

Quality Detection of Sweet Potato Leaves Using YOLOv4-Tiny

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Abstract—In Southeast Asia, people use sweet potato leaves as a type of vegetable for cooking, and they are also used as animal feed. Sweet potato leaves are commonly used in traditional medicine to treat tumors in the mouth and throat. There are different types of sweet potato leaves, including antin sweet potato leaves, papua salosa sweet potato leaves, sweet potato leaves, and Cilembu sweet potato leaves. The method used in this study is to detect the quality of sweet potato leaves, namely by going through the dataset process, bounding box, then the training process and finally the evaluation using the Mean Average Precision (mAP). The results of the quality detection test for sweet potato leaves using YOLOv4-Tiny can be concluded that the maximum results according to the grade of each sweet potato leaf starting from the antin yam leaves have an MAP result of 0.79 on grade_a. Furthermore, sweet potato leaves with grade_b have an MAP value of 0.67. The papua salosa type of sweet potato leaves grade_a has a value of 0.70. The process of testing sweet potato leaves on grade_a has an MAP result of 0.82 on grade_b. The last test of Cilembu sweet potato leaves has a mean average precision (mAP) value at grade_a, which has a value of 0.75, and for grade_b. It has a mean average precision result of 0.40. As a result, it can be inferred that the utilization of YOLOv4-Tiny for identifying the quality of sweet potato leaves has been effective.

Keywords—Quality Detection, Antin Leaf Quality, Papua Salosa Leaf Quality, Sari Leaf Quality, Cilembu Leaf Quality

I. INTRODUCTION

Sweet potato leaves serve as a leafy vegetable in Southeast Asia, as well as a potential source of animal feed. Additionally, the leaves high protein content can aid in addressing nutritional deficiencies [1]. In traditional medicine, sweet potato leaves are brewed into a medicinal decoction that is employed to treat tumors located in the mouth and throat [2]. Sweet potato has become a popular crop in tropical gardens due to its uncomplicated cultivation and its ability to yield both edible tubers and leaves. The leaves themselves are a valuable source of protein, carbohydrates, and fat [3]. Research has demonstrated that this particular plant possesses hematinic properties, which have been utilized to treat various conditions, including anemia [4]. Apart from being used as food ingredients such as vegetables, chips, flour, and other food ingredients, sweet potatoes can also be used as medicine, both external and internal medicine. [5]. The external treatment utilizes the tubers and leaves, namely by grating and grinding the sweet potato, then attaching it to the parts that are sick that can be cured, including sprains and wounds [6].

Earlier studies have investigated the disease affecting sweet potatoes in Tanzania. This study utilized the Support Vector Machine (SVM) algorithm to extract features, while the identification task was performed using the Convolutional Neural Network (CNN) approach. [7]. The results of this study obtained the highest accuracy in brown leaf spot disease and brown stem disease at 98%.

Furthermore, there are other studies that are still related to plant damage with symptoms that appear on the leaves of the rhizome [8]. The main objective of this research is to detect different tobacco diseases by examining leaf images, employing the Gray Level Co-occurrence Matrix (GLCM) feature extraction method, which takes into account the pixel relationships. The identification of these diseases is achieved using a Support Vector Machine (SVM) with both Gaussian (RBF) and polynomial kernels [9]. The highest accuracy obtained is 60% on the polynomial kernel [10].

In addition, there is still research related to the use of GLCM feature extraction to identify chili disease from leaf spot symptoms and the appearance of conidia with an identification process using a Probabilistic Neural Network (PNN) with an accuracy of 54.74% for leaf spot recognition, whereas for recognition of conidia obtained an accuracy of 65.31% [11]. In previous studies, research on leaf detection was carried out regarding the study of the quality of organic cassava leaves from a simple composter [11][12]. Tests were carried out using the walkley and black method. Several parameters were tested, such as the homogeneity test, stability test, and method validation for quality control. The accuracy value obtained was 60.26% [13][14].

In previous research, there was research using YOLOv4-Tiny related to object detection. Research on "Object detection in videos using the CNN and Tensorflow methods" in 2018 [15] showed that the resulting accuracy rate ranges from 60% -70%. Research on "Implementation of SSD (Single Shot Multibox Detector) for Face Recognition" resulted in an accuracy rate of around 58%. [16]. Research "Utilization of OpenCV in detecting vehicle types on the road" in 2018 on quiet road conditions resulted in an accuracy of 57.8% [17] in normal road conditions and 68.2% in congested road conditions. Other studies that produce a high level of accuracy range from 70-68%, namely regarding "Utilization of CNN and Tensorflow to detect motorized vehicle number signs on streaming media" [18] [19].

The main objective of this concise presentation was to develop a system capable of detecting the quality of sweet potato leaves through the utilization of the YOLOv4-Tiny approach. The goal of this study was to determine the highest quality cassava leaves among four different types of cassava leaves, including antin yam leaves, papua salosa sweet potato leaves, sweet potato leaves, and cilembu sweet potato leaves. Researchers made Grade A and Grade B because in each sweet potato leaf some were still fresh and some were almost wilted or dead. The researchers employed these various types of cassava leaves in their analysis. Researchers use the YOLOv4-Tiny method because the computational process used is very fast compared to other methods. The process used in YOLOv4-Tiny uses two darknets, namely Darknet53 and CSPNet, to detect sweet potato leaves.

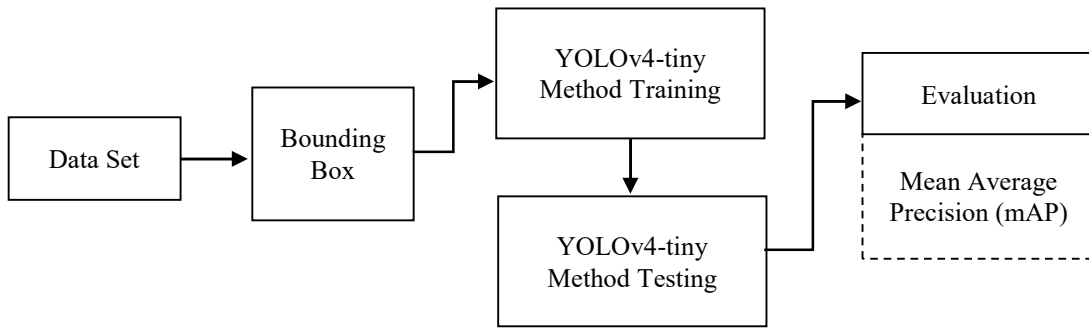


Fig. 1. The quality detection system model for sweet potato leaves uses YOLOv4-Tiny



Fig. 2. Detection of antin yam leaves using YOLOv4-Tiny

II. METHODOLOGY

The method of detecting the quality of sweet potato leaves using YOLOv4-Tiny used in this study is aimed at Fig.1. It can be explained briefly in detecting the quality of sweet potato leaves using a dataset in the form of images of each type of sweet potato leaf. After taking pictures, the dataset will be in a bounding box. This bounding box is the process of labeling sweet potato leaves. The results of this labeling will later be carried out by a training process using the YOLOv4-Tiny method. This training process is carried out by testing all types of sweet potato leaves used. After the training process is carried out, it will be followed by carrying out the testing process. The testing process that uses YOLOv4-Tiny is to validate the results of training and testing of each test used. The results of the validation will later be evaluated using the mean average precision (mAP) parameter.

A. Data Set

This dataset involves the use of cassava leaf images to investigate the detection of cassava leaf quality. The collected data comprises 1000 cassava leaves categorized into four classes: antin yam leaves, papua salosa sweet potato leaves, sweet potato leaves, and cilembu sweet potato leaves. Each type of cassava leaf is represented by 250 images, making a total of 1000 images in the dataset.

B. Bounding Box

To detect the quality of sweet potato leaves, a bounding box technique was utilized to label each individual leaf. This labeling is to determine each type of sweet potato according to the class used in the study. This bounding box is used in

detecting the quality of sweet potato leaves to become a parameter in determining each class of each sweet potato leaf.

C. YOLOv4-Tiny Method Training

The YOLOv4-Tiny method's training process involves executing the code developed by the researcher. There seems to be no context in the statement provided. It looks like a list of items. Please provide more information or context to paraphrase it correctly. In this training process, the collected dataset will be processed to get the testing value thus that the results in testing can later be used as a comparison.

D. YOLOv4-Tiny Method Testing

When detecting cassava leaves, the testing phase involves comparing the outcomes of the test with the training results. This test is based on comparing the parameters of each sweet potato leaf type. The evaluation of the training data outcomes and the testing data outcomes will be performed based on the test results obtained.

E. Evaluation

In the last phase, known as the evaluation stage, we assess the outcomes of the YOLOv4-Tiny test. The evaluation involves utilizing parameters such as mean average precision (mAP), with specific calculations applied to (1). In equation (1), the variable "n" signifies the true value. The value "i" corresponds to the precision of the curve along both the x and y axes. Later on, the plot's results will utilize point interpolation to separate the curve outcomes and the x and y coordinates.

$$mAP = \frac{1}{n} \sum_{i=1}^n AP_i \quad (1)$$

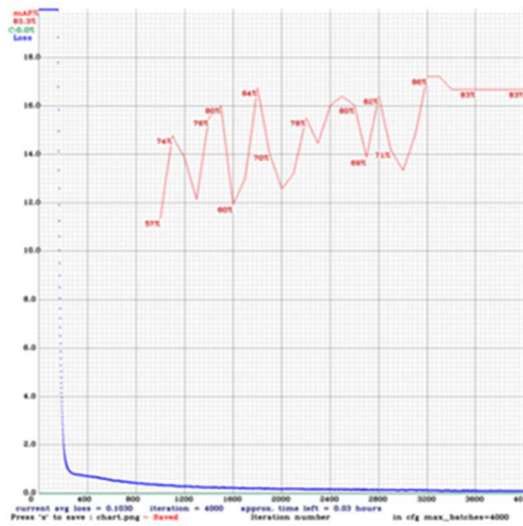


Fig. 3. mAP results of antin yam leaf detection using YOLOv4-Tiny

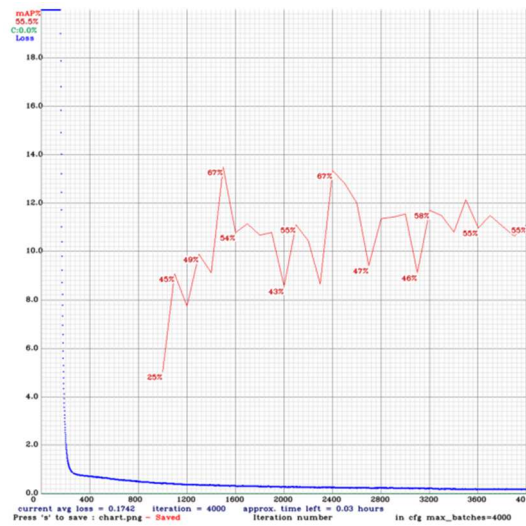


Fig. 5. mAP detection results for papua salosa sweet potato leaves using YOLOv4-Tiny



Fig. 4. The results of papua salosa leaf detection using YOLOv4-Tiny

III. RESULT AND DISCUSSION

The results of the antin yam leaves detection test are shown in Fig. 2, which indicates that the mAP value for grade_a is 0.79. Then on grade_b, it results in 0.67 on sweet potato leaves. The detection results used on YOLOv4-Tiny in detecting antin yam leaves are fairly good. Antin yam leaves can be recognized and detected according to their respective grades. In Fig. 3, it can be explained that the value obtained from the detection test for antin-type sweet potato leaves with various iterations obtained maximum results with an accuracy rate of up to 86.1%. In detection, it takes approximately 0.03 hours to produce a mean accuracy precision (mAP). The error rate in detecting whole antin yam leaves is 0.1000.

Then in the second test, using the test data for papua salosa sweet potato leaves aimed at Fig. 4. On the detection of papua salosa's sweet potato leaves, it can be explained that grade_a has an mAP value of 0.70. Then on grade_b, it yields 0.40 on papua salosa sweet potato leaves. The detection results used on YOLOv4-Tiny in detecting papua salosa sweet potato leaves were fairly good. Papua salosa sweet potato leaves can be recognized and detected according to their grades. In Fig.

5, it can be explained that the value obtained from the detection test for papua salosa sweet potato leaves with various iterations obtained maximum results with a *mean accuracy* rate of up to 67.0%. In detection, it takes approximately 0.03 hours to produce a mean accuracy precision (mAP). The error rate in detecting the whole papua salosa sweet potato leaves is 0.1742.

Furthermore, the results in testing the detection of sweet potato leaves are aimed at Fig. 6. It can be explained that grade_a has an mAP value of 0.82. Then on grade_b, it has a result of 0.35 on sweet potato leaves. The performance of YOLOv4-Tiny in detecting sweet potato leaves is deemed satisfactory based on the detection results. These sweet potato leaves can be recognized and detected according to their respective grades. In Fig. 7, it can be explained that the value obtained from the detection test of sweet potato leaf extract with various iterations obtained maximum results with an accuracy rate of up to 82.0%. In detection, it takes approximately 0.03 hours to produce a mean accuracy precision (mAP). The error rate in detecting whole cassava leaves is 0.1130.

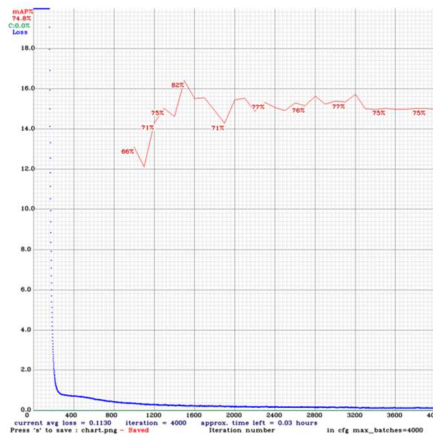


Fig. 7. Results of mAP detection of sweet potato leaves using YOLOv4-Tiny

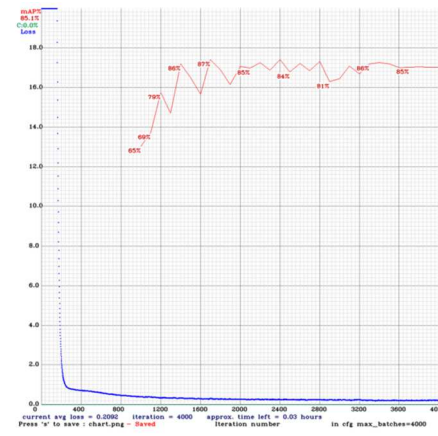


Fig. 8. mAP results for detection of Chinese sweet potato leaves using YOLOv4-Tiny

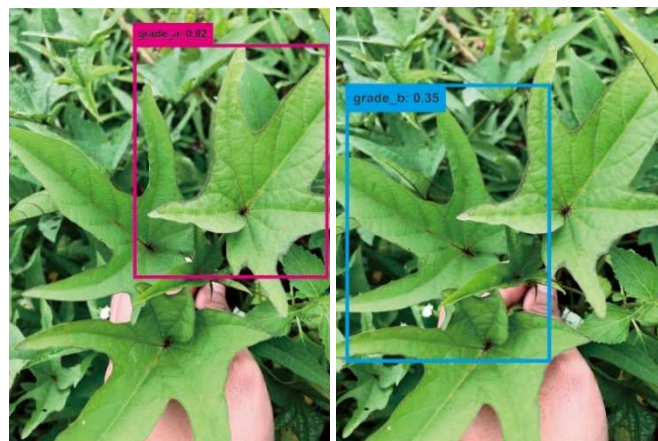


Fig. 6. Detection results of sweet potato leaf using YOLOv4-Tiny



Fig. 9. Detection results of Cilembu sweet potato leaves using YOLOv4-Tiny

Then the next test is the detection of Cilembu sweet potato leaves aimed at Fig. 8. It can be explained that grade_a has an mAP value of 0.75. Then on grade_b, it has a result of 0.40 on Cilembu sweet potato leaves. According to the detection results, YOLOv4-Tiny's performance in identifying Cilembu sweet potato leaves is considered satisfactory. The different grades of Cilembu sweet potato leaves can be identified and detected accordingly. In Fig. 9, it can be explained that the value obtained from the cilembu-type sweet potato leaf detection test with various iterations obtained maximum results with an accuracy rate of up to 82.0%. In detection, it

takes approximately 0.03 hours to produce a mean accuracy precision (mAP). The error rate in detecting Cilembu sweet potato leaves as a whole is 0.1130.

In Fig. 10 the evaluation of the mean average precision (mAP) for sweet potato leaf quality detection using YOLOv4-Tiny yielded outstanding results. Antin sweet potato leaves, grade_a has a mean precision mean (mAP) value of 0.79. Then the antin-type sweet potato leaves on grade_b have a mean average precision (mAP) value of 0.67. The second test using sweet potato leaves of the papua salosa type on grade_a has an mAP value of 0.70.

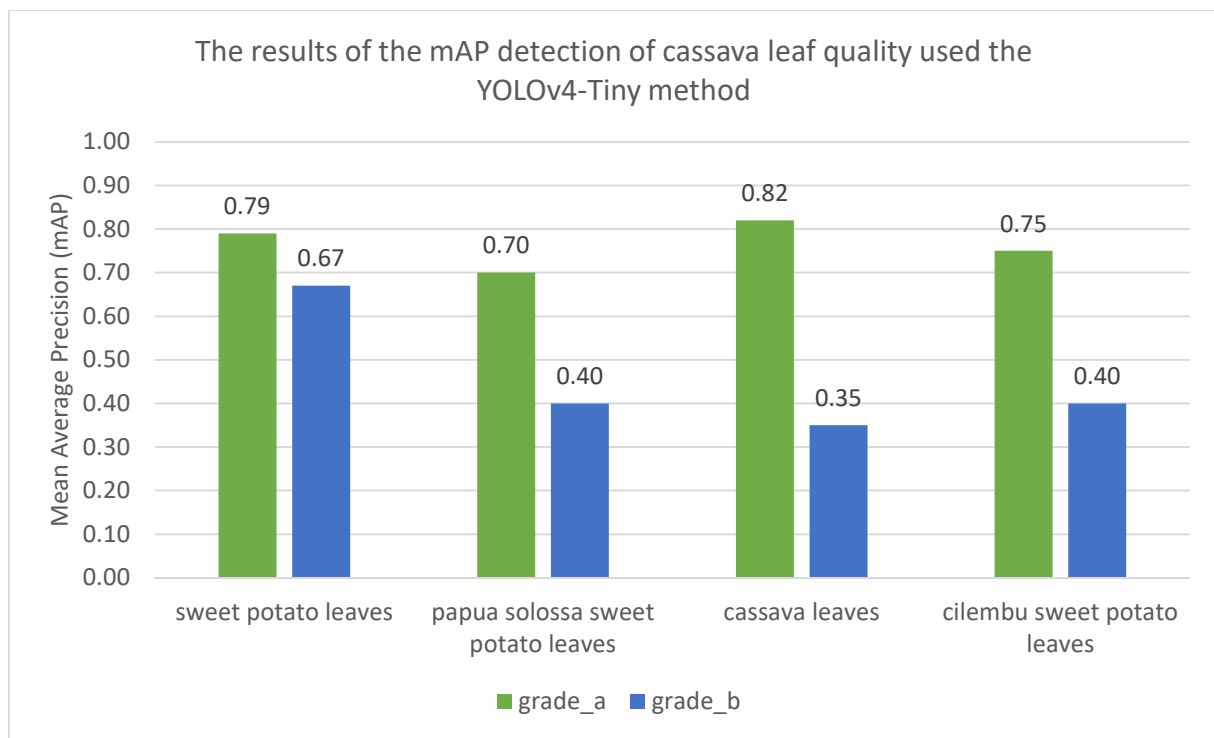


Fig. 10. Mean average precision (mAP) quality detection of sweet potato leaves using YOLOv4-Tiny

TABLE I. COMPARISON OF THE RESEARCHED METHOD WITH THE PROPOSED METHOD

Researcher	Method	Object Detection	mAP
[20]	Yolov3	Strawberry Leaves	0.45
Our Proposed	YOLOv4-Tiny	Grade A Sweet Potato Leaves	0.79
		Grade B Sweet Potato Leaves	0.67
		Grade A Papua Salossa Sweet Potato Leaves	0.70
		Grade B Papua Salossa Sweet Potato Leaves	0.40
		Grade A Cassava Leaves	0.82
		Grade B Cassava Leaves	0.35
		Grade A Cilembu Sweet Potato Leaves	0.75
		Grade B Cilembu Sweet Potato Leaves	0.40

The test results on the papua salosa grade_b sweet potato leaves also had an mAP value of 0.40. In detecting the quality of sweet potato leaves, tests were also carried out using types of sweet potato leaves. The results obtained on grade_a reached 0.82, and the kinds of sweet potato leaves on grade_b were 0.35. The final test uses Cilembu sweet potato leaf data with grade_a having a mean average precision (mAP) of 0.75, and Cilembu sweet potato leaf detection has a mean average precision (mAP) value of 0.40.

In the Table I can explain that research on the use of YOLO has been carried out to detect plant diseases. In this study, the YOLO method was used to look for diseases in a plant. The results in this disease study on strawberry leaves had a MAP level of 0.45 using YOLOv3. For this reason, researchers propose Detection of Quality of Sweet Potato Leaves Using YOLOv4-Tiny. In this case the researchers used 4 types of sweet potato leaves where each type had grade A and B results. Grade A was the highest and grade B had a decrease in quality. The results in this study Grade A Sweet Potato Leaves had a mAP result of 0.79. In Grade A Papua Salossa Sweet Potato Leaves has a mAP result of 0.70. While Grade A Cassava Leaves has a mAP result of 0.82. The results that are in Grade A Cilembu Sweet Potato Leaves have a mAP result of 0.75 on the quality detection of sweet potato leaves.

IV. CONCLUSION

Based on the results of the quality detection test for sweet potato leaves using YOLOv4-Tiny, it can be concluded that the maximum yield according to the grade of each sweet potato leaves leaf starting from the antin yam leaves has an mAP result of 0.79 on grade_a. Furthermore, sweet potato leaves with grade_b have an mAP value of 0.67. Then, papua salosa grade_a has an mAP value of 0.70, while papua salosa grade_b has an mAP value of 0.40. Testing sweet potato leaves on grade_a has an mAP result of 0.82, and on grade_b. It has a value of 0.35. The last test of Cilembu sweet potato leaves has a mean average precision (mAP) value at grade_a, which has a value of 0.75 and at grade_b. The average precision result is 0.40. To summarize, the implementation of YOLOv4-Tiny has resulted in the successful detection of sweet potato leaf quality, as well as the effective identification of different grades based on their corresponding species.

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