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# Disease Segmentation in Purple Sweet Potato Images Using Yolov7

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***Abstract***

*Purple sweet potato is a very important plant in many parts of the world and a major crop in tropical and subtropical climates. Its cultivation can significantly increase production and consumption, and it is beneficial for the nutritional status of people in both rural and urban areas. However, purple sweet potatoes are susceptible to disease outbreaks, which can cause substantial losses to the agricultural industry. To prevent the spread of these diseases and minimize financial losses, it is crucial for farmers to identify purple sweet potato diseases as early as possible. Utilizing deep learning technology to separate areas of purple sweet potatoes marked with disease can effectively address this problem. In this study, researchers employed a segmentation method using the YOLOv7 algorithm. The study's results demonstrated a mean Average Precision (mAP) value of 98.6% from a dataset of 1500 images, divided into two classes: healthy sweet potatoes and diseased sweet potatoes with tuber rot. The mAP value for healthy sweet potatoes was 96.1%, while the mAP for diseased sweet potatoes with tuber rot was 98.6%. The YOLOv7 method, therefore, produces high accuracy values for the segmentation of purple sweet potato diseases. This research significantly contributes to agriculture by enhancing the productivity and quality of sweet potato harvests and can assist farmers in improving the efficiency and sustainability of purple sweet potato production.*



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## I. INTRODUCTION

Purple sweet potato a very important plant in many parts of the world an a major crop in tropical and subtropical climates, so it can increase production and consumption, and it is beneficial for the nutritional status of people in rural and urban areas [1], [2], [3]. Also the fourth largest source of carbohydrates in Indonesian after rice, corn, and cassava [4]. Purple sweet potatoes are susceptible to disease outbreaks, which might cost the agriculture industry a significant amount of money [5], [6]. In order to stop diseases that cause financial loss from spreading, farmers must identify purple sweet potato disease as soon as feasible [7].

Physical examination is commonly used to identify diseased purple sweet potatoes. At the same time, identification is achievable with the use of digital technological equipment, namely by researching disease signs in purple sweet potatoes using digital images. A problem in this regard is that digital technology can accurately represent the symptoms of sickness purple sweet potato [8]. Identification uses deep learning technology [9], [10] by separating areas of purple sweet potatoes characterized by disease. Deep learning is a type of learning that employs artificial, or multilayer, and neural networks [11]. In this case, it is intended to help effectively solve the problem of purple sweet potato disease [8].

There was no study of disease segmentation in purple sweet potatoes in the previous study. The segmentation method is an important method in image processing that is used to split or separate images depending on a variety of criteria [12]. The researcher then used purple sweet potato to conduct a study on disease image segmentation. This study will use the segmentation of purple sweet potato disease using the YOLOv7 algorithm. YOLOv7 has a higher detection speed and accuracy than the previous algorithm [13], [14]. This research contributes significantly to agriculture by improving the productivity and quality of sweet potato harvest, and can assist farmers in improving the efficiency and sustainability of purple sweet potato production. It will reduce losses caused by disease attacks on sweet potatoes in the long run.

## II. RELATED WORKS

Most of the research related to sweet potato has been done using deep learning methods [15], [16]. Previous research has been conducted on "Classification of Sweet Potato Variety using Convolutional Neural Network". The study uses the method of Convolution Neural Networks or CNN. The data set of images used is 600 and each image consists of spider beads with different shapes. In the study, the results of more information used in training data increases and decreases classification by producing training data (70% image dataset, 20% image validation, and 10% test data level) and an average accuracy of 96.33% [17].

An additional research project, the Yolov4-Tiny algorithm was utilized to detect the grade of purple sweet potato. This research uses a detection approach based on the Yolov4-Tiny algorithm for sweet potato quality. During the detection stage, the authors do the following steps: Literature Review, Data Collection, Pre-Processing, Method Implementation, YOLOv4-Tiny Method Training, YOLOv4-Tiny Method Testing, and Evaluation. The data used in this study are 20 different types of purple sweet potato data detection. The results of the study show that the detection system using yolov4-tiny on purple sweet potato can produce 5 grade classes that meet export industry standards with the highest mAP of 99.15% [18].

In a similar study, To identify the quality of sweet potato fertiliser, researchers employed YOLOv4-Tiny. The results were obtained from worm cage fertilizers in class_a with a mAP value of 0.69 and worm cages in class_b with a mAP value of 0.55. Then tested the mineral fertilizer in class _a with mAP value of 0.75 and the mineral bage fertiliser in grade _b with mAP value of 0.69 [19]. Similar studies employ the YOLOv4-Tiny algorithm and detection techniques to determine the quality of sweet potato leaves. One thousand sweet potato leaves were employed in this investigation, and the results included four categories. According to the research, antin yam leaves have a beginning value of 0.79 mAP value in grade_a, indicating that detection using YOLOv4-Tiny yields maximum results. The mAP value of papua salosa sweet potato leaves grade_a is 0.70, but the mAP value of papua salosa sweet potato leaves grade_b is 0.67. The mAP result for the cassava leaves testing procedure is 0.82 in grade_a and 0.35 in grade_b. The mAP results from the most recent test on cilembu sweet potato leaves were 0.40 on grade b and 0.75 on grade a. The results of the study show that it is extremely effective and efficient to use YOLOv4-Tiny to identify the quality of sweet potato leaves in order to differentiate between different quality levels [20].

## III. METHODS

This is the method used to segmentation image of disease in purple sweet potatoes can be shown in Figure 1. The first start of the input process is that the researchers will enter a data set of pictures of purple sweet potatoes. In the next process, the modeling process is divided into two stages: Pre-Processing and YOLOv7 algorithm modeling. In the Pre-processing process, where the datasets are annotation and augmentation, the process is modeled using epoch parameters and data training. The next process is implementation where there are two phases namely training and testing. Using YOLOv7, the training procedure is carried out by running a script created by the researchers. Subsequently, a dataset created in the form of a image purple sweet potato diseases is used in the testing procedure to provide predictions. The Mean Average Precision parameter will subsequently be used to assess the test outcomes.

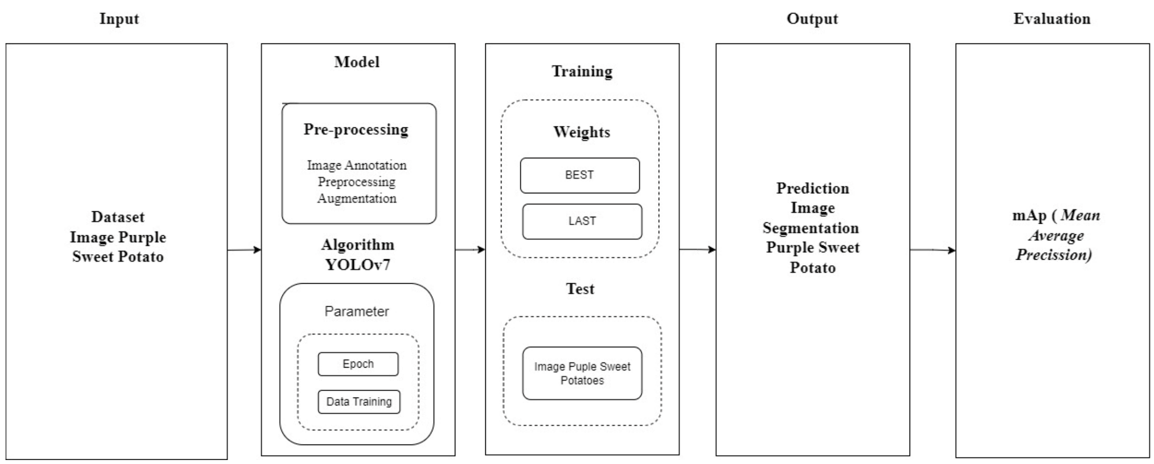


**Figure 1.** a framework for the disease segmentation of purple sweet potato using yolov7

### *A. Data Set*

The research involved the utilization of 1200 images of purple sweet potatoes for data collection purposes. These images were systematically categorized into three distinct groups: test, validation, and training sets. Specifically, the test set comprised 50 images, the validation set contained 100 images, and the training set was the largest, consisting of 1050 images. This comprehensive dataset facilitated the development and evaluation of the model. Furthermore, the data processing was focused on two primary categories, ensuring a structured approach to analyzing the purple sweet potato images. This methodical categorization and substantial dataset allowed for robust training, validation, and testing phases, thereby enhancing the accuracy and reliability of the research findings.

### *B. Data Preprocessing*

Preprocessing is a crucial phase in data processing that aims to eliminate noise and variations present in the data while enhancing its quality and contrast. This process not only filters out unwanted or disruptive elements but also normalizes the images to ensure consistent brightness and contrast levels. Furthermore, data preprocessing addresses uneven intensity within images, thereby eliminating artifacts that can interfere with data analysis. This step is essential because artifacts and intensity irregularities can lead to errors in pattern recognition or data classification. Consequently, through preprocessing, the data quality becomes more homogeneous and ready for further processing, ultimately improving the accuracy and efficiency of the overall data analysis process [21].

### *C. Annotation Image with Roboflow*

In the study of the image segmentation of purple sweet potato disease using YOLOv7, the second step is to annotate the image. Annotation is the process of marking a particular area or object in the image to train the model to carry out the next process [14],[22]. The researchers used Roboflow in picture annotations. Roboflow is a platform that can help in this task, making it easier to mark and manage annotated data efficiently [23]. In Roboflow, researcher applied the Smart Polygon feature in labelling datasets.

### *D. Method Implementation*

In this research, the concept was put into practice by employing YOLOv7, a sophisticated algorithm for object detection. The researchers developed a specialized algorithm specifically tailored to utilize the capabilities of YOLOv7 in segmenting sweet potatoes. This involved carefully designing and coding different components to ensure accurate detection and segmentation. The development stage included rigorous testing and refinement, during which the researchers adjusted the algorithm to address the unique characteristics and challenges posed by sweet potato images. The custom algorithm was then integrated into the YOLOv7 framework and underwent a series of validations and fine-tuning to enhance its performance. The result was a robust and efficient segmentation tool that followed the researchers' custom code, ensuring that each step of the implementation process aligned with the study's initial conceptual framework and objectives.

### *E. YOLOv7 Method Training*

The training process is crucial for executing the developer's code within the YOLOv7 framework effectively. It plays a pivotal role in refining and optimizing the algorithm's performance. In this study, the training primarily focuses on two distinct classes: sick sweet potato tuber rot and healthy sweet potato. These classes are fundamental for the algorithm to accurately learn and differentiate between diseased and healthy sweet potato tubers. Throughout the training process, the algorithm is exposed to datasets containing images of both sick and healthy sweet potatoes from these two classes. These datasets are carefully curated to cover a wide range of scenarios and conditions, ensuring the algorithm's robustness and adaptability. As the training progresses, the algorithm iteratively adjusts its parameters and internal representations to minimize errors and improve accuracy in classifying sweet potato tubers. Additionally, test scores are periodically obtained during the training phase. These scores are derived from processing separate test datasets, which include samples from both sick and healthy sweet potato classes, along with a third class for comparison purposes. The test results serve as valuable metrics for evaluating the algorithm's performance and identifying areas for enhancement. Through this iterative training and evaluation process, the algorithm gradually evolves into a more refined and effective tool for accurately detecting and classifying sweet potato tubers based on their health status.

### *F. YOLOv7 Method Testing*

The YOLOv7 testing process is essential for researchers to implement code previously annotated using the model. It serves as a crucial step in evaluating the accuracy and efficiency of the developed algorithm. Researchers rely on the most effective data gathered from earlier training sessions for this testing phase, ensuring that the algorithm is assessed using high-quality and representative datasets [24]. Throughout testing, the algorithm is exposed to diverse scenarios and conditions to accurately simulate real-world environments. This comprehensive testing approach enables researchers to evaluate the algorithm's performance across various contexts and identify any potential shortcomings or areas for improvement. The insights gleaned from the test results are valuable for refining the algorithm and optimizing its effectiveness to meet specific objectives and criteria. Furthermore, the test outcomes can also be used as a reference point for comparing the algorithm's performance against alternative methods or algorithms, providing valuable insights into its relative efficacy. Ultimately, the YOLOv7 testing process is critical for validating the algorithm's performance and ensuring its suitability for practical implementation in diverse applications.

### *G. Evaluation*

The final phase in this research procedure is to evaluate. In performance evaluation, the mean average precision (mAP) is applied (1). One of the main metrics used to assess a model's accuracy that has been trained on a specific collection of data is Mean Average Precission [25]. The workings of this algorithm are determined by comparing the segmentation results of YOLOv7 to the actual data. For this model, the maximum value is determined.

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \tag{1}$$

Equation (1) defines the real value as the value of n. The number represents the precision of the curve along the x and y axes. The charting process will employ point interpolation to differentiate the curve results from the x and y axes.

## IV. RESULTS AND DISCUSSIONS

Figure 2 displays purple sweet potatoes according to the illness segmentation prediction outcome. The healthy sweet potato (*ubi jalar sehat*) has a mean average precision (mAP) value of 0.94, while the ill sweet potato tuber rot (*ubi jalar sakit busuk umbi)* has a mAP value of 0.96. The segmentation findings obtained using YOLOv7 for the purple sweet potato are quite accurate. Purple sweet potatoes can be distinguished and classified based on their health status. The segmentation procedure is highly efficient, with preprocessing taking only 0.6 milliseconds, inference taking 59.8 milliseconds, and postprocessing taking 29.1 milliseconds per image. The speed of inference is a crucial factor in evaluating an object detection or segmentation model, as faster models can be more effectively utilized in real-time applications or with larger datasets.

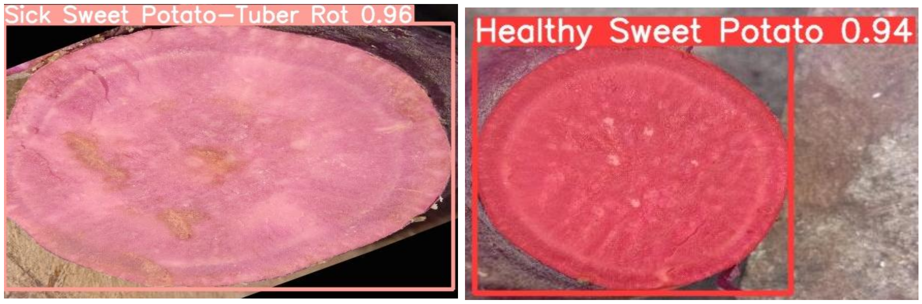


**Figure 2.** Prediction Result of Purple Sweet Potato Using YOLOv7

Figure 3 demonstrates that a lower loss value corresponds to a higher level of accuracy in the model's ability to accurately separate real items in the image. In contrast, a higher score on a metric measuring precision indicates that the model is better at producing segmentations that closely match the real item.

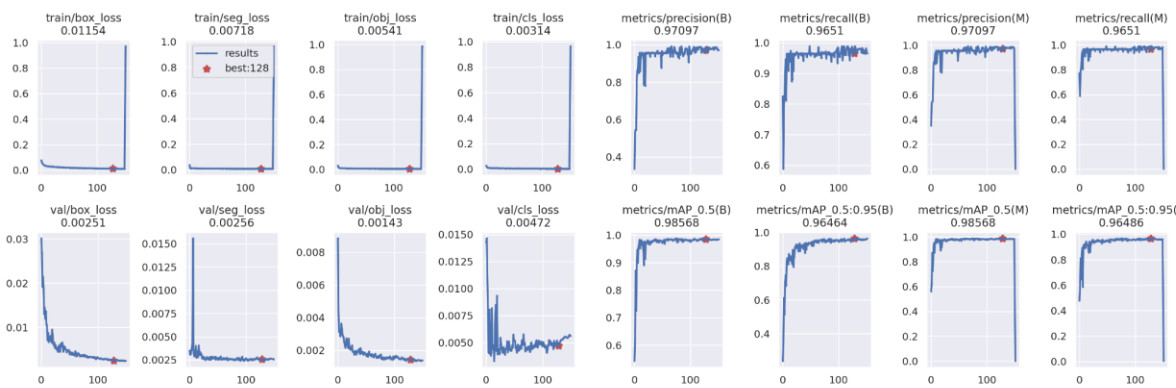


**Figure 3.** Accuracy and Loss Comparison Chart for the Purple Sweet Potato Model

The YOLOv7 instance segmentation model is trained and tested using a set of 640x640 pixel purple sweet potato photos that have been uploaded to Google Colab. Here, GPU T4 hardware acceleration and the Python 3 runtime type are employed. A restricted and free version of Google Colab was utilized by the researchers. Table 1 shows the experimental results of determining the optimal YOLOv7 model for segmenting disease purple sweet potatoes across 150 epochs.

**Table 1.** Result of Purple Sweet Potato Segmentation Training

| Class | Instances | Box and Mask | | |
|---|---|---|---|---|
| | | Precision | Recall | mAP50 |
| All | 107 | 0.971 | 0.965 | 0.986 |
| Healthy Sweet Potato(*Ubi Jalar Sehat*) | 63 | 0.984 | 0.953 | 0.961 |
| Sick Sweet Potato Tuber Rot(*Ubi Jalar Sakit Busuk Umbi*) | 44 | 0.958 | 0.977 | 0.986 |

The precision-recall calculation result is presented in Table 1, which compares the accuracy outcomes for individual classes and all classes collectively. The highest model accuracy achieved throughout the 150 training epochs was 0.986, based on the IoU (Intersection over Union) requirement of 0.49. The model's ability to reliably identify various items will be quantified and given as instances.

**Table 2.** Result of Earlier Research Methods Compared to The Proposed Method

| Research | Method | Object Detection | Object Segmentation | mAP / Accuracy |
|---|---|---|---|---|
| [17] | CNN | Sweet Potato Variety | - | 96,33% |
| [18] | YOLOv4-Tiny | Export Purple Sweet Potatoes | - | 99,15% |
| [19] | YOLOv4-Tiny | Fertilizer for Purple Sweet Potato (worm manure grade_a) | - | 0.69 or 69% |
| | | Fertilizer for Purple Sweet Potato (worm manure grade_b) | - | 0.55 or 55% |
| | | Fertilizer for Purple Sweet Potato (mineral grade_a) | - | 0.75 or 75% |
| | | Fertilizer for Purple Sweet Potato (mineral grade_b) | - | 0.69 or 69% |
| | | Fertilizer for Purple Sweet Potato (husk grade_a) | - | 0.69 or 69% |
| | | Fertilizer for Purple Sweet Potato (husk grade_b) | - | 0.55 or 55% |
| [20] | YOLOv4-Tiny | Sweet_Potato_Leaves (grade_a) | - | 0.79 or 79% |
| | | Sweet_Potato_Leaves (grade_b) | - | 0.67 or 67% |
| | | Papua_Sweet_Potato_Leaves (grade_a) | - | 0.70 or 70% |
| | | Papua_Sweet_Potato_Leaves (grade_b) | - | 0.40 or 40% |
| | | Cassava_Leaves (grade_a) | - | 0.82 or 82% |
| | | Cassava_Leaves (grade_b) | - | 0.35 or 35% |
| | | Cilembu_Sweet_Potato_Leaves (grade_a) | - | 0.75 or 75% |
| | | Cilembu Sweet Potato Leaves (grade_b) | - | 0.40 or 40% |
| Our Proposed | YOLOv7 | Healthy Sweet Potato and Sick Sweet Potato-Tuber Rot | | 98.6% |

In Table 2, It can be explained, that research has been done to classification varieties of sweet potatoes using the CNN algorithm resulting in an accuracy value of 96.33%. Then for three other researches performed object detection using the YOLOv4-Tiny algoritm have a value mAP up to 99.15%. In previous researches only detected objects have not done segmentation of objects. As a result, the researchers would use a variety of techniques, such as segmentation and YOLO but with a greater version, to raise mAP levels.

For this reason, the researchers proposed using YOLOv7 to perform disease segmentation on images of purple sweet potatoes.

## V. CONCLUSIONS

The researcher came to the conclusion that the segmentation model employed was highly accurate in identifying purple sweet potato disease based on the results of the segmentation test. The findings suggest that there is significant potential for assisting farmers in monitoring and controlling purple sweet potato disease. This discovery prompted further investigation into the application of image processing in the field of agriculture.

The study concludes that the segmentation of purple sweet potatoes created has a well-balanced variance, enabling the YOLOv7 approach to accurately detect purple sweet potato segmentation. The maximum results are achieved when the mean average precision (mAP) value of healthy sweet potatoes and sweet potatoes affected by tuber rot is 98.6%. The mAP value for healthy sweet potatoes is 96.1%, but for sweet potatoes affected by tuber rot, it is 98.6%. The precision of purple sweet potato segmentation outcomes achieved with YOLOv7 is highly satisfactory. Purple sweet potatoes can be distinguished and categorised based on their health status. During the segmentation process, the time required is relatively short. Specifically, the preprocessing step takes 0.6 milliseconds, the inference step takes 59.8 milliseconds, and the postprocessing step takes 29.1 milliseconds per image.

The successful use of YOLOv7 for purple sweet potato segmentation has enabled the accurate identification of sick objects. Furthermore, the model demonstrated high efficiency, characterised by quick processing times. This demonstrates significant promise in the surveillance of diseases in purple sweet potatoes.

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