Tomato Plant Growth Monitoring System Using Computer Vision and Deep Learning

[1] **Singgih Wisnu Pranata,** [2] **Sigit Widiyanto,** [3] **Hustinawati**
[1,3] Department of Management Information System, Gunadarma University, [2] Department of Computer Science, Gunadarma University
[1] singgihwisnupranata@student.gunadarma.ac.id,[2] sigitwidiyanto@staff.gunadarma.ac.id, [3] hustina@staff.gunadarma.ac.id

Article Info
Page Number: 9408 - 9417
Publication Issue:
Vol 71 No. 4 (2022)

Abstract

The utilization of information technology or agricultural systems aims to support agricultural efficiency and productivity. Manual monitoring, from planting seeds to harvest time on a plant, has many limitations caused by human physical factors, including fatigue, discontinuity, non-uniformity, and inaccuracy in making observations. The monitoring system is a process to collect data from various sources. This study conducted monitoring by observing the growth of tomato plants in AIDRO's Green House. AIDRO's Green House lacked farmers and could not constantly or continuously observe plants. These conditions can affect the quality of crops and yields. The process of monitoring tomato growth in this study was carried out using digital image processing and a microcontroller to observe and analyze an object without having direct contact with the object being observed. This research also develops a forecasting system for future plant growth. The results of this study showed that the accuracy of the prediction model for the area of tomato plants from the age of 8 days to 19 days of tomato plants had an average of 92%. The accuracy obtained proves that the model is accurate in detecting tomato plants. The results of this study showed that the accuracy of the prediction model for the area of tomato plants from the age of 8 days to 19 days of tomato plants had an average of 92%. The accuracy obtained proves that the model is accurate in detecting tomato plants. The results of this study showed that the accuracy of the prediction model for the area of tomato plants from the age of 8 days to 19 days of tomato plants had an average of 92%. The accuracy obtained proves that the model is accurate in detecting tomato plants.

Article History
Article Received: *15 September 2022*
Revised: *25 October 2022*
Accepted: *14 November 2022*
Publication: *21 December 2022*

Index Terms— computer vision, deep learning, hydroponic, image processing, smart farming.

I. INTRODUCTION

The utilization of information technology or agricultural systems aims to support agricultural efficiency and productivity. With the support of information technology, it can provide various improvements to the production monitoring function. Continuous manual monitoring from seed planting to harvest time because humans have limitations caused by several human physical factors, including fatigue, discontinuity, non-uniformity, and inaccuracy in making observations. The monitoring system is a process to collect data from various sources. The data collected is real-time data that has one or several quantities (variable or parameter) so that it is within a certain range. Physical variables or parameters include pressure, flow, temperature, altitude, pH, density, and velocity. [1]

In an AIDRO Greenhouse environment, farmers can focus more on observing plant growth. However, the plants in the AIDRO Greenhouse do not necessarily grow evenly. This is due to the shortage of farmers who cannot constantly or continuously observe crops. These conditions can affect crop quality and crop yields, causing losses to farmers because it costs more to care for these plants. Meanwhile, it is possible to observe the quality of a plant by using digital technology devices based on digital image data [2]. Therefore, a tool and application are needed in the form of a prototype that can help carry out constant monitoring and observation of various parameters and indicators of plant growth.

Tomato is a vegetable plant that has been cultivated for hundreds of years. Tomato plants have a habitus of herbs that live upright or lean on other plants and have a strong smell, 30-90 cm. Stems are round and rough, have trichomes, are brittle, and have little branching. The compound leaves are oddly pinnate and have trichomes on the strands and petioles. The growth of tomato plants can be seen from the development of leaves at the beginning of growth until the tomatoes enter the flowering phase [3]. Thus, the growth of tomato plants can be seen with the naked eye, but unfortunately, farmers cannot identify the growth of tomatoes one by one. Therefore, digital-based technology is needed that can function like the human eye and is able to analyze the growth of tomato plants based on the information seen.

The application of computer vision technology in agriculture can be a good solution for observing objects based on digital image processing with several characteristics. Computer vision is a field that involves building machines that use cameras and computers to identify, track, and measure targets for real-world image processing to mimic human vision.[4]. The process of monitoring tomato growth in this study was generally carried out with digital image processing and a microcontroller which is a process for observing and analyzing an object without having direct contact with the object being observed. This computer vision is designed in an applicative manner that can solve problems that occur in monitoring the growth of tomato plants.

This study aims to create a monitoring information system to determine the level of development of tomato plants based on leafy trend data or plant area. With the existence of trend data, it can be used as material for consideration of other systems to make decisions about whether plants need to be given more water and fertilizer or not. With the uniform growth of tomato plants, it is expected to provide optimal results both from harvest time and yield.

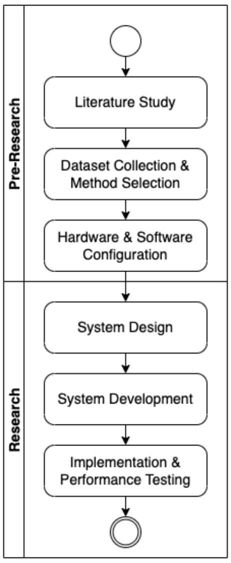
Several similar studies have been developed in the development of monitoring systems for tomato plant growth. Lilik Sutiarso et al.'s research entitled Web-Based Plant Growth Monitoring System Application Using Machine Vision [3]. The research conducted is basic research that aims to utilize image processing technology and computational software to support the monitoring function of plant growth in real-time by using the segmentation method to recognize plant objects with other plants. The algorithm used is the method of excess green and color normalization while calculating the area of the plant using the Otsu method by changing to a binary image. The results of the tests obtained from machine vision have a success rate of up to 70% in recognizing plants. Similar research in Growth monitoring is also has been published by Sigit Widiyanto et al [10]. This research applied to monitor the growth of tomato fruit week by week after the plant produce the flower.

The research entitled Designing a Web-Based Green Mustard Growth Monitoring System Application with computer vision, written by Lisandy Yulistia Rahayu et al. This research is similar to the first study, which aims to monitor or monitor plant growth. But computer vision support in this second study refers to green mustard plants and utilizes a microcontroller as a data collection tool during monitoring [5]. Both studies are the basis that can be used in this study with the image management method with the use of a threshold that is used to calculate leaf area and tomato plants. However, this research requires object detection using the segmentation method to get one leaf.

Subsequent research from S Mohana Saranya et al. entitled Deep Learning Techniques in Tomato Plant – A Review [6]. In the discussion, this research reviews several Deep Learning architectures such as CNN, SSD, Faster R-CNN, and Mask R-CNN. These architectures can be used for the detection of tomato plants

II. METHOD

Subsequent research from S Mohana Saranya et al. entitled Deep Learning Techniques in Tomato Plant – A Review [6]. In the discussion, this research reviews several Deep Learning architectures such as CNN, SSD, Faster R-CNN, and Mask R-CNN. These architectures can be used for the detection of tomato plants.



Picture1. System planning

In Figure 1, the research method consists of pre-research and research. The first stage in this research is pre-research which has 3 stages, including literature study, dataset collection and method selection, and hardware and software configuration. At the literature study stage, the researcher looks for references from previous studies related to this research. This stage is carried out to have material that can be used as a reference in conducting research. The next stage is dataset collection and method selection. At this stage, the dataset collected is tomato plants from GreenHouse AIDRO. After the dataset has been collected, it is followed by selecting the right method to be the object detection model for the dataset has been collected.

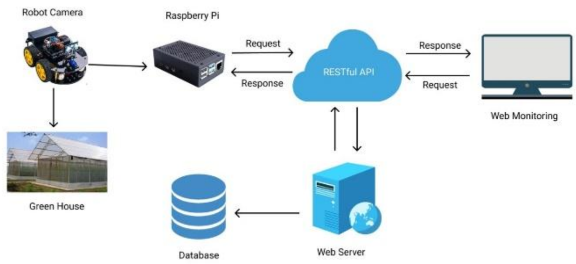


Figure 2. System Infrastructure

In Figure 2, can be seen the system infrastructure that is done by configuring the hardware and software needed in system development. Hardware configuration includes IP Camera and Raspberry Pi configuration as a mini computer used to run the monitoring system. While software configuration by configuring the IDE for system development. The next stage was system development by building a tomato plant growth information system using the python programming language to develop computer vision and using Vue JS to develop a monitoring website.

A. Plant Area Detection using Faster R-CNN

At this stage, plant area detection is carried out using Faster R-CNN. Detection of this plant area is needed to get which area is taken for monitoring system purposes. The following in Figure 3 is the process of making the Faster R-CNN model for detecting plant areas.

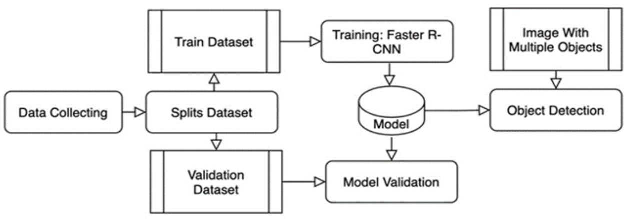


Figure 3. The process of making the Faster R-CNN model

The first stage is to collect a dataset of tomato plants taken from GreenHouse AIDRO. This dataset was taken using an ESP32 camera with a vertical position facing down, which automatically takes pictures at 09.00, 12.00, and 15.00. Then the data is stored on the Raspberry Pi. Then the data is divided into validation data and training data for use in the next stage. The next stage is to build the Faster R-CNN model and conduct training on the training data. Meanwhile, validation data is used to build a validation model. After the model is built, then the model is used to detect plant areas. This process entirely occurs on the Raspberry Pi, which automatically detects crop areas every time the camera uploads images at those times. In Figure 4, you can see the detection results from the system, namely the plant area. Furthermore, the area of the plant is pruned so that it can be used as the object of further research.

Figure 4. Plant area detection results

B. Leaf Measurement

At this stage, the area of the tomato plant that has been detected will be processed, and then look for the area value of the object area from the leaves. The search for the area value of the leaf object area is carried out in 3 stages; namely, the first stage uses the mask method to identify leaf color based on the color range, the next stage uses the threshold method to separate the leaf object from the background, then uses the open morphology transformation to remove noise on the leaf object and the last stage calculating the area of the leaf image that has been segmented.

The first stage is to detect leaf objects using a mask with a color range that all leaves may have in the HSV color space using the OpenCV library in the python programming language. The HSV color space is commonly used in image segmentation, object recognition or feature detection, and image processing [7]. The first step is to convert the image from the default color format in OpenCV, namely BGR, into the HSV color format using the library in OpenCV, namely cv2.COLOR_BGR2HSV. Next, determine the range of color values that are likely to be owned by all leaves for segmentation purposes. The purpose of segmentation is to get a representation of an image so that it is easier to process [8]. To find a particular color in the HSV color space, look for the appropriate range of Hue, Saturation, and Value by looking at the upper and lower values. The value of Saturation and Value or luminance varies from 0 to 255[9]. The leaf color obtained has values in the range from (40,25,25) to (70,255,255) in the HSV color space. After finding the appropriate range of leaf color values, then create a mask using cv2.inRange() from the OpenCV library. In Figure 5, you can see the display of the results of this stage, that the mask takes the leaf object from the set color range.

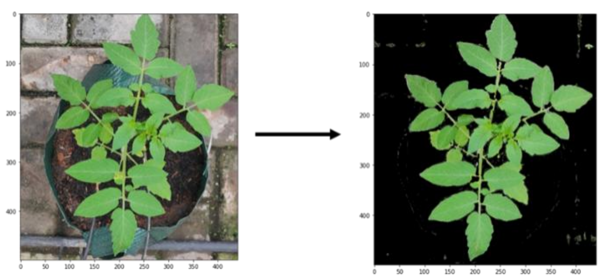


Figure 5. The results of the leaf mask

The next step is to separate the leaf object from its background using the threshold method. The threshold method is one of the image segmentation methods that can separate objects from the background in an image based on differences in brightness levels. The output of the thresholding process is a binary image with a pixel intensity value of 0 or 1. There are several methods commonly used for image segmentation in agriculture, such as threshold, clustering, area, and model [2]. The binary image is an image that has two gray levels (black and white), depending on whether the pixel value is greater or less than T. The threshold method is used to get the limit of the value that has been obtained so that it can separate the object from the background. The leaf image will be converted into a grayscale color format using cv2.COLOR_BGR2GRAY in the OpenCV library. The following Figure 6 is the result of converting leaf images.

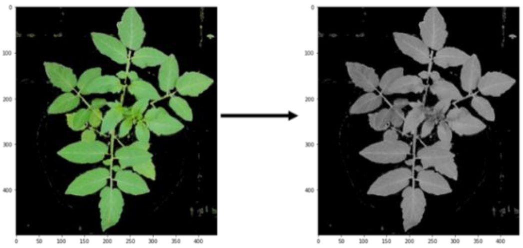


Figure 6. Image conversion results to grayscale color format

For objects that have a gray level greater than the gray threshold value, then the pixel is changed to white, and if the gray level value is less than or equal to the gray threshold value, the pixel will be changed to black. The gray threshold value is automatically taken from the average color value of the input image using the otsu thresholding calculation. So that at this stage, it produces a binary image with a white value of 0 as the object is taken, namely leaves, and a black color with a value of 1 as the background. Figure 7 shows a segmentation process using the threshold method on leaf images.

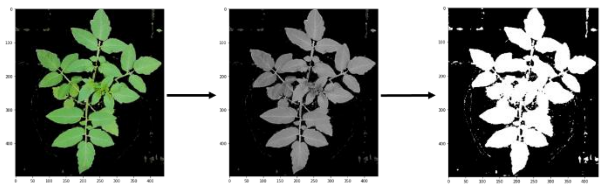


Figure 7. Results of the thresholding stages

The leaf image that has been thresholded is then subjected to open morphology. Open morphology is useful for perfecting the shape of the leaf object you want to take. In Figure 8, the results of leaf segmentation using a threshold still have noise in the form of small white objects, which are assumed to be leaf objects as well.

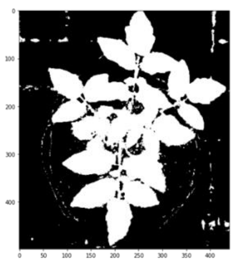


Figure 8. The threshold of the leaf object's mask

Then the noise must be removed using the open morphological transformation. Open morphology discards objects that have a pixel size far from the specified object pixel. The size of the leaf object taken is 7x7 pixels. Morphology transformation can be done with the cv.morphologyEx() function using cv.MORPH_OPEN followed by a kernel value of 7x7 pixels. So the results of the open morphology transformation can be seen in Figure 9.

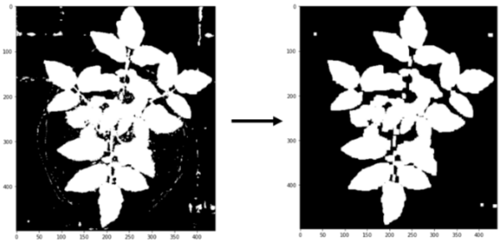


Figure 9. Results of the open morphology transformation

The next step is to calculate the pixels of the leaf object. This stage will use the sum() function in the NumPy library, which can calculate the number of pixels of an image based on predetermined criteria. In this case, the pixel area of the leaf object is calculated so that white objects that have a binary value of 255 will be totaled using np.sum(img == 255).

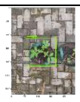
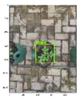
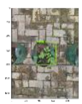
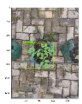
III. RESULT AND DISCUSSION

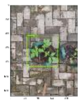
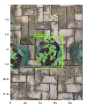
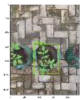
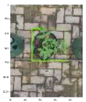
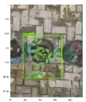
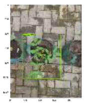
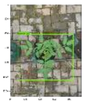
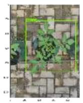
A. Evaluation of Detection Model Performance

This stage evaluates the performance of the Faster R-CNN model in predicting tomato plants. The parameters used are the results of plant measurements for each data taken. The following in Table 1 are the results of the tomato plant detection test.

From the identification results in Table 1, the accuracy of the prediction model for the area of tomato plants from the age of 8 days to 19 days of tomato plants has an average of 92%. The accuracy obtained proves that the model is accurate in detecting tomato plants. Table 1 also shows the results of measuring the thickness of tomato plants in pixels. The results obtained from measuring the thickness of tomato plants show an increase in the thickness of the plants, so it can be concluded that the growth of tomato plants is good.

Table 1. Plant Detection Testing

Age	Accuracy	Size	Results Detection	Results End
8 days	95%	210 px		
9 days	68%	246 px		
10 days	84%	278px		
11 days	97%	339px		

12 days	98%	354px		
13 days	95%	387px		
14 days	93%	405px		
15 days	98%	428px		
16 days	98%	548px		
17 days	93%	576px		
18 days	96%	631px		
19 days	91%	692px		

B. Display of Monitoring Website

The appearance of the website page is useful for providing information on plant growth and predicting the growth of tomato plants. On the "Monitoring" menu, there is a "Leaf" submenu which will display a graph of the growth of tomato plants. The information contained in the graph is the date and size of the plant. The following Figure 10 is the main view of the tomato plant growth monitoring website.

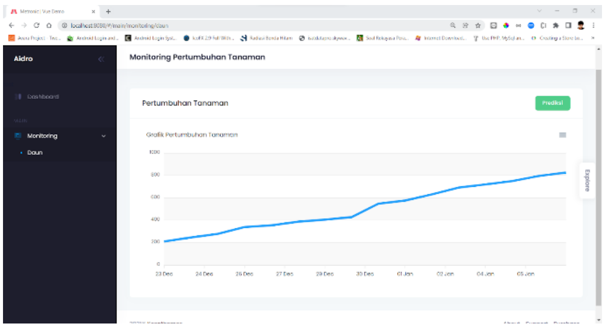


Figure 10. Graphic Display of Tomato Plant Growth

C. Discussion

It can be seen from the method used to obtain optimal measurement results that can be done by using plant area detection. The use of this plant area detection helps to find the plant area to be measured so that noise or objects contained in the image object are not captured during the crop masking process. The model created using the Faster R-CNN method is quite good because it gets an average test result with a detection score of 92%. In the measurement process where there is an open morphology method that helps eliminate noise or pixels that do not have pixels that match the size of the leaf. The use of morphology is not much different from the results of measuring leaves. However, it can be seen from the results that there is still pixel noise in the image. Thus, the use of morphology is not fully optimized.

IV. CONCLUSION

It can be concluded that this research is developing a Tomato Growth Monitoring System using Computer Vision and Deep Learning with several methods to obtain optimal results. The method consists of a Faster R-CNN, which is used to model plant area detection, then plant measurements use Masks and use the Morphology method to remove noise from the plant area being measured. Making the Faster R-CNN model uses a dataset on tomato plants that have an age of 1 to 5 weeks. The results of this model are quite good because it gets a test score with an average of 92%, where there is the smallest accuracy value of 68% and the largest accuracy value is 98%. So, it can be concluded that the detection of tomato plants is accurate.

AKNOWLEDGEMENT

This research was funded through the Higher Education Applied Research grant program under the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia with contract numbers 456/LL3/AK.04/2022.

REFERENCES

[1] SY. Hari, YAK Utama, and A. Budijanto, "Development of Smart Control Systems and Monitoring in Tomato Fruit Cultivation," Monday. Nas. Science and Technology. therapy. V, pp. 151–156, 2017.

[2] K. Anwar and S. Setyowibowo, "Segmentation of Damage to Rice Leaves in Digital Image,"J. Education and Researcher. inform., vol. 7, no. 1, p. 39, 2021, doi: 10.26418/jp.v7i1.42331.

[3] L. Sutiarsoet, "Application of Web-Based Plant Growth Monitoring System Using Machine Vision Application of Web-based Monitoring System for Plant Growing by Using Machine Vision," Agritech, vol. 31, no. 4, pp. 1–1, 2012, doi: 10.22146/agritech.9644.

[4] H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, "Computer vision technology in agricultural automation —A review," inf. Process. Agric., vol. 7, no. 1, pp. 1–19, 2020, doi: 10.1016/j.inpa.2019.09.006.

[5] LY Rahayu, A. Mulyana, U. Sunarya, FI Terapan, and R. Pi, "Web-Based Green Mustard Growth Monitoring System Application Design Using Computer Vision Design System Application Monitoring for the Growth of Green," vol. 4, no. 3, pp. 2567–2574, 2018.

[6] S. Mohana Saranya, RR Rajalaxmi, R. Prabavathi, T. Suganya, S. Mohanapriya, and T. Tamilselvi, "Deep Learning Techniques in Tomato Plant - A Review," J. Phys. Conf. Ser., vol. 1767, no. 1, 2021, doi: 10.1088/1742-6596/1767/1/012010.

[7] Molla, J. P., Dhabliya, D., Jondhale, S. R., Arumugam, S. S., Rajawat, A. S., Goyal, S. B., . . . Suciu, G. (2023). Energy efficient received signal strength-based target localization and tracking using support vector regression. Energies, 16(1) doi:10.3390/en16010555

[8] Raghavendra, S., Dhabliya, D., Mondal, D., Omarov, B., Sankaran, K. S., Dhablia, A., . . . Shabaz, M. (2022). Development of intrusion detection system using machine learning for the analytics of internet of things enabled enterprises. IET Communications, doi:10.1049/cmu2.12530

[9] P. Ganesan and V. Rajini, “Assessment of satellite image segmentation in RGB and HSV color space using image quality measures,”2014 Int. Conf. Adv. electr. Eng. ICAEE 2014, 2014, doi: 10.1109/ICAEE.2014.6838441.

[10]AA Nurcahyani and R. Saptono, "Identification of Rice Quality with Digital Image,"sci. J. Informatics, vol. 2, no. 1, pp. 63–72, 2016, doi: 10.15294/sji.v2i1.4530.

[11]M. Sarifudidn, “Digital Image and Video Processing: Theory, Application, and ProgrammingUsing MATLAB,” Erlangga Publisher, no. January 2016, p. 305, 2016, ISBN: 9786022985283.

[12]S. Widiyanto, DP. Nugroho, A. Daryanto, M. Yunus, and DT. Wardani, “Monitoring the Growth of Tomatoes in Real Time with Deep Learning-based Image Segmentation” International Journal of Advanced Computer Science and Applications (IJACSA), 12(12), 2021. http://dx.doi.org/10.14569/IJACSA.2021.0121247