system can be plucked by a mechanical robot apparatus from the frontal region. However, in order to harvest concealed tomatoes, the trajectory of the robot arm must be determined by taking into account the positioning of the obstructions. In a study conducted by Ikeda et al. (2021), a technique was proposed to distinguish between hidden and visible tomatoes. Subsequently, the usage of the "Hough Circles" method from the Open CV library enabled the detection of whether a tomato is concealed or not by identifying a circular shape. In this particular detection, the underlying assumption is that the tomatoes possess a circular shape. In the event that this circular shape is perceptible, it is identified as an observable tomato. Conversely, if the circular shape fails to be perceptible, it is classified as a concealed tomato. There exist concealed tomatoes that cannot be detected or harvested owing to the existence of obstacles in their proximity.

Researchers have leveraged the advancements in machine learning-based detection systems by employing the powerful capabilities of CNN convolutional neural network. In their study, Zeng et al. (2023) adopted a deep learning approach to enhance the precision of diagnosis. To identify the whereabouts of tomatoes, they utilized YOLO (You only look once) as a detection technique. Impressively, their detection system exhibited a remarkable processing speed of 26 images per second. Operating at such a rapid image input rate, their algorithm achieved an impressive accuracy rate of 92% in correctly identifying ripe tomatoes within the images.

A harvesting robot consists of three main parts:

1) Robotic platform with the ability to move in three directions X, Y, Z

2) Imaging and image processing system (computer vision) to detect product position

3) The end effector of harvesting the tomato

After conducting a thorough analysis of multiple sources, it has been determined that the identification of ripe tomatoes continues to pose a significant challenge. This difficulty arises from the intricate backdrop of the greenhouse's natural environment, making it arduous to pinpoint the exact pixel representing the product. The recognition system greatly benefits from the distinct coloration of ripe tomatoes. However, complications arise when dealing with semi-ripe tomatoes and obstructions caused by stems and leaves obstructing the product. These issues were thoroughly investigated in the course of this research, subsequent to the construction of the robot.

In order to develop an automated tomato harvesting system at Tabriz University, a three-axis platform was meticulously constructed. This sophisticated robot was controlled by an image processing management system, which effectively executed the necessary tasks on the tomatoes with precision. Once the target, which in this case is a tomato, was identified, the system skillfully maneuvered the end arm towards it and delicately picked it up.

MATERIALS AND METHODS

In order for a robot to be able to perform automatic harvesting operations, it must have four parts of a mobile robotic platform with the ability to move in three directions x, y and z, and a computer vision system to detect tomatoes, product holder clip and if needed, product collar cutting system.

The tomato harvesting robotic system was built in the electrical and instrumentation laboratory at Biosystem Engineering department in University of Tabriz, which consisted of three main parts.

The Cartesian robotic platform

The platform is capable of movement along three axes, namely X, Y, and Z. The utilization of the Cartesian robotic system was prevalent in the majority of the reviewed sources due to its compatibility with the conventional layout of tomato cultivation in greenhouses. This research focuses on the geometric attributes of the planting rows and the precise positioning of tomato products on the plants. A rectangular robotic platform, also known as a Cartesian platform, was constructed with dimensions of 1.0 × 0.5 × 3 meters (height, width, and length respectively). In the context of tomato cultivation, the tomatoes are typically positioned at a distance of approximately 2 meters from the ground. Within a 1-meter range, there are no tomato present, only the main stems of the plants. Consequently, the vertical arm of the Cartesian manipulator can extend up to approximately 200 cm. The moving component of the manipulator was situated on a stationary platform that can traverse alongside the rows of plants. The wheels of the platform were powered by a single DC gearbox-motor. As the manipulator's parts move in a linear fashion, a rotational to linear conversion mechanism was necessary to drive the main parts of the manipulator in a linear direction (Figure 1).

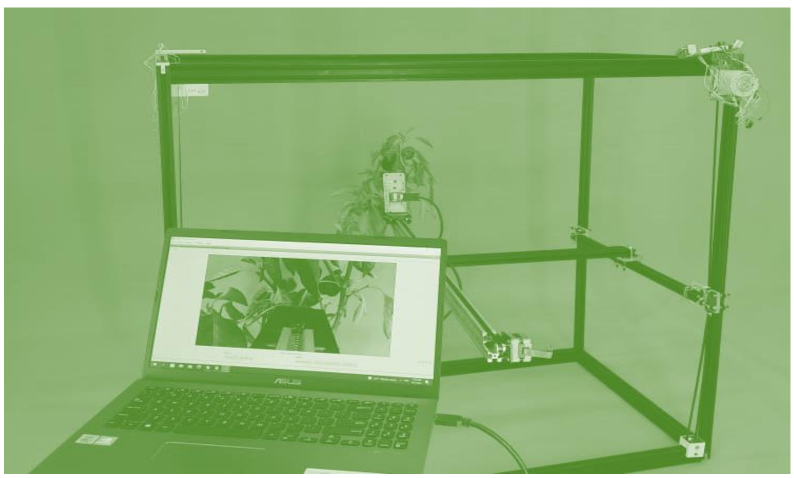


Figure 1. The Cartesian manipulator for tomato harvesting

Stepper motor 17 was used to create movement in three movement directions. The TB6600 circuit was used as a driving circuit and computer interface, which was transmitted to the driver by Arduino Mega 2560.

In order to convert the rotational motion of the motor into linear motion, two systems were needed to convert the rotational motion into linear motion and a linear motion guide.

For motion conversion, there were three belt and gantry options, lead screw ball screw, which used a gantry and belt assembly to increase the speed of movement. To keep the movement of the gantry, two supporting axes were used. The camera and illumination system were mounted on the ganry (Figure 2).

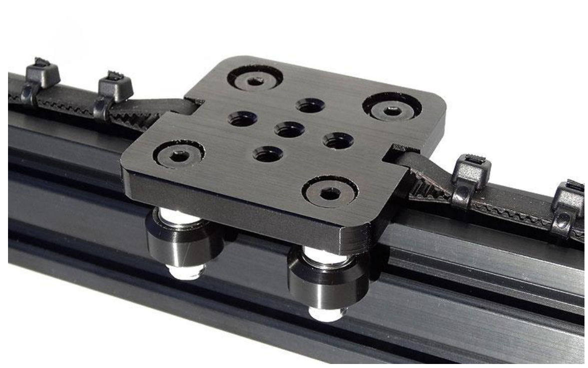


Figure 2. linaer displacement by using the gantry mechanism

The gripper that is placed at the end of the Z and grabs the tomato.

A finger-shaped end effector, known as a gripper, has been assigned the duty of seizing and enclosing the tomato for the purpose of picking it up (Figure 5). The detachment of most tomato varieties from the stem can be achieved by a simple pulling action. Nevertheless, specific types of tomatoes might necessitate the use of cutters or high voltage separators to facilitate the separation process. The gripper has the ability to securely hold the tomato by adjusting the gap size between its fingers. To ensure that the tomato is not dropped, the gap size should be slightly larger than the dimensions of the tomato. The closure of the fingers was initiated upon detection of the tomato within the gripper by the depth sensor. According to the geometric relationship between the camera installation position and the robot arm position, the end effector is transferred to the vicinity of the tomato using the inverse kinematic calculation of the operator (Figure 1).

Computer vision system

The gripper was accompanied by a Basler Aca1920 color camera, which effectively captured frames in the RGB color space of the tomato plant scene. These captured frames were then transferred to the computer via the USB3 interface port. A Python code was utilized to process the frames and detect the position of the fruits. Achieving optimal lighting conditions and considering the influence of external light sources presented a major challenge during the tomato detection step.

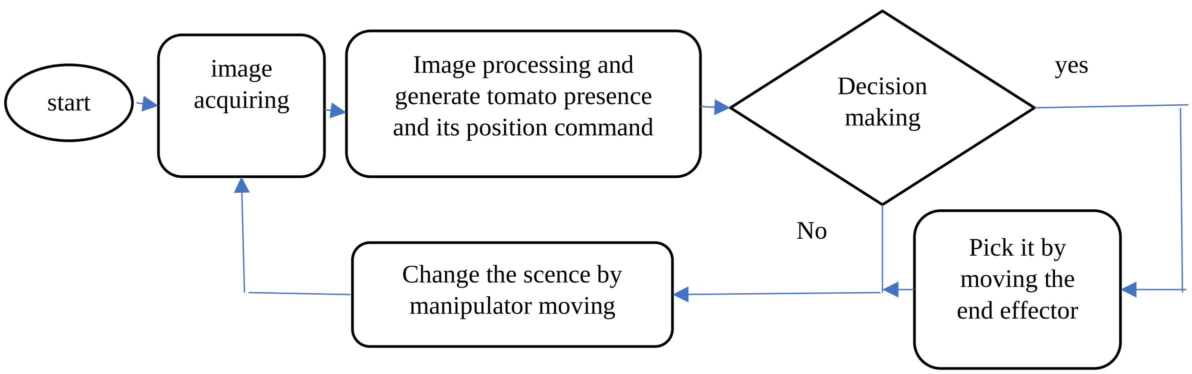


Figure 3. tomato detection algorithm based on image processing

Following the acquisition of the image, a color space channel that is appropriate is chosen, and segmentation is carried out on the grayscale image obtained at the previous stage. Through the utilization of thresholding, a binary image is obtained, where the white pixels correspond to the tomato and the background is represented by black pixels. Subsequently, the total number of white pixels is computed, and if this value exceeds a predetermined threshold, it indicates the presence of tomatoes in the scene, thereby necessitating the execution of the harvesting operation by moving the manipulator and utilizing the gripper (Figure 3).

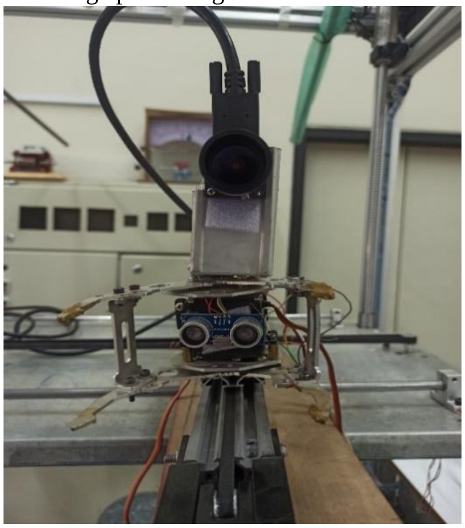


Figure 4. camera and depth sensor position related to gripper

Image processing of ripe and semi-ripe tomatoes

In order to detect the presence of ripe tomatoes in the imaged scene (Figure 5) and to determine the position of the tomato itself and its stem as a cutting site (if needed), a segmentation operation must be carried out. In order to execute the segmentation process, it is essential to eliminate not only the background pixels but also distinguish the pixels associated with the ripe product from those of the unripe product. The effect of natural light irradiated by the sun and the variability of its intensity and direction was the main challenge of this research.

Figure 5. a) tomato plant, b) dtected tomato position in the image

DISCUSSION AND RESULTS

By default, the information related to the pixels of color images called by the considered library in Python can be obtained in three separate channels, B, G and R, respectively. Being seen more distinctly in terms of the human visual system is a visual recognition based on the brain's processing system that apparently humans see as distinct components in the image.

In the first step, to differentiate the pixels related to ripe colored tomatoes, the best color space was first selected among the three-color spaces, YCbCr, Lab, and HSV.

A quantitative criterion for this diagnosis is a frequency chart or histogram, which provides a threshold level value for distinguishing two or more distinct objects. Therefore, in this research, the basis of the work for detecting ripe tomatoes was the thresholding method based on the histogram diagram. Unlike the human brain, in computers, processing is usually based on single-channel data processing. As can be seen in Figure 6 and 7, The difference cannot be detected in the image histogram for any of the three channels, specifically B, G, and R. In the histogram diagram, the presence of a distinct valley is a decision criterion.

B **G** **R**

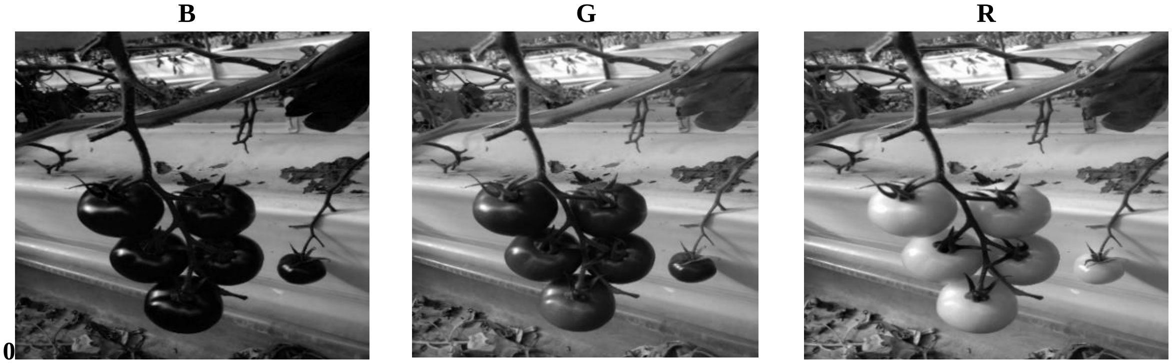


Figure 6. Three splited color channels of RGB space color

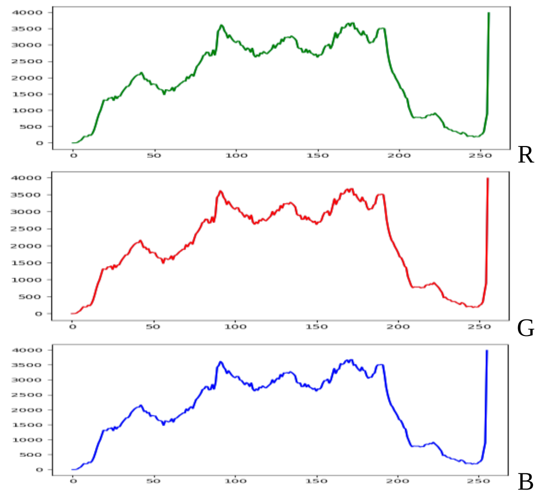


Figure 7. The histogram of channels of RGB color space

a) Component a represents the greenness-redness of a pixel, with lower values indicating green objects and higher values associated with magenta (Gonzalez, 2009). Red objects are expected to have higher values. The presence of a larger amount of 'a' in ripe tomatoes aids in determining their ripeness Figure 8.

b) Component b represents the blueness-yellowness of a pixel. So, yellow pixels have a higher values of b (Gonzalez, 2009). So, immature areas of tomatoes may have larger values of b.

The L channel is independent of color information and encodes brightness only, So, it is not expected to be utilized for tomato color detection.

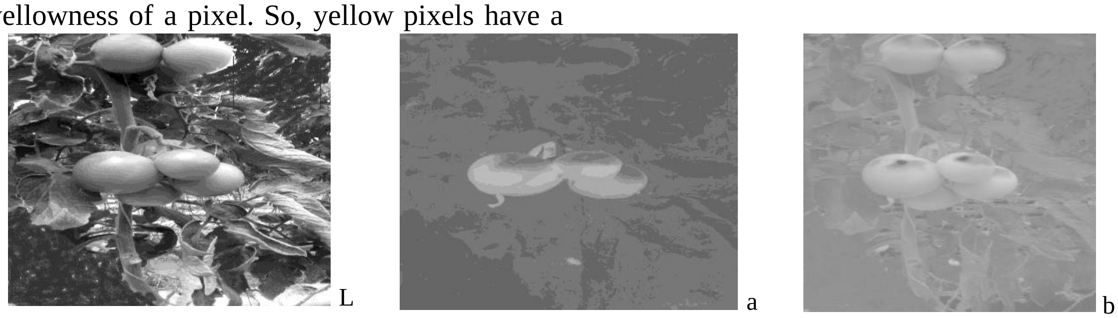


Figure 8. splied channels of Lab color space

a) Cr channel: This channel is related to the Cr component (red-yellow color component) which is usually used in skin detection and related colors (Gonzalez, 2009). Ripe tomatoes may have larger amounts in this channel.

b) Cb channel: This channel corresponds to the Cb component (blue-yellow color component), which indicates color differences in the blue-yellow axis (Gonzalez, 2009). This channel can also be used to detect color differences between unripe and ripe.

Y channel in YCrCb (YCbCr in MATLAB) color space in similar to L in Lab color space.

Y Cr Cb

Figure 9. Y component - Cr component - Cb component of YCrCb color space

A) Scale of color levels (Value/V): This feature indicates the brightness of the color (Gonzalez, 2009). Ripe tomatoes usually have larger V values than unripe tomatoes, indicating a higher color intensity in ripe tomatoes.

b) Color saturation scale (Saturation/S): This feature shows the amount of color in the color. Ripe tomatoes usually have lower S values than unripe ones (Gonzalez, 2009).

c) H stands for Hue, which represents intensity of color or chroma of an object (Gonzalez, 2009).

Figure 10. H, S, and V channels of HSV color space

In this research, the image processing method was evaluated for accurate detection of tomato fruits, including ripe, semi-ripe and unripe fruits.

To better evaluate the detection performance of tomatoes, 50 tomato images were randomly selected from the dataset and the total number of ripe and semi-ripe tomatoes in all three components of the selected color space was examined.

The area under the Precision-Recall graph, known as Average Precision (AP), can be used as a metric to summarize the performance of the object recognition model. This method uses precision and recall criteria to evaluate the performance of the model in the validation stages (Table 1). The number of True Positives (TP) represents the number of ripe tomatoes correctly identified as ripe tomatoes. False Positive (FP) represents the number of background regions detected as ripe tomatoes, but actually background. False Negative (FN) represents the number of ripe tomatoes identified as background regions, but are actually tomatoes. True Negative (TN) represents the number of context regions that are correctly identified as context. Equation 1 was used to determine the accuracy.

Table 1. Concepts used to determine accuracy

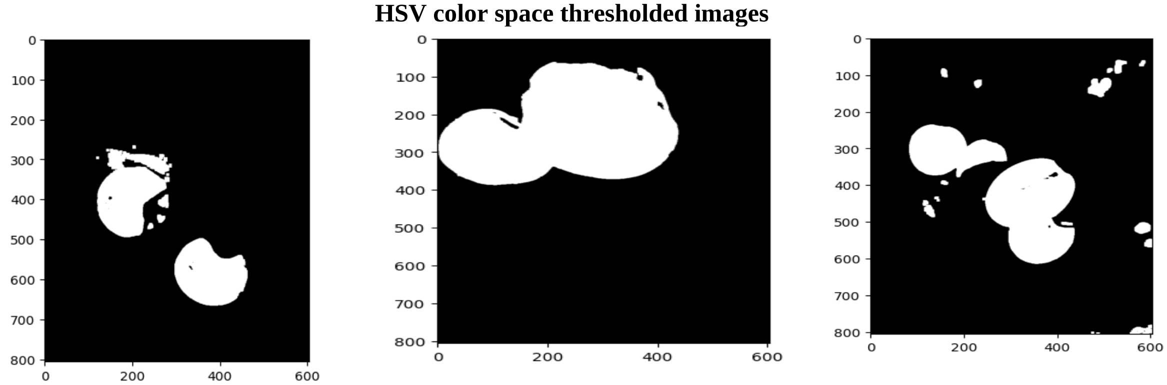
		Prediction by algorithm	
		Yes	No
Real label	Yes	TP	FN
	No	FP	TN

$$accuracy = \frac{TP}{TP + FP} \quad (1)$$

The accuracy of detecting ripe tomatoes in channel H of HSV color space was the highest and 87%. After that, the Cr channel of images in YCrCb color space were obtained with an accuracy of 82% and the images taken in a channel of Lab color space were 78%. The apparent difference between the segmented images was not large. The main reason for this difference in accuracy was the threshold level values in the histogram diagram related to H channel, due to the more distinct distance of the peaks.

By examining the results of the tomato ripeness identification test based on image processing, it was determined that due to the overlaps made by the stem and leaves, the shine of the leaves, the system should be modified. By examining the images that were wrongly segmented, it was found that corrections should be made in the type of lighting. The application of deep learning methods is unavoidable as the authors are completing the data sets required for system training.

HSV color space thresholded images



HSV color space histogram plots

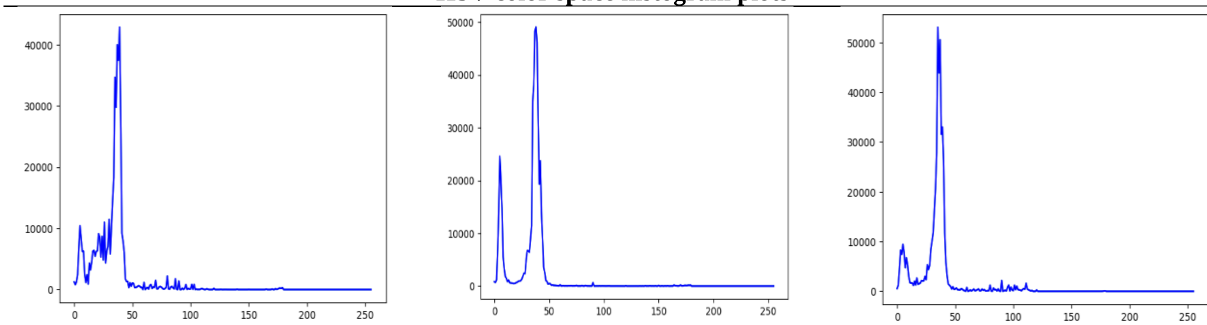
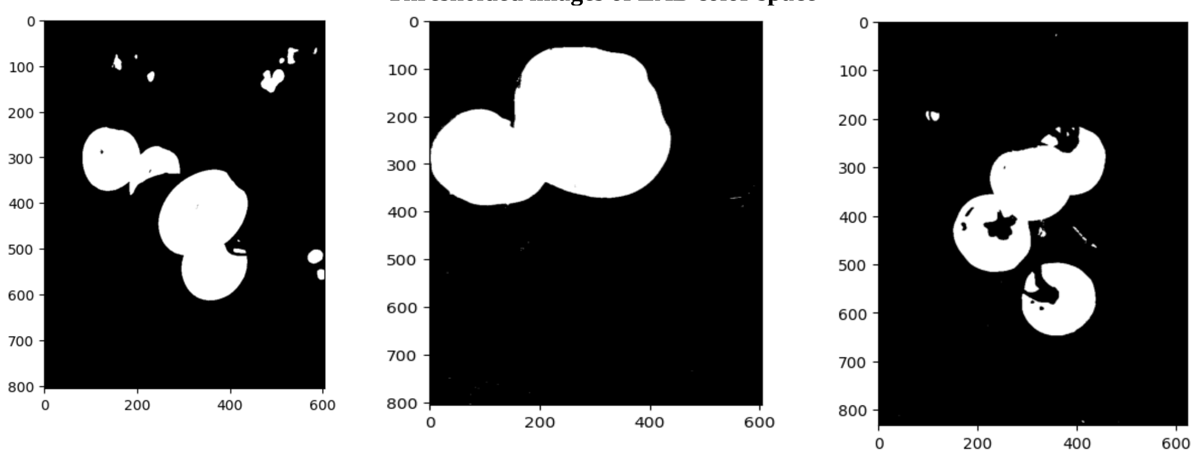


Figure 11. Histogram and thresholded images for channel H of HSV color space for 3 different images

Thresholded images of LAB color space



LAB color space histogram charts

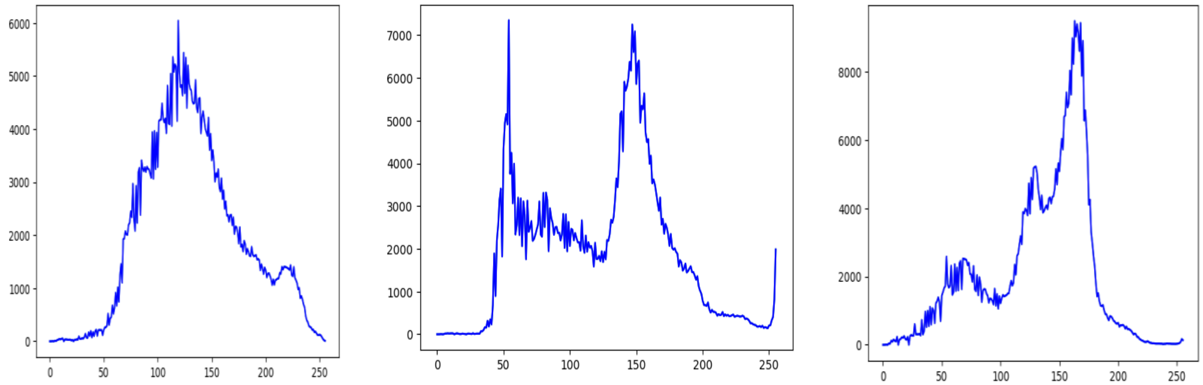
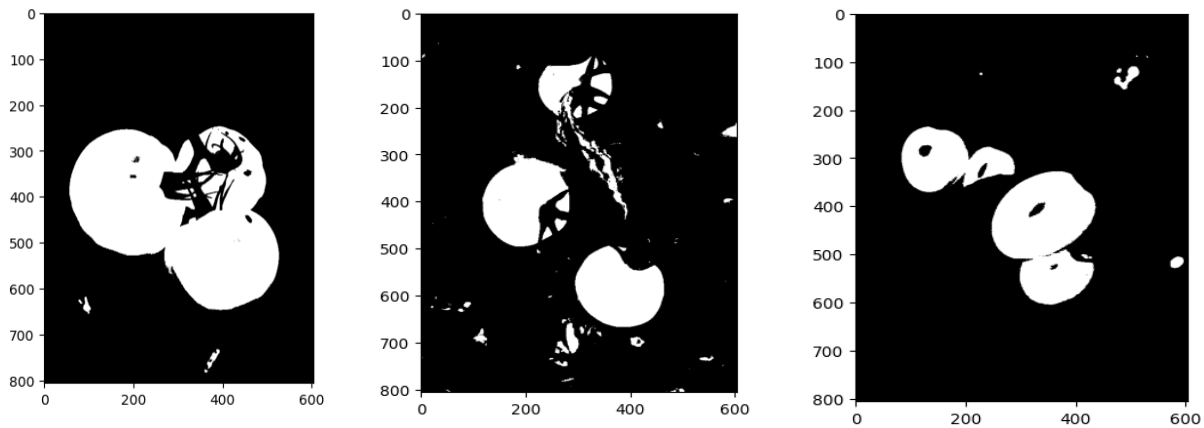


Figure 12. Histogram diagram and thresholded images for channel a of Lab color space

YCRCB color space thresholded images



YCRCB color space histogram charts

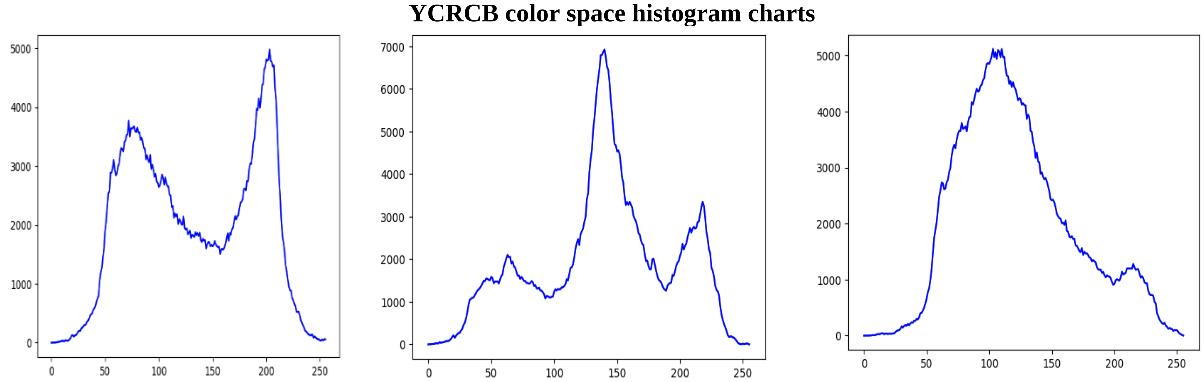


Figure 14. Histogram diagram and thresholded images for channel Cr of YCrCb color space

CONCLUSION

As the histogram shows, although the peaks in the H channel are close to each other, the peaks are completely different from each other. Also, the valleys have extended to the bottom, which means that the abundance is almost zero. Therefore, the possibility of mistakes in segmentation is less. In the rest of the channels, despite the better distance between the peaks, the valleys were not completely distinct and clear. In practice, it was found that the range of the threshold level is wider than that of the H mode, and this causes that if a fixed threshold level value is selected, unfortunately, a part of the ripe tomato is recognized as the background. For this reason, component a of the Lab color space is removed, and H was selected from the two components Cr in the YCrCb color space and H component in the HSV color space.

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