Decision Support System for In Situ Melon's Fruit Harvesting Time Based on Fuzzy Logic and Single Shot Detector (SSD)

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***Abstract*—Melon has a large variety in horticultural and is widely used in scientific research such as biology and geneticist's developments. This study aims to develop a system for detecting the correct harvest time. The farmers currently harvest melons based on their experience, and melon cannot maintain their quality after harvesting. Thus, the melon needs to be harvested at the right time. Melon harvesting is a daily task; Melon is not mature on the same day even though the melon plant was planted in the same period due to genetics and environment. Therefore, the decision support system should detect and classify the ripeness level of the fruit on the tree. The system will categorize the maturity level into three categories: Ripe, About to Ripe, or Under Ripe (within a rate from 0 to 10 obtained from fuzzy inference system result). The ripeness levels are confirmed by the expert, depending on the skin color of the fruit. As a result, we get 100% accuracy in classifying each category using phone camera images and video. Furthermore, this decision support system can be implemented in melon's harvesting robot. The melon used in this study is *honeydew Cucumis melo L*, var. *Alisha F1*.**

***Index Terms*— fuzzy logic, HSV color space, image processing, melon harvesting, skin color extraction, SSD-Mobilenet.**

I. Introduction

THE agricultural development is one of the most powerful approaches for ending extreme poverty, promoting shared prosperity, and feeding an estimated 9.7 billion people by 2050 [1]. According to WBG (World Bank Group), growth in the agricultural sector is two to four times more effective in increasing income among the poor than in other sectors. Employment in agriculture in 2016 analyses found that 65% of poor working adults earn their livelihood through agriculture. Agriculture is also essential for economic growth. In 2014, it accounted for a third of global GDP [1].

It's challenging to apply the Decision Support System (DSS) in agriculture due to the farmer and scientist's information management challenge to increase the economic and crop productivity rate. However, it is essential to explore, and model data flow between decision-making processes and the user's feedback for successful outcomes. And this can be done by implementing the DSS, which provides crop selection with precise and comprehensive agricultural details [2].

Melon has inner and outer characters, including skin color, aroma, and taste, determining melon quality. Quality must be preserved before harvest, as production cannot be maintained after harvest. Norms of quality are based chiefly on plant genetics. Therefore, critical fruit production, managing, and maturation conditions are essential at harvest times [3], [4]. When we talk about quality and freshness, melon's fruit and many other fruits strongly relate to their skin color. Thus the color is the main factor to identify fruit quality and freshness [5]. Harvesting takes place daily because ripening is uneven simultaneously, which reduces melon profits for farmers if collectors conduct total soluble solids (TSS) inspections to define their sweetness level, whereas there are amounts of damaged fruits. Measuring the maturity of a melon by humans is a dynamic phenomenon based on internal and external factors, as discussed in [6]. Thus, the selection for an object is maintained by a person's eyes to identify the object and deciding the personal experience. At the same time, the automated decision doesn't possess the human mind and uses a sensor and control system to simulate the selection process; the automated decision is processing the information of the fruit that comes from a camera by image processing or sensors. It recognizes the target fruit and correctly locates the target fruit [7], [8].

This study's type of melon fruit is *honeydew (Cucumis melo L.)* of *Alisha F1* variety; it has a flattened shape and a crunchy flesh texture. The under-ripe skin color is green, and the ripe one is yellow. The flesh color is a white-orange. For more details about this melon, refer to this study [9]. Making the harvesting decision will be based on these melon characteristics to classify and detect the ripe, about to ripe, and under-ripe melon by using Fuzzy Logic and find the desired harvest time.

Ambiguous logic is a section of human reasoning. The methods are synthesized by establishing a computer program called a fuzzy rule-based system [10]. The theory that applies mathematics to diffused concepts was forwarded by Lofty Asker Zadeh in 1965 and tried to approach human reasoning by fuzzy sets, also described by linguistic variables [11]. Fuzzy logic has a statistical output for which can be used for better and accurate decision-making in such a variety of applications. The fuzzy control system is represented in shape close to the primary language form for showing the actual knowledge needed for a task in different

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manners. Fuzzy logic does not need to be modeled using a complex mathematical design, and easily converting the expert experience to rules programmatically, and finally, system behavior can be implemented and adapted easily and quickly. As a result, the long-term modification will quickly be done [11], [12].

Fuzzy logic has several computation types that are used regarding the number of input and output. The commonly used one is *Mamdani* for this work that needs to translate the expert's natural language to the machine by formulating what he suggests as *IF-THEN* rules.

A series of optimization standards is undertaken for decision-making according to planning criteria. The current assay develops a DSS to detect melon in the image using a Tensorflow pre-trained deep learning model SSD [13], then employing Fuzzy Inference System (FIS) to manage melon's fruit aiming at good cultivation.

II. Methodology

A. *Data*

The data used are images of *honeydew Cucumis melo L*, var. *Alisha F1* melon captured by phone camera at ATP greenhouse owned by IPB University in Bogor, Indonesia. The phone used was the iPhone 6s, the rear camera that has ((12 MP (f/2.2, 29mm, 1/3 inch), dual-LED), and default image size 4032*3024). When capturing, the camera's distance was 25-35 cm with an eye-level angle about the same level as the melon's fruit. The captured images were in July 2020; the time was 4 PM to 7 PM. The total pictures are 190, 170 are the captured images, and 20 others were collected from Google Image. All images were resized to 640*480—and the labeling of the pictures done by the greenhouse expert's guidance.

The melon age was captured at 60 days in the first attempt, and we continue capturing every two days until the age of 78. The harvesting was every day while collecting the images; thus, at age 78, the last harvesting was done of the reminded melon group. The planting of all melons in the greenhouse was on 15/May/2020.

In December 2020, there was another planting of the same melon type. We captured new images in February 2021 to test our Fuzzy Logic output. The details of the new images are explained in the discussion section of this paper.

B. *System Development*

The harvesting time varies for each fruit in the greenhouse. There are ripe and under-ripe melons at more or less than 70 days' ages. The expert decided where the ripe one is to be harvested depending on the skin color. Thus, we need to convert this experience from the expert/farmer to the machine. To find the ripeness level, we must dive into four steps, as explained in Fig. 1.

1) *Melon's Fruit Detection*

The first step of this method is to find the existence of the melon fruit in the image. There is a possibility that multiple melon fruit existed in one picture due to the environmental condition. The dataset is separated into two classes. Our desired Melon class and the other class are the backgrounds that included images for unwanted objects (i.e., small melon, far or on the left/right corner of the image tree's

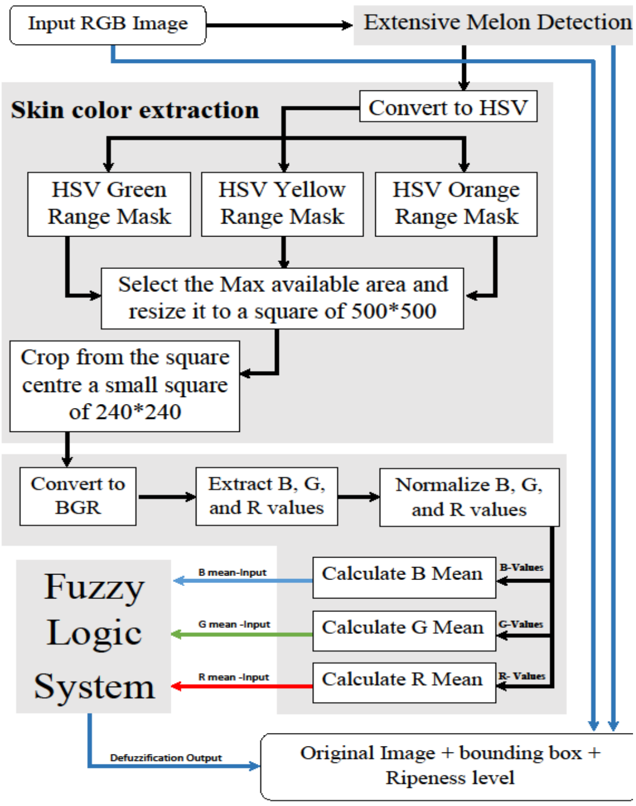

Fig. 1. The process of the Decision Support System for melon harvesting. 1) Detect the Melon by SSD-Mobilenet, 2) extract skin color, 3) convert to BGR and prepare Fuzzy Logic inputs, and 4) use B, G, and R Means as inputs for fuzzy logic system and calculate Defuzzification output.

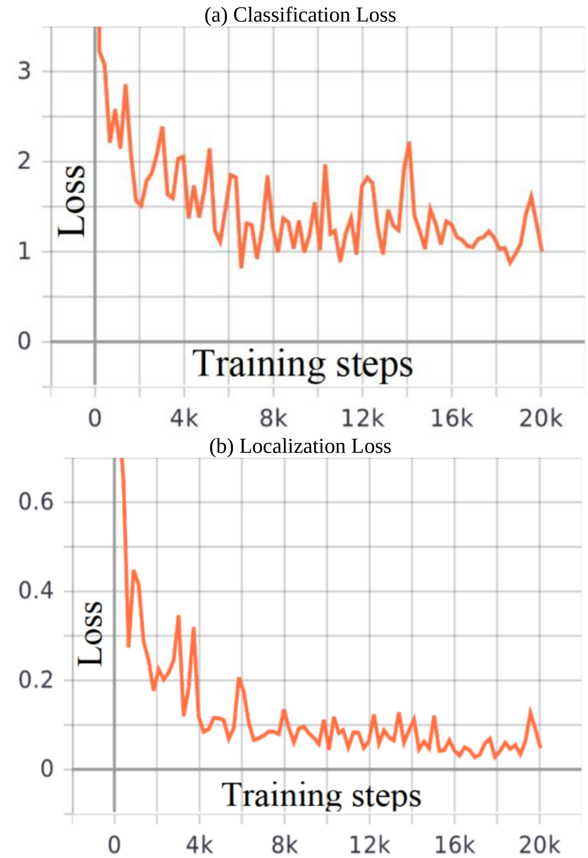

Fig. 2. The loss of Tensorflow SSD-MobileNet training. The (a) graph is the Classification Loss of the hostile class objects and the extensive Melon class object. The (b) graph is the Localization Loss that is the best loss for the object detection task in Tensorflow API.

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stem, leaves, and roots). The images are annotated by drawing a rectangle (i.e., the bounding box) on each object in the image. e.g., if the image includes the Region of Interest (ROI), then annotate it as melon, and annotate all other parts of the image as a background), the total annotated objects in 190 images are 554 annotations (i.e., 554 bounding boxes coordinates for each object in all images). The annotation process is done by using the labeling application [14]. We were then separating the annotated images dataset to 85% for training and 15% for testing.

The model is trained on 554 bounding boxes (20% background, 20% melons not in the center of the image of the hostile class), and (60% for the desired class, that is the most existence melon object located in the middle of the image)

A Pre-trained deep learning model SSD-Mobilenet that is preferred for extensive object detection in an image [15], used with Tensorflow object detection API [13], to train the images dataset on Colab pro *(also known as, Google colaboratory, Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis, and education*), the Colab-pro version is to provide a consistent massive GPU by subscribing for a periodic payment [16].

The SSD- Mobilenet configuration for the training process is shown in Table. I.

TABLE I
SSD-MOBILENET CONFIGURATION

The input image size		480 width, 360 height
Batch size		24
Number of layers		6
Scales	**Min scale**	0.2
	Max scale	0.95
aspect_ratios		1.0 2.0 0.5 3.0 0.3333
Initial learning rate		0.004
Max detections per class		2
Max total detections		2

You can notice that the (Max detections per class and the Max total detections) is 2 for both, to force the detection in detecting the preferred object that is where the camera pointing and not the melons in the background, also controlling what class/object we want to detect easily.

The training was 20,000 steps takes around 5 hours, with an excellent low loss for localization and classification, as shown in Fig. 2. As you can see, the localization loss was the best at step 18,853, so use this step because our interest is more toward the localization rather than the classification in this step.

After training is accomplished, we employ the trained model, which contains the model structure with the values of the required variables, such as weights, in the *Opencv-dnn* library (i.e., Optimized Computer Vision-Deep Neural Network) [17] for faster and simple detection usage. In this step, we localize and classify the Melon Fig. 3(a) compared to negative objects (i.e., background, small melons objects, and tree's contents).

Fig. 3 (a)

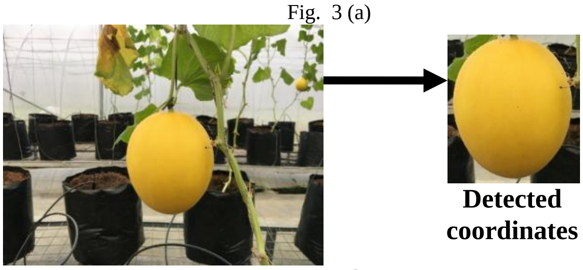

Fig. 3 (b)

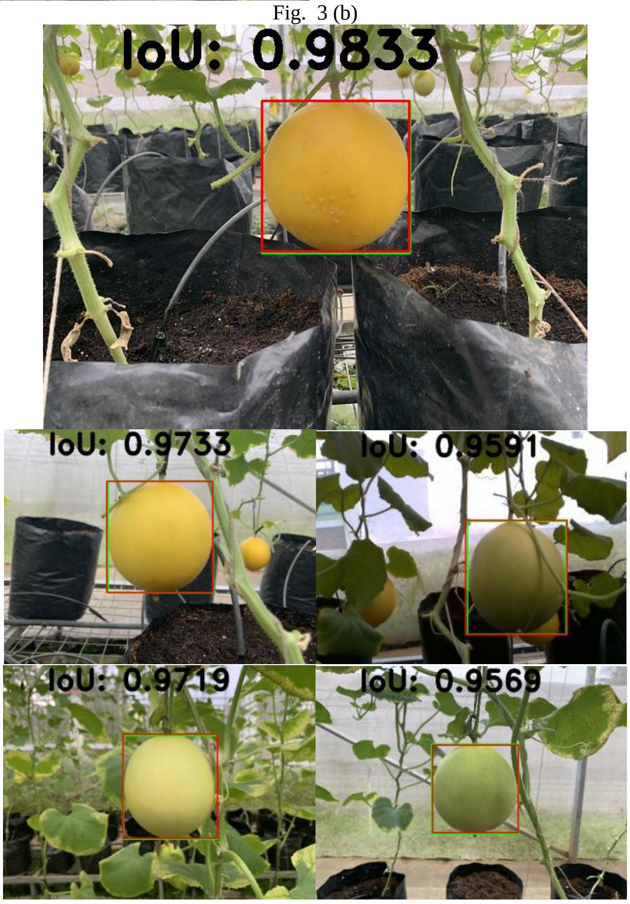

Fig. 3. In (a) showing the input image and the detected bounding box, the detected melon image is cropped and prepared to be mapped to the next step (i.e., Image segmentation step).
In (b) are some examples of applying IoU on multiple images picked randomly from the test dataset, where the green rectangle is the GT box, and the red one is the predicted box. The IoU for all images is more than 0.9, so the accuracy of the detection is excellent, according to [18] study.

To test the accuracy of the predicted bounding box, we have used the Intersection of Union (IOU) approach introduced by [18]. It's simply works by comparing the Ground truth (GT) boxes (i.e., the boxes specified by our hand) versus the predicted boxes using (1). The accuracy showed and explained in Fig. 3 (b).

$$IoU = \frac{|A \cap B|}{|A \cup B|} \qquad (1)$$

Where, $|A \cap B|$ is Area of overlap, and $|A \cup B|$ is Area of Union. In general, the IOU calculate the distance between GT box and predicted box.

2) Image Segmentation

Color Image segmentation is to partition the image based on some features. In this step, the segmentation will be based on color. The input image used is colored in RGB color space pixel p(i), which is defined by red, green, and blue at pixel coordinates (r(i), (g(i), b(i)), implies for three columns (R for red channel, G for green channel, and B for blue channel) [19], [20]. The image segmentation was applied after detecting the desired melon and recognize it from the greenhouse environment, then derive to this step to extract skin color by segmenting the image to remove noise such as tee's root or a part of leaf blocking the fruit. Also, to be sure that we got a pure skin color extraction, to calculate the R, G, and B means of the skin color.

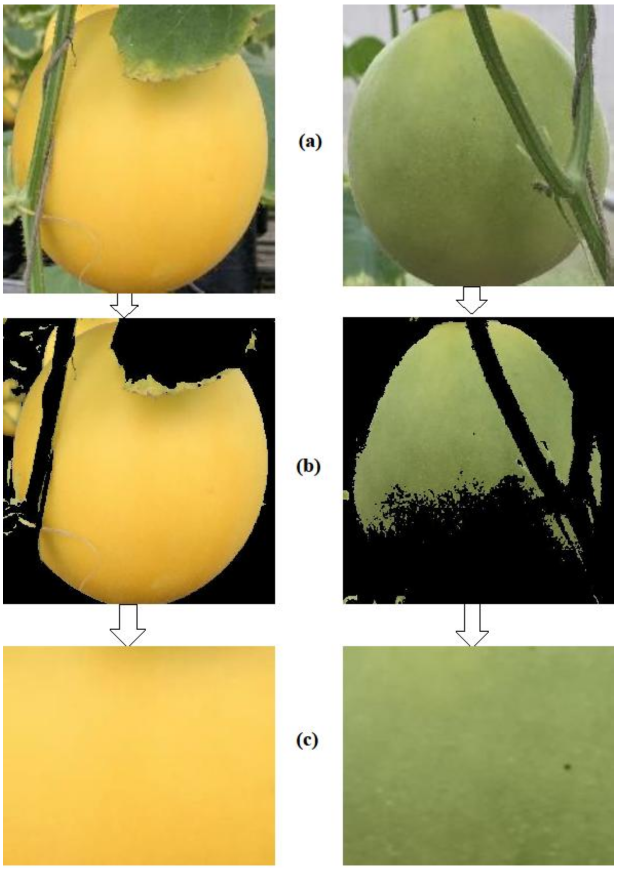

Fig. 4. The segmentation-based HSV color space for a ripe orangey melon covered partially with stem and left on the left side, and a green baby melon blocked with tree stem on the right side. The image in (c) level was extracted by taking the max mask for the detected melon.

There are many types of color space, and the most used are L*A*B* and HSV [21], [22]. Reference [23] is an image segmentation study that compares L*A*B* with HSV, and they have found that the HSV (Hue Saturation Value) color space is the best choice for colored image segmentation.

Thus, we studied and analyzed the image color using HSV color space to find the color range that has the ROI—then converting the RGB image to HSV. And creating a group of HSV ranges for the available melon categories. Then the detected melon will pass through the following HSV ranges,

- Green range mask = is the HSV Range of (min Green and max Green).
- Yellow range mask = is the HSV Range of (min Yellow and max Yellow).
- Orang range mask = is the HSV Range of (min Orang and max Orang).

Here we got three ranges for the detected melon. As an example, if the melon was under-ripe (i.e., green melon's color), then the most extensive area of the image will be the green one, and the same case for yellow or orange melon color (Fig. 4 (a)). The purpose of the masking is to remove the unnecessary background and noise, such as the tree's root, stem, or leaf that overlapping with the melon target. Thus, the remaining area will be considered as an ROI candidate (Fig. 4 (a) and (b)). Then it will consider the most extensive available area as shown in Fig. 4 (b) and (c). The largest mask area among those three masks will be used as the final mask. An area (square, with size 240*240 as shown in Fig 4 (c)), is taken from the last mask, and thus it is used for the next step.

3) Preparing Fuzzy Logic Input (R, G, B)

Sun reflection or other light noise may change the pixels' intensities. Thus, the reference values that we will set later may or may not matches the future lightness effects on the inputted image and will leads to mismatches between the fuzzy rules and the input (i.e., R, G, and R means). So we need to normalize the pixel intensities for the skin sample produced in the previous step. Then, R, G, and B intensities will be the same or close to the reference ranges after normalizing. This step explained in two parts:

a) Normalizing RGB

RGB normalization is used to keep the pixel intensities in a standard range. For example, at 11 AM, the RGB values of a pixel in an image are (200, 150, 120), and at 4 PM were (190, 170, 100). So we have to normalize these values to get rid of lightness changes.

The typical approach to normalize RGB values is using MIN-MAX standardization [19]. The maximum value in RGB channels is 255 representing a white pixel, and the minimum is 0 representing a black pixel. Equation (2) to (7) is used to normalize R, G, and B pixels intensities.

$$f(x,y) = (R,G,B) \tag{2}$$

$$Total = R + G + B \tag{3}$$

$$R' = \frac{R}{Total} \times 255 \tag{4}$$

$$G' = \frac{G}{Total} \times 255 \tag{5}$$

$$B' = \frac{B}{Total} \times 255 \tag{6}$$

$$thus, g(x,y) = (R',G',B') \tag{7}$$

b) RGB Mean Calculation

The Mean of each channel of RGB color space of the sample area of the image is used as input of the Fuzzy Logic (i.e., the Mean for each column in the image matrix). The formula for obtaining the Mean of each color channel in RGB color space is shown in (8), (9), and (10) below. This step was performed on a Melon image that is mapped from the previous step. The range value (minimum and maximum) of the RGB values for each category (Ripe, About to Ripe, and Under Ripe) is obtained from the above calculation. Then the fuzzy rules will use them as references when classifying the melons into their categories.

$$R\mu_X = R' / \text{No. of Pixels} \tag{8}$$

$$G\mu_X = G' / \text{No. of Pixels} \tag{9}$$

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$$B\mu_X = B' / \text{No. of Pixels} \qquad (10)$$

Where,

R' = Normalized Red pixel.

G' = Normalized Green pixel.

B' = Normalized Blue pixel.

$R\mu_X$ = Mean value of normalized Red channel.

$G\mu_X$ = Mean value of normalized Green channel.

$B\mu_X$ = Mean value of normalized Blue channel.

4) Fuzzy Logic to Detect the Ripeness of Melon Fruit

We are using Fuzzy Logic to classify the melon fruits into ripe, about to ripe, and under-ripe categories. The classification is made based on the original images mentioned earlier in this paper, the images captured by the iPhone 6s rear camera. The melon images are already labeled with their corresponding ripeness categories by expert guidance. The Fuzzy Logic algorithm is selected due to its ability to convert expert experience to computational logic. The fuzzy logic algorithm process is explained in three steps; Firstly, it defines the input/output Membership Function (MF). Secondly, it is setting the rules and combining all the rules and MFs in the control system. Lastly, it produces the output for each rule based on the input. The computation is calculated using *scikit-fuzzy*; A fuzzy logic toolbox for Python programming language [24]. The representation of MFs for (R, G, and B) and the Defuzzification output are shown in Fig. (5 to 6).

The input set of crisp values is the Mean of the normalized R, G, and B intensities. The reference RGB values for each category are the min-max range of all data, as shown in Table. II below.

TABLE II
MIN-MAX (R, G, AND R) FOR EACH CATEGORY

CATEGORY	RED Min	RED Max	GREEN Min	GREEN Max	BLUE Min	BLUE max
ABOUT TO RIPE	94	102	96	106	50	62
RIPE	126	138	90	103	21	37
UNDER RIPE	92	95	100	104	56	62

Min and Max of (red, green, and blue) Means values for each category. These values from images captured by iPhone camera, other cameras, or different light environments may change the RGB pixel intensities and will differ from the reference. Thus, this will lead to lousy classification.

In the case was ripe melon, and its blue channel value is more than the Max reference of blue for ripe melon, then it will consider "About to Ripe." To get rid of such a problem, we multiply the Medium-blue-MF (M_blue) by 0.7 to decrease the MF output as shown in Fig. 5(c) M_blue MF), thus, ignoring the blue when compared to red by using the "OR" operator (11) [25].

$$Ripe \text{ using } (OR) = MAX\left(M\_blue,\ red\right) \qquad (11)$$

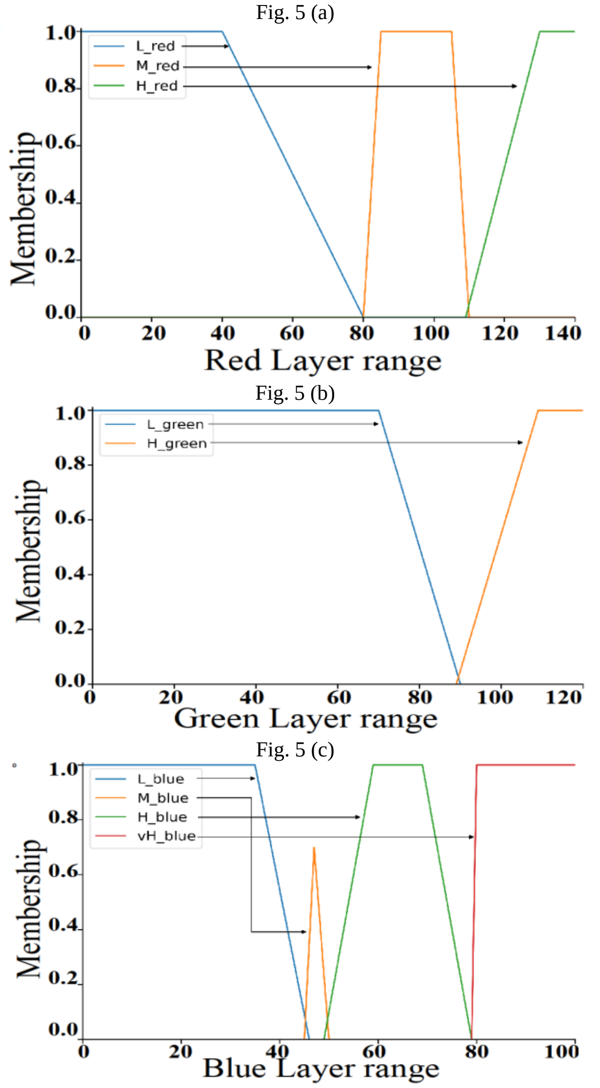

Fig. 5. The membership functions of the inputs, (a) are the MF of red, (b) is the MF of green, and (c) is the MF of blue. Note that the (L, M, H, and vH) that MFs names start with are meaning (Low, Medium, High, and Very High, respectively).

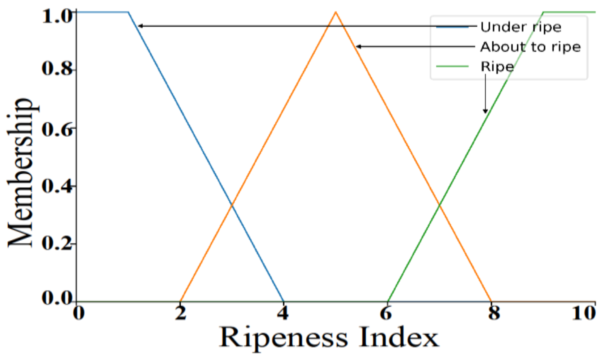

Fig. 6. The Defuzzification output membership function. The (blue, orange, and green) lines represent MFs output of Under-ripe, About to Ripe, and Ripe, respectively.

In this case, the red MF will be the winner because the "M_blue" MF will never reach 0.8. In comparison, red values are always "High-red" (i.e., Fig. 5 (a) H_red MF) in the "ripe" category.

For example, samples of the used rules to classify the melon categories are shown below:

1. If (red is low) and (blue is very high) then (Melon is Under Ripe).
2. If ((red is high) or (green is high)) and (Blue is high) then (Melon is About to Ripe).

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3. If ((red is medium) or (green is high)) and (Blue is medium) then (Melon is About to Ripe).
4. If (blue is low) and (red is high) then (Melon is Ripe)
5. If (blue is medium) or (red is high), then (Melon is Ripe). Refer to (8).

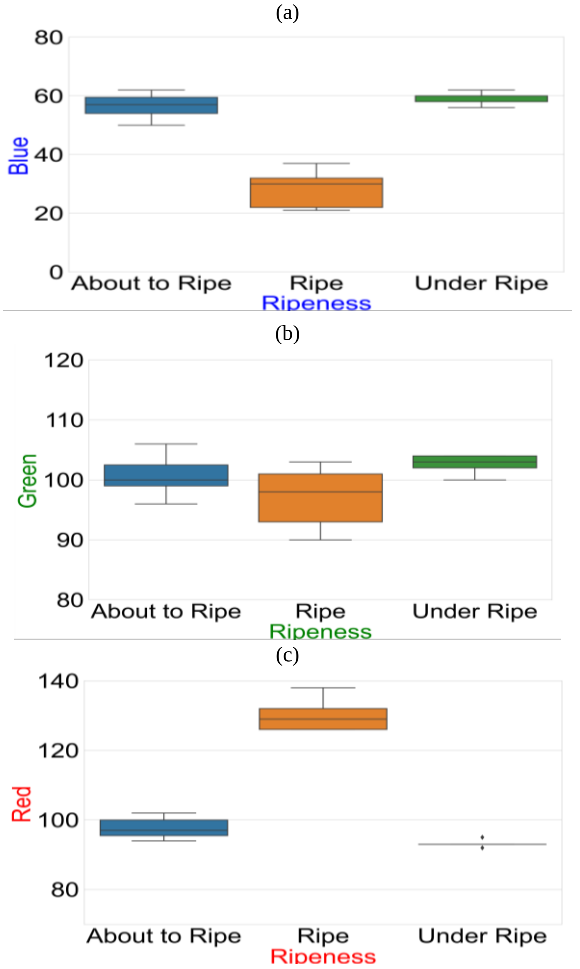

Fig. 7. (a) Is the blue mean values, (b) for green, and (c) for the red channel.

The above rules will determine the melon category and show the results in Fig. 6, the Defuzzification output in the range of "0 to 10", calculated using the centroid method. The Defuzzification output explained as follow:

1. Less than 2, the melons are "Under Ripe."
2. From 2 to 6, the melons are "About to Ripe."
3. More than 6, melons are "Ripe."

III. RESULTS AND DISCUSSION

It is so rare to find a classification of fruit ripeness from the tree. Lighting that varies from one to another fruit in the greenhouse is impacted by direct sunlight, shadows, or other light noise.

For the sake of testing our system, we captured new 50 images for available melons categories of the new planting in the same greenhouse on 20/February/2021. We used the same distance from the camera and camera direction that mentioned earlier in the Data section, but different phone camera (i.e., iPhone XS, 12-megapixel (f/1.8, 1.4-micron) + 12-megapixel (f/2.4), and default image size 4032*3024). Also, we picked 31 labeled images from our previous dataset (i.e., used for training Melon detection). The images used for testing the output of the Fuzzy Logic system are 81 images in total.

Box-plot created for each channel to find the range of each category. The box plot explained in Fig. 7 as follow:

1. (a) Plot is the normalized blue means values for all melon categories.
2. (b) Plot is the normalized green means values for all melon categories.
3. (c) Plot is the normalized red means values for all melon categories.

We noticed that blue and red highly correlated with the maturity level. You can see in Fig. 7 ((a) blue) and ((c) red) the "ripe" category has the lowest blue values and highest red values, whereas the opposite for the "under-ripe" category. The magic of detecting the "about to ripe" category is by far the difference between green and red. The green value is less than red and the opposite in the "under-ripe." Also, this category has a slightly lesser red than "ripe," whereas blue is high. We can sum up all these in the following points:

1. Under Ripe: B is high, and G > R, R is low.
2. About to Ripe: B is high, R > G. R is average.
3. Ripe: B is shallow, and R is the highest in all categories.

The testing procedure is as follow:

1. Creates a loop function to iterate over our melon fruit images labeled with their actual categories.
2. Input each image value to the fuzzy logic system.
3. Create a data frame for the actual labels and fuzzy logic output.

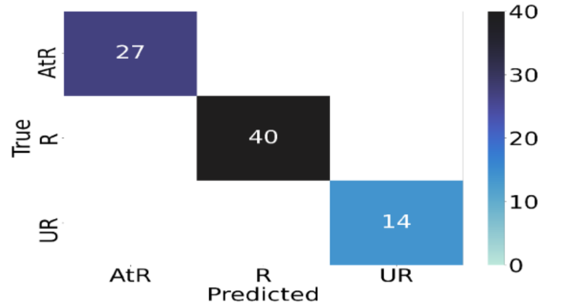

Fig. 8. A heat-map graph to describe the confusion matrix. The actual melon labels with their corresponding categories on the "True" axis and the system output on the "Predicted" axis.

A confusion matrix has been used to compare the system output versus the actual labels to get the accuracy. As shown in Fig. 8, we get a 100% accuracy in classifying (Ripe, About to Ripe (AtR), and Under Ripe (UR)) melons. "AtR" has close similarities to "Ripe" in color; thus, using a different camera leads to less accuracy in classifying "AtR" versus "Ripe" because of the various camera lens that causes more or less than our references R, G, and B values of the corresponding categories. Still, in general, the R values were the highest in the ripe category, and this will be solved by using (11) by taking the maximum (M_blue Fig. 5(c) OR H_red Fig. 5(a)). However, different light environments may or may not leads to less classification accuracy. The accuracy in classifying "UR" or "R" will still be good because of the vast color differences between the ripe and under-ripe.

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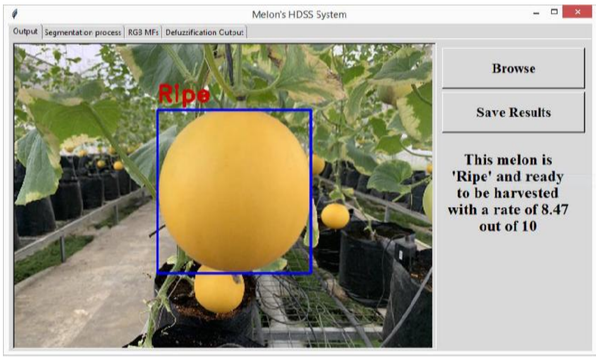

Fig. 9. The output of the DSS for melon harvesting (M-HDSS) using a Graphical User Interface (GUI).

As a result, we built a Graphical User Interface (GUI) to help farmers and scientists manage the harvesting of Alisha-F1 Melon fruits. The first window of the GUI displays the detected melon labeled with its category name as shown in Fig. 9.

IV. Conclusion

A novel of melon's fruit harvesting system is accomplished in this study by detecting the melon on the tree, applying image processing technique on the detected melon extract melon's color, and finally, using Fuzzy Logic to classify melon fruit into (ripe, about to ripe, and under-ripe categories). We got 100% classification accuracy by using iPhone rear camera as an image source. Whereas using another camera (another image source) may lead to different accuracies, thus changing the reference values for various image sources are essentials because of the environmental lightness or other camera specifications. And to get rid of this, we have used a reference image that will be used to apply the normalization based on it. Lastly, the system can be modified to classify other fruit's maturity levels using skin color.

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