Image Processing Techniques For Tomato Segmentation Applying K-Means Clustering and Edge Detection Approach

2021 International Seminar on Machine Learning, Optimization, and Data Science (ISMODE) | 978-1-6654-0544-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/ISMODE53584.2022.9742740

Anindita Septiarini
Dept. of Informatics
Engineering Faculty
Mulawarman University
Samarinda, Indonesia
anindita@unmul.ac.id

Hamdani Hamdani
Dept. of Informatics
Engineering Faculty
Mulawarman University
Samarinda, Indonesia
hamdani@unmul.ac.id

Sri Ulan Sari
Dept. of Informatics
Engineering Faculty
Mulawarman University
Samarinda, Indonesia
sriulansari98@gmail.com

Heliza Rahmania Hatta
Dept. of Informatics
Engineering Faculty
Mulawarman University
Samarinda, Indonesia
heliza_rahmania@yahoo.com

Novianti Puspitasari
Dept. of Informatics
Engineering Faculty
Mulawarman University
Samarinda, Indonesia
novipuspitasari @unmul.ac.id

Wiwien Hadikurniawati
Faculty of Information Technology
Universitas Stikubank
Semarang, Indonesia
wiwien@edu.unisbank.ac.id

***Abstract*— The implementation of image processing techniques in the plantation field has been extensively researched and developed, for example, to identify fruit maturity and control fruit harvesting robots. The main procedure, termed segmentation, is required by those systems in order to determine the fruit and background area. This work aims to put into practice a method of tomato segmentation. The method consists of four main processes: region of interest (ROI) detection, pre-processing, segmentation, and post-processing. The resize and K-means clustering were applied in ROI detection. The color space conversion of RGB into HSV was applied in pre-processing, followed by implementing edge detection using the Canny operator. In post-processing, morphology operation was carried out to discard the remaining noise. The performance evaluation of the tomato segmentation method against 300 images showed the average value of segmentation accuracy, false positive and false negative obtained reached Sc, FPe, and FNe 91.43%, 2.84%, and 4.77%, respectively.**

Keywords—image processing, segmentation, edge detection, canny operator, morphological operation.

I. Introduction

Computer automation systems, particularly in agriculture, have been widely emerged in recent years [1], [2]. There have been various applications developed for image and video-based systems that use image processing techniques as their main input data. For example, for detection of ripeness of various types of citrus fruits [3], [4] apples [5], tomatoes [6], and oil palms [7], [8] which can be applied to fruit quality sorting systems or automatic harvesting machines as well as leaf disease detection [9], [10]. Image processing techniques related to fruit ripeness detection are applied in those works: the segmentation process. This process is needed to separate the fruit area and the background. Segmentation of several types of fruit has been applied to citrus [11], apples [5], [12], [13], mango [14], [15], bayberry [16], pomegranate [17], oil palm [18], and tomatoes [19].

Since tomatoes have several beneficial components, such as antioxidants and vitamins C and A for eye health, and because they are ingested on a daily basis, tomatoes are one of the plants that warrant additional examination. A large number of tomatoes are also produced by sauce producers and processed meals, which contributes to the overall supply. It is projected that the demand for high-quality tomatoes will continue to expand in the future. When it comes to fresh tomatoes, the quality is determined by the level of maturity and the size of the fruit. As a result, while sorting, this must be taken into consideration.

Fruit can be automatically sorted for quality control purposes, saving time and cost. With the application of image processing techniques, specific segmentation was required to construct the system. The goal of the segmentation process is to discriminate between the tomato area and the surrounding area. The deployment of edge detection techniques is one of the most extensively used segmentation approaches today. Some of the edge detection operations that have been used for the segmentation of produced objects include those developed by Sobel [20], [21], Prewitt [22], and Canny [10], [23], among others.

Many ways for segmenting various fruits have been created in past research, which was a continuation of such efforts. The segmentation of citrus fruits was used to develop an autonomous harvesting system. In this case, the methodology utilized combines the AdaBoost algorithm trained on the texture of the Leung-Malik Filter Bank and HSV color characteristics and other techniques. The performance evaluation results revealed that the precision and recall values were 0.867 and 0.768, respectively, for the test [11]. The detection of citrus fruits or the development of an automatic citrus fruit picking system was carried out using two segmentation approaches, Otsu and Watershed, in the meantime. It used a morphological operator to get rid of the background noise. It was possible to achieve a recall value of 0.86 with the system's performance [4]. Next, the Local Binary Pattern (LBP) algorithm was applied in features extraction, where the results were used as input for the ensemble classifier-RUSBoost. The performance of the citrus fruit detection method was evaluated using three parameters, namely recall, precision, and F-measure, which achieved values of 80.4%, 82.3%, and 81.3% [3].

In addition, a robust method for fruit segmentation was tested on three different types of fruit: citrus, grape, and litchi, among others. It was necessary to use the wavelet transform to equalize the illumination. Following that, the fruit area was segmented using the K-means clustering algorithm. The datasets were collected on two different types of days: sunny days and cloudy days, respectively. The maximum accuracy rating of 97.2 % was achieved on sunny days when testing against the grapefruit [24]. Furthermore, multiple image processing techniques, such as color model conversion, thresholding, and histogram equalization, were used to create the segmentation method for orange tree green fruit counting; the result was an accurate count of green fruits. Subsequently, the spatial filtering was carried out using the Laplace and Sobel operators and Gaussian blur. The method obtained a tolerated error of 5% using this approach [25].

Many previous works have been conducted to improve the methods of fruit segmentation that are currently in use [5], [11], [15], [19]. However, the uneven illumination, which resulted in any noises, was still judged unsatisfactory. The private dataset was used in order to apply the segmentation method that is capable of automatically detecting both foreground and background in a tomato image. The K-means clustering algorithm is required to obtain the coarse area of tomatoes. Meanwhile, the Canny operator was utilized to detect edges of the tomato region segmentation process. The morphology operator consists of dilation and opening was needed to reduce the amount of background noise. The HSV color space was selected for the segmentation procedure since it was the most appropriate.

II. Materials and Methods

The dataset utilized comprises 300 tomato images representing three levels of maturity: 100 ripe tomatoes, 100 half-ripe tomatoes, and 100 raw tomatoes with an artificial background (white color). The images were taken using a digital camera included in the smartphone (Zenfon max plus) and stored in JPEG format. The camera was around 20 cm distant from the tomato. Indoors, with adequate and even lighting, the purchase took place. Additionally, as detailed in [26], ground truths were produced for all images to validate the technique. These were created using an image editing application. The tomato images and the ground truth are presented in Fig. 1.

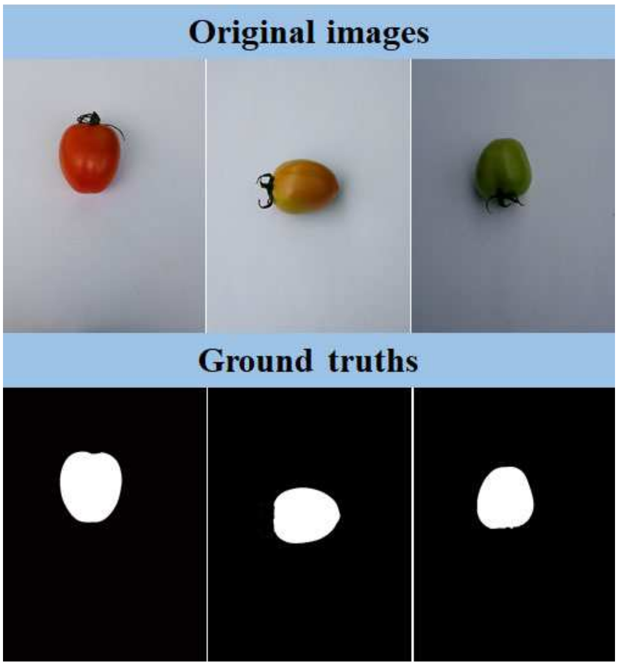

Fig. 1. Several tomato example images and ground truth

This segmentation approach uses tomato images with an artificial background as input data, which are then segmented. Fig. 2 depicts the three main steps that were used: (1) ROI detection, (2) pre-processing, (3) segmentation and post-processing, and (3) segmentation and post-processing. The binary image of the tomato region produced by the proposed method is the result of the technique. The evaluation process determined the performance of the created approach.

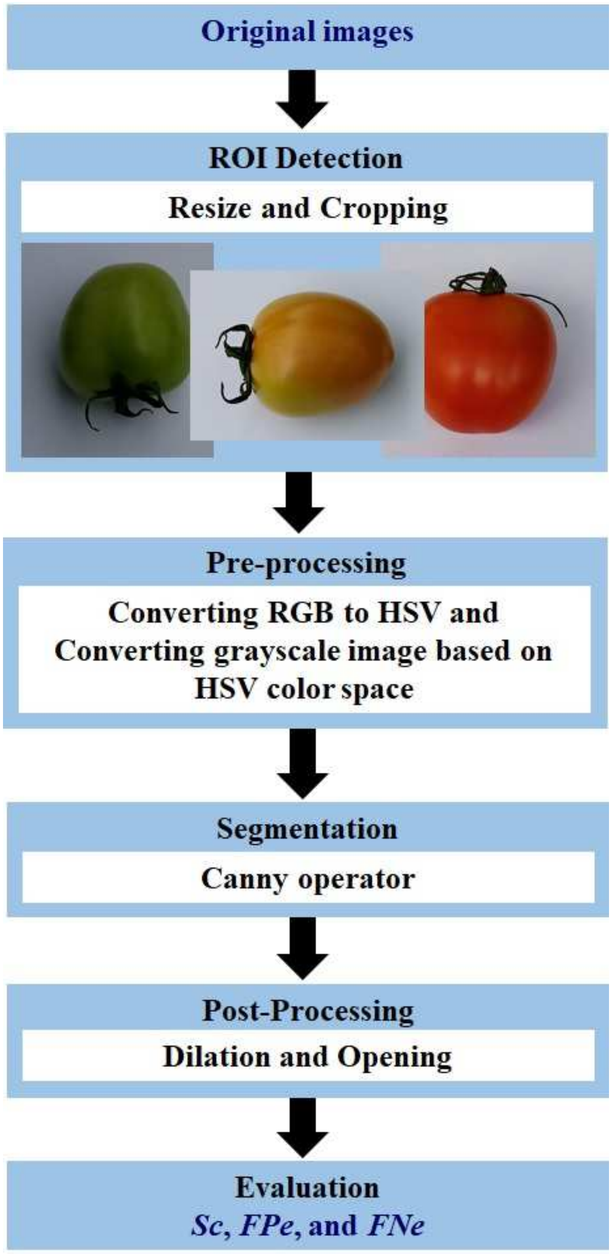

Fig. 2. The main processes of the tomato segmentation method

A. ROI Detection

The ROI detection process aims to form a sub-image that begins with resizing the tomato image with the size of 3456 × 4608 pixels and the result of resizing the size of 1728 × 2304 pixels to speed up the computation time of the following process. Coarse area of tomato is generated based on clustering method using K-means clustering algorithm. The value of K is two because the image's area was divided into two parts: the tomato area and the background area. The following are the steps that produce this algorithm's steps [10], [27], [28]:

- Step 1: Using the number of data samples, randomly select cluster centroids (*Ci*) (pixels in an image).
- Step 2: Classify each point according to its proximity to the nearest cluster center using the distance function.
- Step 3: Recalculate the arithmetic mean of each cluster to update the new cluster center.
- Repeat steps 2 and 3 until no further modifications to the cluster centroid are made.

B. *Pre-processing*

Pre-processing is intended to improve the quality of images in order to achieve the best possible segmentation results. It was possible to accomplish this method by transforming the RGB color space into the HSV color space on the ROI detected image. Fig. 3 depicts an example of a converted image that has been enhanced. The RGB color space conversion to the HSV color space is defined as follows using Eqs. (1) – (4) [7], [29]:

$$H = \begin{cases} \theta, & B \le G \\ 360 - \theta, & B > G \end{cases} \quad (1)$$

where

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[x(R-G)^2+(R-B)(G-B]^{1/2}}\right\} \quad (2)$$

$$S = \begin{cases} 0, & \max(R,G,B) = 0 \\ 1 - \dfrac{\min(R,G,B)}{\max(R,G,B)}, & otherwise \end{cases} \quad (3)$$

$$V = \max(R,G,B) \quad (4)$$

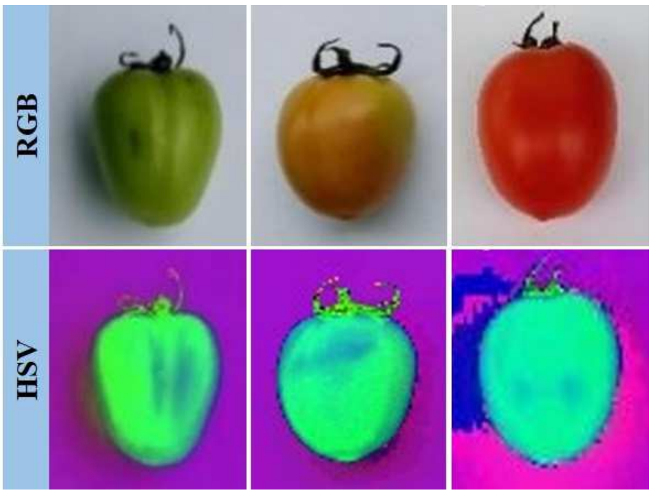

Fig. 3. Several tomato example images and ground truth

C. *Segmentation*

The tomato segmentation procedure proposes discriminating between the area of the tomato and the background in the image. This method was carried out utilizing edge detection with the Canny operator on the S channel, which was based on the color space of the input signal. The Canny operator was chosen since it has been widely employed in several earlier works relating to fruit object segmentation, including this one [10], [23]. While this was going on, Channel S was selected because, visually, the edge detection results had less noise. In comparison to the H and V channels, the representation of the tomato area has better represented. Fig. 4 depicts a comparison of the edge detection results obtained for each channel in the HSV color space.

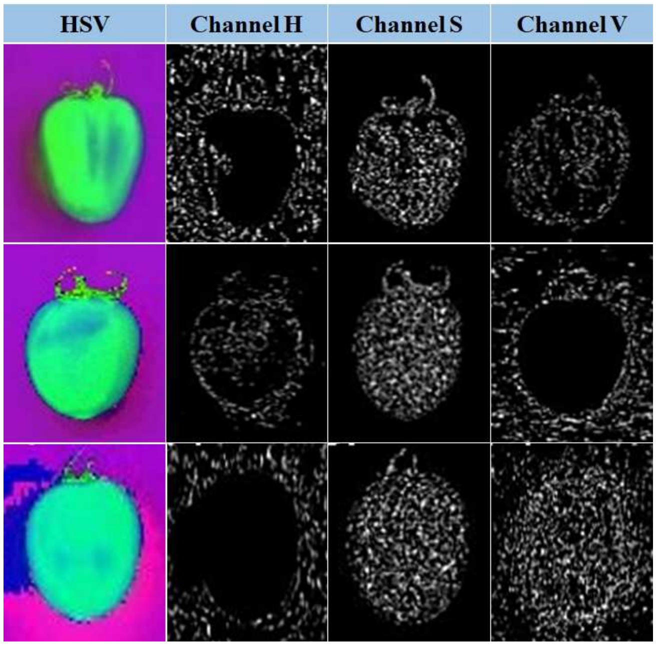

Fig. 4. Comparison of the edge detection results of each channel in the HSV color space: (a) channel H, (b) channel S, and (c) channel V

D. *Post-processing*

Post-processing consisted of three steps in this work, including dilation, filling holes, and opening. A dilation operation was performed to clarify and connect the broken edge of the tomato. Subsequently, filling holes operation were needed to form the tomato area whole. Lastly, the opening operation was applied to reduce the noise that frequently occurred on the petals (top) of the fruit. Fig. 5 illustrates various examples of images that have been post-processed.

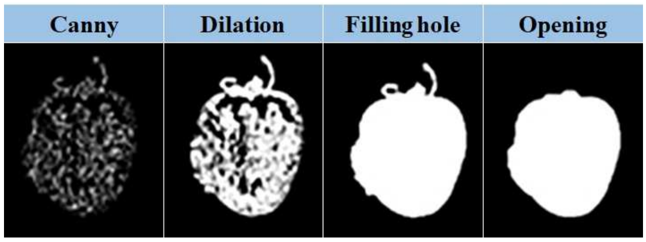

Figure 5: An illustration of a post-processed image

E. *Evaluation*

In order to evaluate the tomato segmentation method against an artificial background, it was required to compare the image segmentation result with the ground truth, which was performed. In this case, the segmentation accuracy (*Sc*) parameter was used to identify the overlapped area between the two images. Meantime, the method indicated that the error rate of the background area was detected as the tomato area. The error rate of the tomato area was detected as the background by the method indicated that the error rate of the background area was recognized as the tomato area using the parameters of False Positive (*FPe*) and False Negative (*FNe*). The values of the parameters are in the range of 0 to 100 in terms of numerical value. If the value of *Sc* is close to 100, the technique performs well; otherwise, the *FPe* and *FNe* values are close to 0, and the method performs poorly. The three evaluation parameters were computed using Eqs. (5) - (7) as follows [18], [24]:

$$Sc = (A_P \cap A_R)/(A_P \cup A_R) \times 100\% \quad (5)$$

$$FP_e = |A_P - (A_P \cap A_R)|/\bar{A}_R \times 100\% \quad (6)$$

$$FN_e = |A_R - (A_R \cap A_P)|/A_R \times 100\% \quad (7)$$

The A_P variable represents the number of white pixels recognized by the algorithm as the tomato area. On the other hand, the A_R value represents the number of white pixels that were detected as the tomato area by the ground truth. The value of $\bar{A}_R$, which is the complement of A_R, reflects the number of black pixels that were identified as background.

III. Results and Discussion

This work aims to develop a method for segmenting tomatoes in an artificial background by utilizing the S channel of the HSV color space. The method was validated using 300 images of tomatoes at three levels of maturity: raw, half-ripe, and ripe. This work determined the coarse area of tomato in an image using the Canny operator. Additionally, the dilation and filling holes operation formed the entire tomato area, which was followed by an opening operation to reduce noise. Three parameters were used to evaluate the segmentation method's performance: *Sc*, *FPe* and *FNe*. Fig. 6 shows examples of segmentation results compared to the ground truth on tomatoes of various maturities and the method's performance.

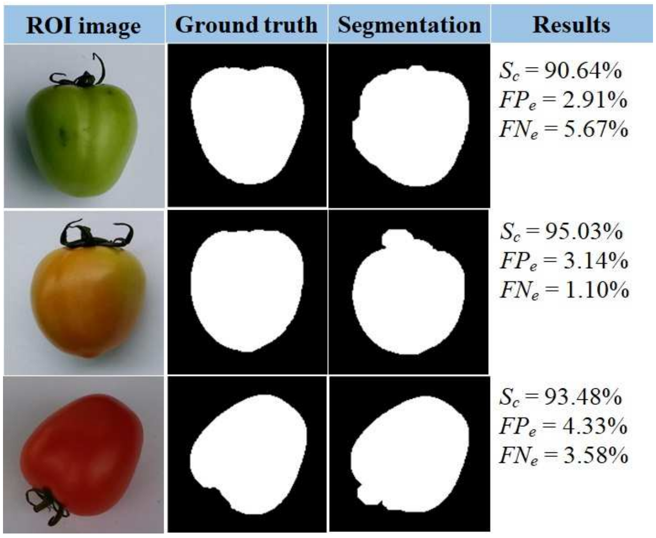

Fig. 6. The examples of the ground truth, the segmentation results, and the performance result

Fig. 6 depicts the under segmentation that occurred as a result of the tomato area being incorrectly classified as a background. This mistake shows that the value of *FPe* is close to 0 and that the value of *FNe* is greater than the value of *FPe*. According to the experimental findings, under-segmentation was more common than over-segmentation. Fig. 6 depicts an image of over-segmentation, with the petals being classed as the tomato area as an example. Additionally, as illustrated in Fig. 6 (first line), shadows could result in over-segmentation. Furthermore, the segmentation method's performance obtained *Sc*, *FPe*, and *FNe* values of 91.43%, 4.77%, and 2.84%, respectively.

According to the results, the image with half-ripe tomatoes and no flowers had the highest *Sc* value, which was 98.48%. On the other hand, the minimal *Sc* value is 78.30%, with the majority of petals designated as tomato areas. Fig. 7 depicts the results of the two experiments. As a result of the experiments, it was revealed that over-segmentation occurs in the petals and shadow areas produced by insufficient lighting.

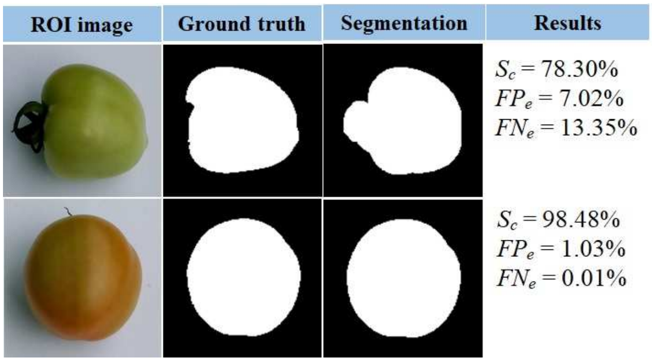

Fig. 7. The experiment results with minimum and maximum segmentation accuracy

IV. Conclusion

The segmentation process is needed to distinguish between the fruit area and the background, which can be used for several purposes. The K-means clustering, Canny edge detection, and morphology operation were used for segmentation of the tomato in this method. These operations, which were carried out during the process of ROI detection, segmentation, and post-processing processes, are carried out in the HSV color space. There were 300 tomato images with three different maturity levels used to evaluate the segmentation method (raw, half-ripe, and ripe). The performance of the segmentation method was tested using three parameters: *Sc*, *FPe*, and *FNe*, which had values of 91.43%, 4.77%, and 2.84%, respectively, in this study. The observation that *FPe* is higher than *FNe* indicates that over-segmentation is more likely to occur. In places near the petals, segmentation errors are more common than in other areas. As a result, developing a better approach for tomato segmentation can still be accomplished based on erroneous results. Furthermore, the proposed method is constrained in that it can only be employed with the dataset presented in this work. It follows that the scope of this work can be broadened to include different segment types of crops other than tomatoes.

Acknowledgment

During the year 2021, this research was supported and funded by the Faculty of Engineering at Mulawarman University in Samarinda, Indonesia.

References

[1] J. Zheng, H. Fu, W. Li, W. Wu, L. Yu, S. Yuan, W.Y.W. Tao, T.K. Pang, and K.D. Kanniah, Growing status observation for oil palm trees using unmanned aerial vehicle (uav) images, *ISPRS J. Photogramm. Remote Sens.*, vol. 173, pp. 95–121, 2021.

[2] Hamdani, A. Septiarini, and D. M. Khairina, "Model assessment of land suitability decision making for oil palm plantation," in *2016 2nd International Conference on Science in Information Technology (ICSITech)*, 2016, pp. 109–113.

[3] J. Lu, W. S. Lee, H. Gan, and X. Hu, "Immature citrus fruit detection based on local binary pattern feature and hierarchical contour analysis," *Biosyst. Eng.*, vol. 171, pp. 78–90, 2018.

[4] J. J. Zhuang, S. M. Luo, C. J. Hou, Y. Tang, Y. He, and X.Y. Xue, "Detection of orchard citrus fruits using a monocular machine vision-

based method for automatic fruit picking applications," *Comput. Electron. Agric*., vol. 152, no. July, pp. 64–73, 2018.

[5] J. Llorens, R. Sanz-cortiella, A. Escol, J. Morros, J. Ruiz- hidalgo, and J. R. Rosell-polo, "Fruit detection in an apple orchard using a mobile terrestrial laser scanner Jordi Gen," *Biosyst. Eng.*, vol. 7, 2019.

[6] 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.

[7] A. Septiarini, A. Sunyoto, H. Hamdani, A. Ahmad, F. Utaminingrum, and H. R. Hatta, "Machine vision for the maturity classification of oil palm fresh fruit bunches based on color and texture features," *Sci. Hortic.*, vol. 286, pp. 110245, 2021.

[8] A. Septiarini, H. R. Hatta, H. Hamdani, A. Oktavia, A. A. Kasim, and S. Suyanto, "Maturity grading of oil palm fresh fruit bunches based on a machine learning approach," in *2020 Fifth International Conference on Informatics and Computing (ICIC)*, 2020, pp. 1–4.

[9] A. Septiarini, H. Hamdani, T. Hardianti, E. Winarno, S. Suyanto and E. Irwansyah, "Pixel quantification and color feature extraction on leaf images for oil palm disease identification," in *7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*, 2021, pp. 1–5.

[10] H. Hamdani, A. Septiarini, A. Sunyoto, S. Suyanto, and F. Utaminingrum, "Detection of oil palm leaf disease based on color histogram and supervised classifier," Optik, vol. 245, pp. 167753, 2021.

[11] G. Lin and X. Zou, "Citrus Segmentation for Automatic Harvester Combined with AdaBoost Classifier and Leung- Malik Filter Bank with C," *IFAC-PapersOnLine*, vol. 51, no. 17, pp. 379–383, 2018.

[12] J. Lv, H. Ni, Q. Wang, B. Yang, and L. Xu, "A segmentation method of red apple image," *Sci. Hortic.*, vol. 256, no. June, p. 108615, 2019.

[13] J. Lv, F. Wang, L. Xu, Z. Ma, and B. Yang, "A segmentation method of bagged green apple image," *Sci. Hortic.*, vol. 246, no. November 2018, pp. 411–417, 2019.

[14] R. Kestur, A. Meduri, and O. Narasipura, "MangoNet : A deep semantic segmentation architecture for a method to detect and count mangoes in an open orchard," *Eng. Appl. Artif. Intell.*, vol. 77, no. April 2018, pp. 59–69, 2019.

[15] C. Zheng, P. Chen, J. Pang, X. Yang, C. Chen, S. Tu, and Y. Xu, "A mango picking vision algorithm on instance segmentation and key point detection from RGB images in an open orchard," *Biosyst. Eng.*, vol. 206, pp. 32–54, 2021.

[16] L. Xu, K. He, and J. Lv, "Bayberry image segmentation based on manifold ranking salient object detection method Inverse Fast Fourier transform Fast Fourier transform," *Biosyst. Eng.*, vol. 178, pp. 264–274, 2018.

[17] 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 Biol. Technol.*, vol. 154, no. April, pp. 52–57, 2019.

[18] A. Septiarini, H. Hamdani, H. R. Hatta, and K. Anwar, "Automatic image segmentation of oil palm fruits by applying the contour-based approach," *Sci. Hortic*, vol. 261, pp. 108939, 2020.

[19] R. Xiang, "Image segmentation for whole tomato plant recognition at night," *Comput. Electron. Agric.*, vol. 154, no. June, pp. 434–442, 2018.

[20] T. Peng-o and P. Chaikan, "High performance and energy efficient sobel edge detection," *Microprocessors and Microsystems*, vol. 87, no. November, pp. 104368, 2021.

[21] Z. Wang, K. Wang, F. Yang, S. Pan, and Y. Han, "Image segmentation of overlapping leaves based on Chan–Vese model and Sobel operator," *Inf. Process. Agric.*, vol. 5, no. 1, pp. 1–10, 2018.

[22] Y. Lee, "Improved quality using newly designed algorithms in gamma- and X-ray fusion images with a photon counting CZT detector: Combining the median modified Wiener filter and edge detection method," *Optik*, vol. 245, pp. 167681, 2021.

[23] A. Septiarini, D. N. Siswoyo, H. Hamdani, M. Wati, J. A. Widians and N. Puspitasari, "Tomato Segmentation on Natural Background Using Multi Operation of Edge Detection And Reconstruction," in *2021 IEEE URUCON*, 2021, pp. 571–575.

[24] 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.

[25] W. Maldonado and J. C. Barbosa, "Automatic green fruit counting in orange trees using digital images," *Comput. Electron. Agric.*, vol. 127, pp. 572–581, 2016.

[26] S. Sun, H. Song, D. He, and Y. Long, "An adaptive segmentation method combining MSRCR and mean shift algorithm with K-means correction of green apples in natural environment," *Inf. Process. Agric.*, vol. 6, no. 2, pp. 200–215, 2019.

[27] K. Tian, J. Li, J. Zeng, A. Evans, and L. Zhang, "Segmentation of tomato leaf images based on adaptive clustering number of k-means algorithm," *Comput. Electron. Agric.*, vol. 165, pp. 104962, 2019.

[28] A. Septiarini, H. Hamdani, E. Setyaningsih, E. Arisandy, S. Suyanto and E. Winarno, "Automatic Segmentation of Optic Nerve Head by Median Filtering and Clustering Approach," in *2021 13th International Conference on Information & Communication Technology and System (ICTS)*, 2021, pp. 118–122.

[29] F. Garcia-lamont, J. Cervantes, A. López, and L. Rodriguez, "Segmentation of images by color features : A survey," *Neurocomputing*, vol. 292, pp. 1–27, 2018.