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CHILI PLANT MONITORING SYSTEM USING YOLO OBJECT DETECTION TECHNOLOGY

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Abstract

Traditional farming in chili cultivation often needs help in monitoring plant conditions efficiently. Farmers generally use manual methods to identify pests and determine soil nutrient requirements, which are often inaccurate and time-consuming. This study aimed to improve the efficiency and productivity of chili cultivation by implementing smart farming technology using the YOLO (You Only Look Once) algorithm for real-time leaf pest detection. The method used is system development, which includes data collection, model training, and system performance evaluation. The test results showed that YOLO technology can identify pests with reasonably high accuracy, allowing farmers to take quick and precise action. The implementation of smart farming is expected to increase productivity, reduce losses due to pests, and support sustainable agricultural practices. The main contribution of this study was the development of a YOLO-based monitoring system that can support the efficiency of chili farming in Indonesia.

Keywords: Agriculture, Chile plants, Research and development, Smart farming, YOLO.

1. Introduction

Chili plants are vulnerable to pests like fruit flies, whiteflies, aphids, and mites, which harm growth and yield [1, 2]. Whiteflies can spread diseases like the yellow curl virus [3]. Traditional monitoring relies on manual observation, which is time-consuming and resource-intensive [4]. YOLO (You Only Look Once), a deep learning-based object detection method, offers fast, accurate real-time monitoring, making it ideal for precision agriculture [5-8]. YOLO is widely used in agriculture, but its application in monitoring chili plants in Indonesia remains under explored. Most studies focus on controlled environments, overlooking Indonesia's unique conditions that affect detection accuracy. Limited integration with sensor data like soil moisture and air temperature also hinders holistic farming systems. This research seeks to create a more integrated and scalable field-ready solution.

The advancement of computer vision technology, particularly in agriculture, positions YOLO as an efficient and accurate monitoring tool for addressing challenges in chili cultivation in Indonesia. Integrating YOLO into a smart agricultural system is expected to boost chili productivity, minimize pest-related losses, and promote sustainability in Indonesia's horticultural sector.

2. Research Method

This research uses the Research and Development method. Research and development methods comprise an array of techniques applied in various domains to propel knowledge forward, resolve issues, and foster innovation. Researchers in software engineering use systems development methodologies to participate in all phases of the research and development process [9]. Using qualitative research procedures, theory building entails moving from concept introduction to evaluation, necessitating appropriate research methods at each round [10]. Research and development steps consist of ten steps as follows: (i) potential and problems; (ii) data collection; (iii) product design; (iv) design validation; (5) design revision; (vi) product trials; (vii) product revisions; (viii) usage trials; (ix) product revisions; and (x) mass production [11]. However, due to time and resource limitations, this research only covers product trials without proceeding to the full implementation stage.

3. Results and Discussion

This stage includes collecting datasets from various sources, one of which is from the Kaggle website. This dataset comprises five classes: Healthy Chili, Leaf Curl, Yellowish, Whitefly, and Leaf Spot. To increase the accuracy of the model, this image was taken with different plant conditions and various viewpoints. Dataset labelling is the most important step before training the YOLO model. This labelling is the process of giving a bounding box and name labels according to class. This labelling process uses Rob flow as the labelling platform. It is also quite time-consuming because you have to label each image one by one. The dataset used consists of 479 images. This Dataset pre-training process includes data splitting, preprocessing, and data augmentation. Spilled data divides the images into a Train Set, a Valid Set, and a Test Set. Here, the researcher divides them into 92% for the Train Set, 4% for the Valid Set, and 4% for the Test Set. Then, data preprocessing will be carried out; in this case, the researcher will resize the image to be the same, namely 640x640. Next, data augmentation is carried out, namely increasing the amount of data by modifying the existing data. This augmentation can increase accuracy when carrying out the object detection process because the dataset is more varied. There are several common ways to augment data: flipping, cropping, and rotating. The number of images resulting from the data augmentation process, namely with images previously totalling 478 images, after the image augmentation process was carried out, became 1152 images.

The training process for this model uses 1152 images consisting of 5 classes: yellow virus, whitefly, curly leaves, leaf spots, and healthy chilies. Batch 16 and the optimizer Adam W. Produces Confusion using the following parameters. The accuracy of the normalized confusion matrix is around 80.2%. This proves that the results are excellent and accurate in detecting chili pests. Precision, recall, and F1 graphs resulting from the YOLO model training process with epoch 25, Batch 16, and using the optimizer Adam W. The image below shows a graph of the F1 score against the confidence value. From the training results obtained, the F1 score reached the highest average value of 0.50 against a confidence value of 0.355 (see Fig. 1).

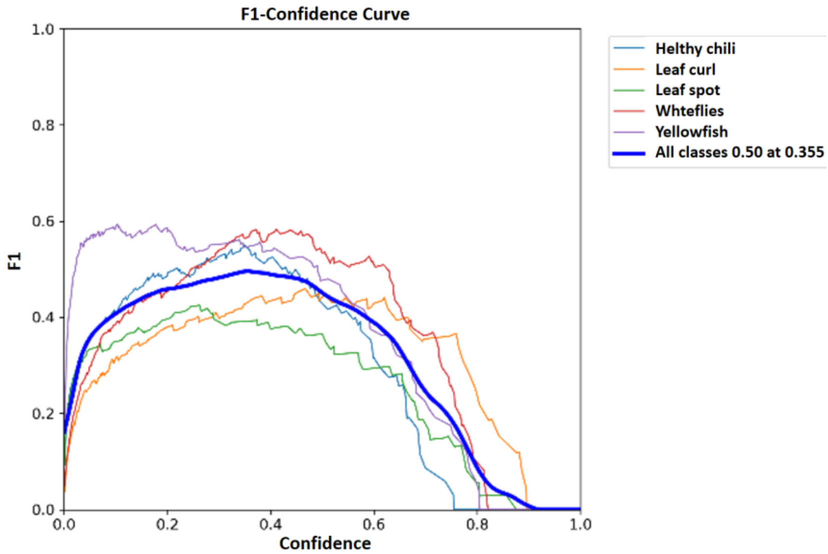

Fig. 1. F1-confidence.

Figure 2 is a graph of precision values against confidence values. From the training results obtained, the precision value produces a maximum average value of 1.00 against a confidence value of 0.910. Figure 3 shows a graph of the Recall value against the confidence value. From the training results obtained, the precision value produces a maximum average value of 0.83 against a confidence value of 0.00. Figure 4 is a graph of the Precision-Recall value against the confidence value. From the training results obtained, the precision-recall value produces a maximum average value of 0.469 with a mAP value of 0.5. The higher the mAP score, the better the performance you get. We tested real-time pest detection of chili plants using a web application and a cellphone camera using Droidcam, although this real-time test still has a delay, so it takes a little time. The results of direct detection can be seen in the image below (see Fig. 5).

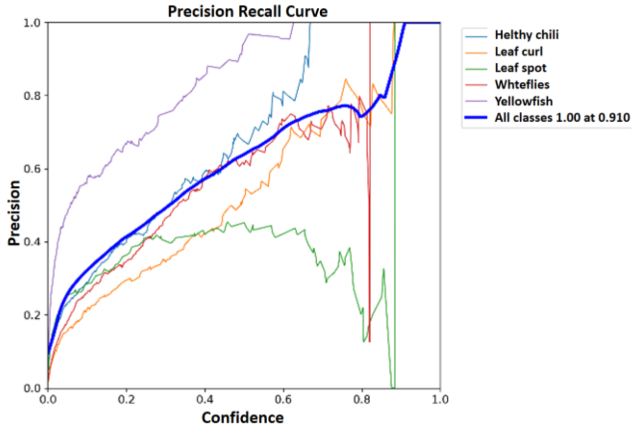

Fig. 2. Precision-confidence.

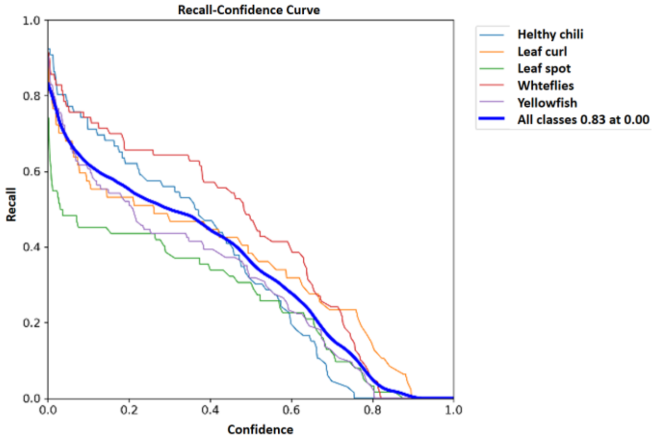

Fig. 3. Recall-confidence.

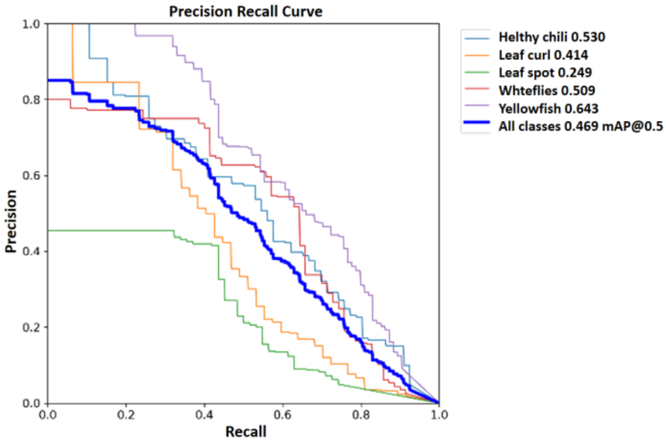

Fig. 4. Precision-recall.

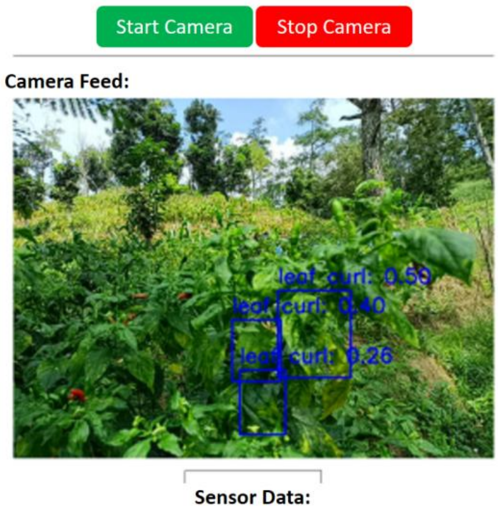

Fig. 5. Real-time detection results.

In Fig. 6, the resulting True Positive (TP) is 5, which is correct. All of them detect curly leaves, and the resulting False Positive (FP) is 0. The results of this test show an accuracy of 100%. In Fig. 7, the resulting TP is 6, which is correct. All of them detect healthy chilies, and the resulting FP is 0 (see Fig. 8). The results of this test show an accuracy of 100%. The result of TP is 3, which is correctly detecting whiteflies, and when the result of FP is 1, it is detecting leaf curl even though it doesn't. The results of this test showed an accuracy of 75% (see Fig. 8).

In Fig. 8, the resulting TP is 60, which is correct; all of them detect healthy chilies. The resulting FP is 2; namely, there is a bounding box that detects curly leaves even though it is not correct. The results of this test showed an accuracy of 97%. The following is a table that combines all the results from detection trials using the image upload method (see Table 1). Finally, this study adds new information in virtual laboratory as reported elsewhere [12, 13].

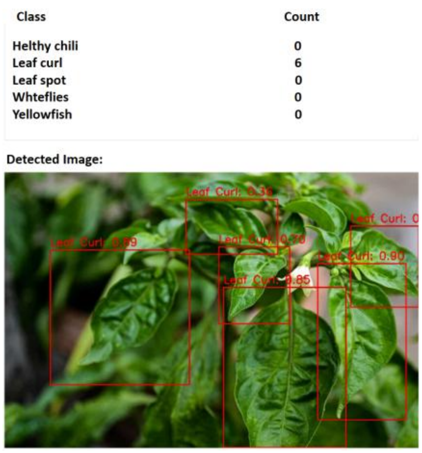

Fig. 6. Direct detection of sample image 1.

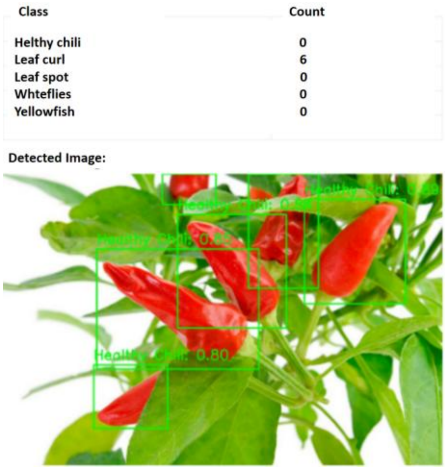

Fig. 7. Direct detection of sample image 2.

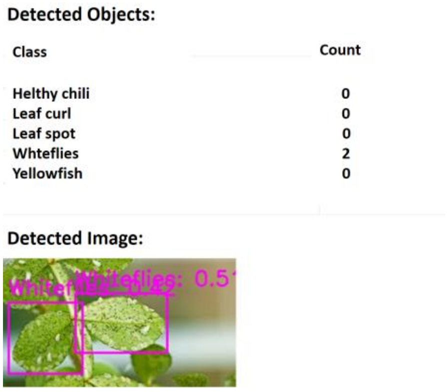

Fig. 8. Direct detection of sample image 3.

Table 1. Detection results data.

Class	Figure 1	Figure 2	Figure 3	Figure 4
Healthy chili	0	6	0	60
Curly leaves	6	0	0	3
Leaf spot	0	0	0	0
Whitefly	0	0	2	0
Yellow virus	0	0	0	0
Accuracy	100%	100%	100%	95%

4. Conclusion

This research designs a chili plant monitoring system using YOLO technology through the R&D method. The model demonstrated good accuracy in detecting pests and diseases, offering a more efficient and accurate alternative to manual monitoring. Its main contribution is enabling timely pest detection, reducing losses, and improving productivity. However, the study is limited to product testing, and future research is needed to implement the system on a larger scale in real-field conditio ns, integrate it with smart farming, and enhance the YOLO algorithm for broader pest detection and real-time data handling.

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