A Segment Anything Model for Melon Pruning Based on Diameter

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ABSTRACT

Melon is a horticultural commodity with high economic value and great potential for cultivation. One important technique to enhance fruit quality is pruning, which limits the number of fruits per plant so that photosynthetic energy is focused on selected fruits. This study aims to implement the Segment Anything Model (SAM) to support pruning decisions by segmenting melon images and measuring their diameters automatically. SAM is a pre-trained model designed to generalize across a wide range of image segmentation tasks. To adapt it for melon imagery, the model was fine-tuned using a specific dataset of melon images under three different optimizer settings: Adam, AdamW, and Stochastic Gradient Descent (SGD). The performance of each configuration was evaluated using two standard metrics, Intersection over Union (IoU) and Dice coefficient. The results showed that the best configuration achieved a segmentation accuracy of up to 0.9 on both metrics. These findings indicate that SAM is capable of precisely identifying and measuring melon diameters, thus providing a reliable and efficient decision-support tool for optimizing pruning strategies and improving overall fruit quality in melon cultivation.

Keywords-melon fruit; pruning; segmentation; fine-tuning; Segment Anything Model (SAM)

I. INTRODUCTION

Melon is a type of horticultural crop that has a significant economic value and can provide good profits for farmers as a source of income [1-3]. Known for its sweetness, melon is a source of vitamins and raw materials for the processed industry [4, 5]. The short harvest life and high selling price make melons a very profitable business commodity [2]. Total melon production in Indonesia reached 138,177 tons in 2020, which only meets about 40% of domestic demand [6, 7]. To meet domestic market demand, attention is needed to improve the quality of melon production. The quality of melons is determined by their fresh weight and sweetness level, which can be affected by attention to nutrition and proper planting techniques [8].

Improving fruit quality through nutritional management can be achieved using pruning techniques [9]. Melon develops generatively because it comes from the results of flower fertilization, so the purpose of pruning is to inhibit vegetative growth and accelerate generative growth [8]. Pruning focuses plant resources on fruit development, by limiting the number of fruits per plant so that photosynthetic energy can be used effectively for the growth of the remaining fruits [10]. Melon plants are capable of producing many fruits, but based on the knowledge of experts at Agribusiness and Technology Park (ATP) Cikarawang [11], no more than two fruits per plant are cultivated as this produces better fruit quality and provides high production values [12].

One solution is to use object segmentation to select melons that are worth preserving based on diameter using the Segment Anything Model (SAM) algorithm [13]. With the introduction of SAM as an innovative basic model for segmentation, it has gained great attention due to its powerful ability to generate accurate object masks in a fully automated or interactive manner [14-16]. SAM by Meta is one of the strongest AI models used in computer vision [17, 18]. This method allows zero-shot generalization to unfamiliar objects and images without the need for additional training [19-21]. SAM is trained on over 1 billion masks in 11 million natural images and can generate segmentation masks for any object on demand [18, 22, 23]. SAM is designed to require a command or a series of commands to produce segmentation masks [24]. It uses a transformer-based architecture [25], which has been shown to be highly effective in natural language processing [26] and image recognition tasks [27]. The SAM method shows several advantages: is has been proven to be a robust framework with generalization capabilities adaptable from medical [28] to agricultural domains [29], and it is fast, capable of real-time processing. The SAM architecture can be optimized to work efficiently, thus revolutionizing the field of segmentation [19].

II. RELATED WORK

Research in the field of segmentation has grown rapidly in recent years, especially with the emergence of increasingly sophisticated deep learning models. Recent studies have begun to explore and evaluate the performance of SAM in various domains such as medicine, agriculture, and satellite imagery. One relevant early approach is the study of the YOLOv4 algorithm for detecting and pruning melons. This study showed that configurations with a batch size of 64, 2000 iterations, and a learning rate of 0.001 produced the best performance, with an F1 score of 84.47% and a mean Average Precision (mAP) of 87.68% [12]. Prior image segmentation studies also explored evolutionary optimization, such as a hybrid differential evolution and genetic algorithm for clustering color and texture features [30]. However, these methods rely on handcrafted descriptors and lack generalization across diverse image types. They are effective in detecting objects using bounding boxes, but have limitations in detailed segmentation because they do not produce precise object boundaries down to the pixel level.

Meanwhile, studies in the medical realm are developing MedSAM for the universal segmentation of medical images. MedSAM shows higher accuracy than specialist models, both in internal and external validation [28]. Furthermore, a study evaluating SAM in clinical radiotherapy showed clinically acceptable automated segmentation results with a Dice score of greater than 0.7 [22]. In the agricultural sector, a study introduced the Agricultural SAM Adapter (ASA), which improved the performance of SAM in 12 segmentation tasks, with an increase in Dice score of up to 41.48% in the segmentation of coffee leaf disease [29].

Previous studies have demonstrated that SAM is not only a powerful tool for image segmentation but also highly adaptable to real-world applications, such as disease detection and point cloud segmentation in underground tunnels using 2D projection and point cloud coloring techniques [31]. These findings highlight SAM's flexibility and accuracy across various segmentation tasks. Building upon this foundation, the present study aims to adopt and evaluate the performance of SAM in the context of melon cultivation, specifically for pruning decisions based on fruit diameter. The implementation of SAM is expected to assist in optimizing the number of fruits per plant, thereby enhancing key quality attributes of melons such as sweetness, crispness, size, and aroma [32]. Whereas previous research has confirmed SAM's effectiveness in general segmentation tasks, its integration into real-time fruit diameter measurement and decision support for pruning in horticulture remains unexplored. This study seeks to fill that gap by applying SAM as a precision tool to support pruning strategies, ultimately contributing to improved yield quality in melon production.

Although previous works have employed clustering-based methods [30, 33], and deep architectures like U-Net 3+ [34] for segmentation in various domains, these approaches either require extensive labeled data or domain-specific customization. Unlike these methods, SAM introduces a zero-shot segmentation paradigm that is largely unexplored for precision horticulture tasks such as fruit pruning based on visual cues like diameter. Therefore, this study bridges that gap by adapting SAM to melon imagery and evaluating its effectiveness in practical pruning applications.

III. METHODOLOGY

This research consists of two main stages, namely the segmentation of melon objects and the pruning technique. The segmentation stage consists of several sub-stages: data acquisition, data pre-processing, fine-tuning with the SAM algorithm, and model testing. The next stage is the pruning process, using the results of the fine-tuned SAM model, wherein the diameter is measured based on the segmentation results for pruning decisions. Figure 1 illustrates the research workflow.

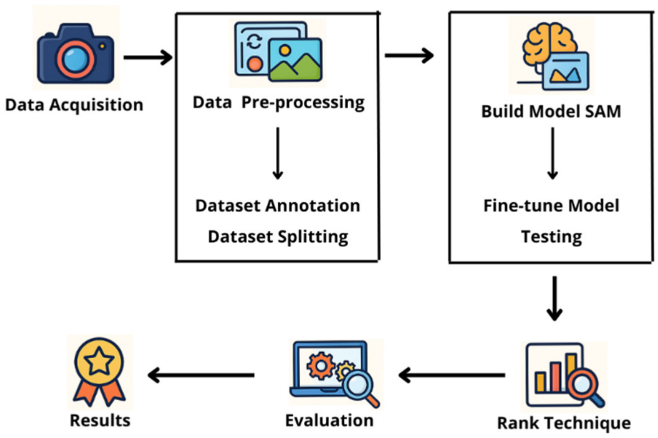


Fig. 1. Workflow of the proposed system.

A. Dataset Acquisition

This study uses secondary data obtained from a previous publication [12], which consists of a dataset collected from Agribusiness and Technology Park in Cikarawang, Bogor, West Java, using an Intel RealSense camera, The image capture process was conducted by photographing parts of melon plants containing young melons from three viewing angles: 0°, 45°, and 90°, and four height levels: 20 cm, 30 cm, 40 cm, and 50 cm from the planting medium. The total dataset used comprised 140 images of melons in .png format.

B. Data Pre-Processing

Pre-processing involves the dataset annotation stage, which is the act of adding meaningful and informative tags to the dataset, making it easier for algorithms to understand and process the data [35]. The data annotation process in this study was carried out using Roboflow with the instance segmentation process. The dataset was labeled with the name 'melon,' and each image was in COCO format, recording the segmentation points in a series of x, y pairs to facilitate the segmentation process. The instance segmentation process can be thought of as a combination of object detection and semantic segmentation [36]. The annotation process is illustrated in Figure 2. The next stage is to split the dataset into 100 images as training data, 20 images as test data to assess model performance, and 20 images as validation data. The process of splitting the dataset is shown in Figure 3.

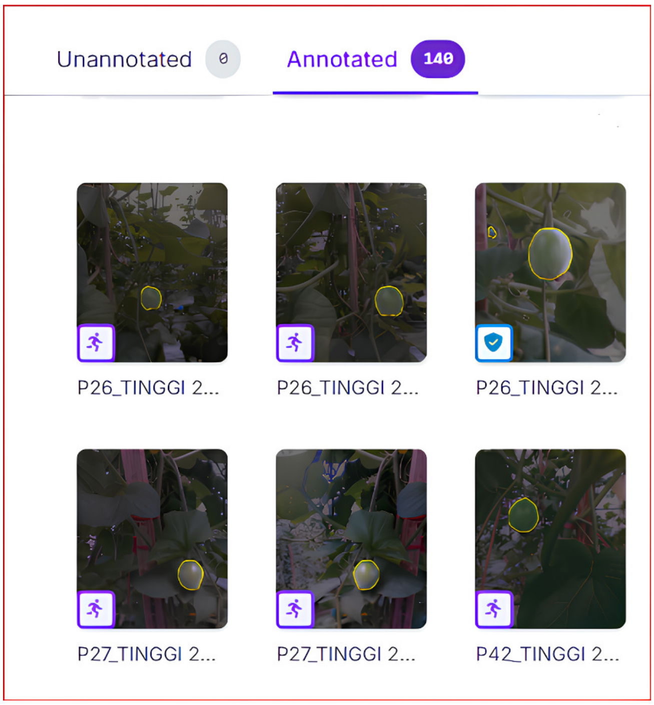


Fig. 2. Melon dataset annotation using instance segmentation in Roboflow.

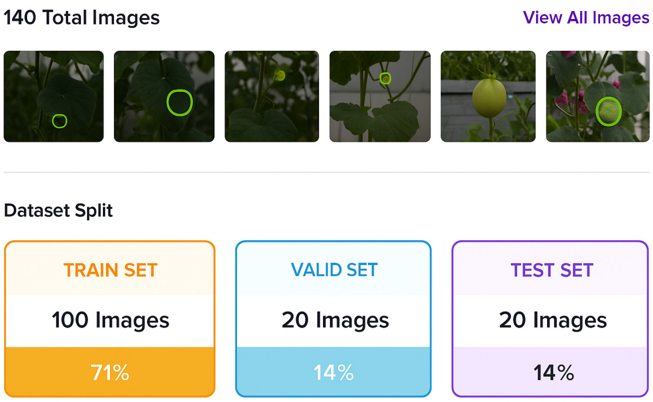


Fig. 3. Dataset splitting into training, validation, and test sets.

C. Building the Segment Anything Model and Fine-Tuning

SAM supports three segmentation modes, namely fully automatic mode, bounding box mode, and point mode [15, 29, 34]. The SAM architecture consists of several components that work together to perform the segmentation process. First, the melon images from the dataset are input into the model. Then, the image encoder converts images into simpler, more compact representations of features. The features are then placed into a numerical embedding representation. Through the input prompt, instructions are given to the model, which are then converted into a numerical representation by the prompt encoder. The mask decoder generates pixel tagging of the image according to the instructions given, ultimately resulting in valid masks, which are the final results of the segmentation process [13, 35, 36]. Figure 4 presents a visual depiction of the of SAM algorithm architecture. Fine-tuning is done based on the hyperparameter configuration, as listed in Table I, to find the optimal combination.

TABLE I. HYPERPARAMTER CONFIGURATION

Epoch	Learning rate	Optimizer
50	0.001	Adam
50	0.001	AdamW
50	0.001	Stochastic Gradient Descent (SGD)

D. Ranking Technique

The ranking technique was applied to the detected masks by taking the horizontal line barrier of the mask which was used as the diameter or width of the fruit. Then the obtained fruit diameters, from largest to smallest, were classified and ranked. The larger the diameter, the lower the ranking, and vice versa. Algorithm 1 presents the pseudocode of the ranking technique.

```
Algorithm 1: Ranking melons for pruning
selection based on diameter using SAM
Input  : Width (horizontal line)
segmentation values
Output : Ranked melons and pruning
decision
image_h, image_w ← image.shape
out_segments, num_segments ←
segment_objects(image,SAM_model)
melon_diameters ← []
for i ←range(num_segments) do
   segment ←out_segments[i]
   x_coords ←[point[0] for point in
   segment]
   y_coords ←[point[1] for point in
   segment]
   min_x ←min(x_coords)
   max_x ←max(x_coords)
   min_y ←min(y_coords)
   max_y ←max(y_coords)
   width ←max_x - min_x
   height ←max_y - min_y
   diameter ←max(width, height)
   melon_diameters.append((diameter,
   segment))
end for
sorted_melons ← sort(melon_diameters,
descending = True)
for rank ←1 to length(sorted_melons)
do
   diameter, segment ←
    sorted_melons[rank - 1]
   print "Melon ", rank, ": Diameter
   =", diameter
   if rank > 2 then
      print "Pruned"
   end if
end for
```

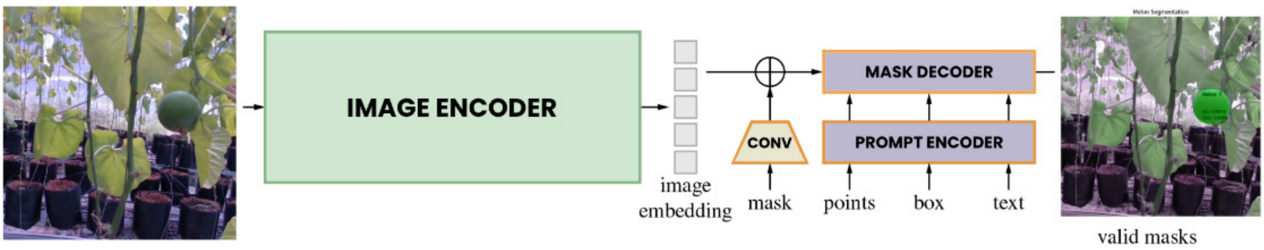


Fig. 4. SAM architecture for melon image segmentation.

E. Model Evaluation

In the evaluation stage, performance was assessed using Intersection over Union (IoU) and Dice coefficient, which consider the similarity between the predicted model and the ground truth [37-39].

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

$$\text{Dice coefficient} = \frac{2\,|A \cap B|}{|A|+|B|} \quad (2)$$

IoU, also known as the Jaccard index, is the most commonly used metric to compare similarities between two arbitrary forms [40-45]. IoU is calculated by dividing the area of overlap between the prediction model (A) and ground truth (B) by the area of union of the two sets. Dice coefficients are often used in image segmentation to measure the similarity between two sets [46-48]. The Dice coefficient calculates twice the area of overlap divided by the sum of elements in both sets.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Fine-Tuning Results

The fine-tuning stage of SAM is performed with three hyperparameter schemes, which differ in the use of optimizers (Adam, AdamW, or SGD). Each scheme runs for 50 epochs and uses a learning rate of 0.001 with the same training process. The loss function used is Mean Squared Error (MSELoss), which compares the results of segmentation converted into a binary mask with a ground truth mask to measure how well the model performs predictions. Accuracy is calculated based on the pixel match between the segmentation results and the ground truth mask. Average losses and accuracy are recorded at each epoch to evaluate the model's performance, so as to determine the most optimal combination of learning rate, epoch, and optimizer for improving segmentation accuracy.

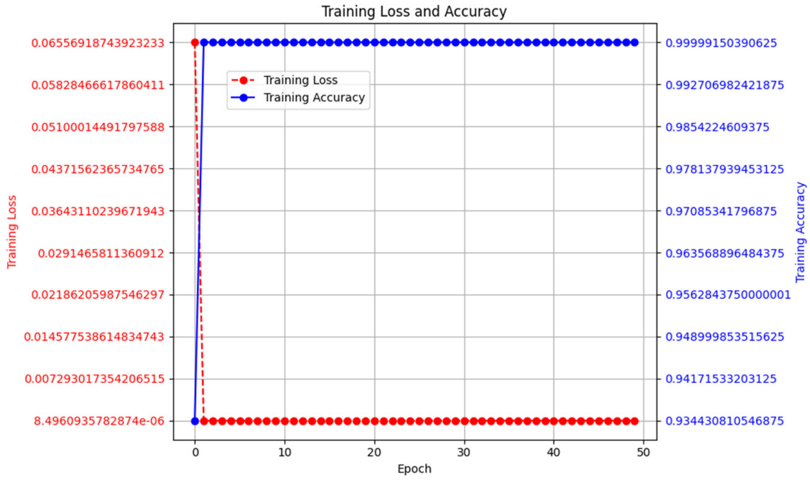
Based on the testing results for the three hyperparameter schemes, presented in Figure 5 and Table II, the second scheme using the AdamW optimizer with a weight decay of 0.01, a learning rate of 0.001, and 50 epochs showed the best performance compared to the other two schemes. This is demonstrated by a very low training loss value and an accuracy close to 100%, which indicates that the model is able to learn optimally from the training data. In addition, convergence occurs rapidly, demonstrating the effectiveness of hyperparameter combinations in accelerating the modeling process. In comparison, the first scheme with the Adam optimizer experienced stagnation in the loss value and accuracy, which remained around 0.000008 and 99.9992%, respectively, without any significant improvement. This phenomenon can indicate that the model is experiencing a plateau, where learning does not develop after a certain number of iterations. Meanwhile, the third scheme using SGD with a momentum of 0.9 also showed similar results, where the training loss remained constant at 0.013010 and the training accuracy did not increase from 98.699% over the 50 epochs. This shows that the use of SGD with a momentum of 0.9 at a learning rate of 0.001 in this scheme is less optimal than Adam. Taking these results into account, the second scheme can be considered the best approach to model training.

After testing the fine-tuning parameters and choosing the best scheme, the next step is to test the model using a test dataset consisting of two images. The main purpose of this test is to evaluate the extent to which the customized model can accurately segment new data that have never been used in the training process. The evaluation of the model's performance was carried out using the IoU and Dice coefficient evaluation metrics. Figure 6 presents the results of the segmentation accuracy evaluation on the test data.

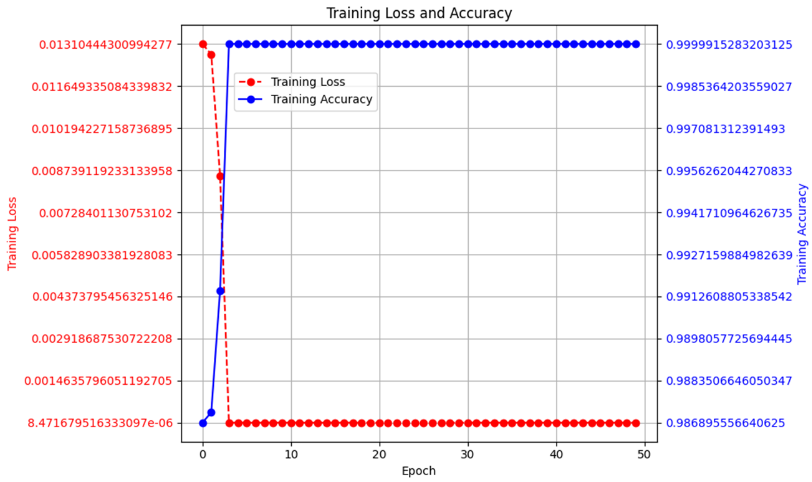
Based on the evaluation of the test data, the SAM showed excellent performance in segmenting melons. The results of the evaluation using IoU and Dice coefficient showed that the model, fine-tuned with scheme b, was able to segment with a high level of accuracy. This can be seen in some of the images, which had an IoU value of more than 0.7, indicating that the model's prediction has a good degree of overlap with ground truth. The Dice coefficient values ranged from 0.8 to 0.9, confirming that the model has a high similarity with the ground truth, especially in objects that are more clearly visible.

B. Pruning Decision Analysis

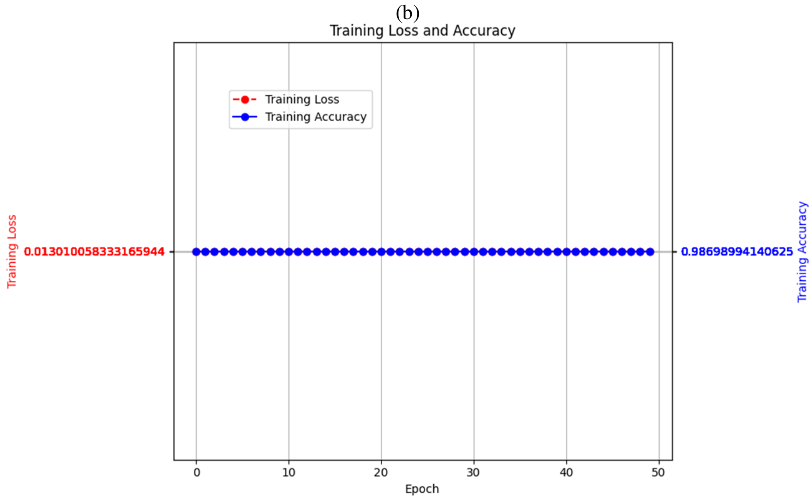
Based on Figure 7, this method shows that SAM can be used effectively for segmentation, measuring melon diameter, as well as assisting in the pruning process. All the melons in the image were successfully detected and segmented. Each melon had an identification label along with a parameter value indicating the quality of the segmentation. The diameter values and evaluations are displayed next to the labels, as shown in Table III.



(a)



(b)



(c)

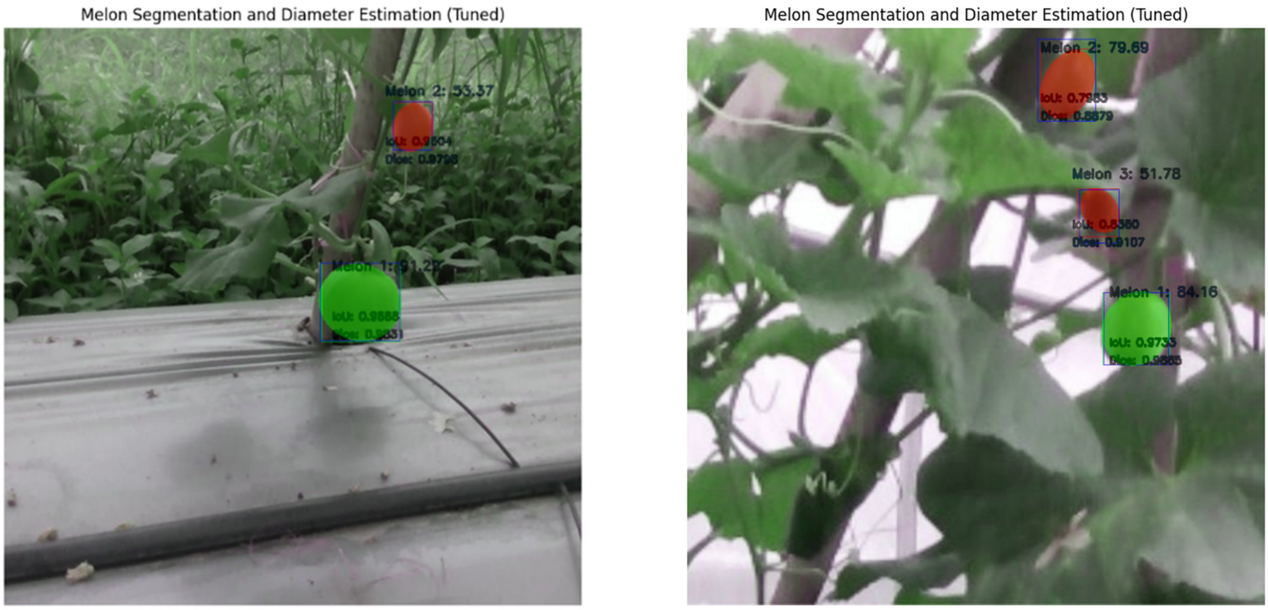
Fig. 5. Fine-tuning results for the three schemes: (a) Adam, (b) AdamW, and (c) SGD.

TABLE II. HYPERPARAMETER RESULTS FOR THE THREE FINE-TUNING SCHEMES

Scheme	Learning rate	Epoch	Optimizer	MSELoss	Accuracy (%)
a	0.001	50	Adam	0.000008	99.9992
b	0.001	50	AdamW	0.000008	99.9992
c	0.001	50	SGD	0.01301	98.6990

(a) (b)

Fig. 6. Segmentation results on test images: (a) melon 1 → IoU = 0.9757, Dice = 0.9877; melon 2 → IoU = 0.9654, Dice = 0.9824, and (b) melon 1 → IoU = 0.8209, Dice = 0.9016; melon 2 → IoU = 0.7038, Dice = 0.8262.



(a) (b)

Fig. 7. Pruning results based on diameter and segmentation: (a) image 1 (ideal conditions), and (b) image 2 (non-ideal conditions).

TABLE III. RESULTS OF PRUNING EVALUATION BASED ON DIAMETER

Images	Melon	Diameter	IoU	Dice coefficient
1	Melon 1	91.29	0.96	0.98
	Melon 2	53.37	0.96	0.97
2	Melon 1	84.16	0.97	0.98
	Melon 2	79.69	0.79	0.88
	Melon 3	51.78	0.83	0.91

IoU and Dice values reflect the quality of segmentation, whereas diameter better reflects the size of the segmented object, regardless of how accurate the segmentation is. Under ideal conditions, as seen in image 1 (Figure 7(a)), the values of diameter, IoU, and Dice are directly proportional. Whereas in non-ideal conditions such as in image 2 (Figure 7(b)), melon 2 has a lower IoU and Dice, but a larger diameter than melon 3 due to the possibility that the segmentation model captured a larger area, potentially because of a more oval shape of the melon. Meanwhile, melon 3 has a higher IoU and Dice, but a smaller diameter, which suggests that the segmentation is more accurate but the object is indeed smaller in size from the start.

In pruning analysis, diameter is not the sole determinant. There must also be precise segmentation, measured by IoU and Dice values. Compared to traditional segmentation methods such as fuzzy clustering with kernel distance [33] and evolutionary-based clustering using hybrid differential evolution and genetic algorithms [30], the SAM-based approach demonstrated in this study achieves significantly higher segmentation precision with minimal pre-processing and no reliance on handcrafted features. Additionally, prior Artificial Neural Network (ANN)-based segmentation in retinal imaging relied heavily on color-texture feature engineering and supervised learning [34], whereas the SAM model in this study required only prompt tuning to yield consistent segmentation results across diverse melon imagery. These findings highlight the potential of SAM as a versatile and efficient model for real-time horticultural decision-making, such as pruning.

The pruning process is greatly aided by accurate segmentation, as segmentation allows the identification and separation of each melon individually from the background and other surrounding objects. With this segmentation information, the system can measure the diameter of each melon automatically and consistently, so that pruning decisions based on size criteria can be made more precisely and efficiently. Without good segmentation, the pruning process is more difficult to automate, as the boundaries and sizes of objects are not clearly defined.

V. CONCLUSION

This study evaluated the performance of the Segment Anything Model (SAM) for melon segmentation and diameter-based pruning analysis by testing three optimizers: Adam, AdamW, and Stochastic Gradient Descent (SGD). The optimal configuration was achieved using the AdamW optimizer with a weight decay of 0.01, a learning rate of 0.001, and 50 epochs, yielding an accuracy of 99%. Experimental results demonstrate that SAM effectively segments melon objects with high precision. Diameter estimation was performed by calculating the maximum dimension of each segmented mask. The segmentation results showed that melon objects were accurately recognized, as indicated by high Intersection over Union (IoU) and Dice coefficient values for most objects. These findings confirm that SAM is capable of identifying object boundaries with high precision in complex agricultural environments.

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