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YOLOv8 Based Object Detection for Chili Plant Diseases

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Abstract

Indonesia is classified as an agricultural country, where agriculture plays an important role in supporting national development and meeting the needs of the population. Among horticultural crops, cayenne pepper (Capsicum annuum L.) has high economic value and is an important source of income for farmers. Indonesia is also one of the largest chili consumer countries in the world. According to data from the Central Statistics Agency (BPS), national cayenne pepper production reached 1.55 million tons in 2022, an increase of 11.5% from 1.39 million tons in the previous year. However, the price of cayenne pepper can fluctuate significantly, often rising sharply when production declines. One of the main factors causing a decrease in yields is the prevalence of plant diseases such as curly leaves, leaf spots, and yellowing. These diseases greatly affect plant health and reduce the quality and quantity of the harvest. To answer this, this study aims to detect and classify diseases in cayenne pepper leaves using the YOLO (You Only Look Once) version 8 object detection algorithm. YOLO is a well-known computer vision model and is used to detect objects in real-time because it has speed and accuracy in identifying objects in images and video frames. With the application of YOLO, the types of diseases that attack chili plants can be identified accurately, so that monitoring and management of diseases can be carried out more effectively. The best level of accuracy obtained with YOLOv8 object detection has a large detection accuracy or mAP (Mean Average Precision) value of up to 0.887 or 88.7%.

Keywords– *YOLOv8, Leaf Disease, Cayenne Pepper, Object Detectio*

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1. Introduction

Indonesia is known as an agricultural country, meaning it relies on agriculture to support development and meet the needs of its population. Indonesia's agricultural sector is divided into sub-sectors such as food crops, horticulture, plantations, fisheries, livestock, and forestry (Ibrahim et al., 2022). Cayenne pepper (*Capsicum annuum L.*) is one of the vegetable horticultural plants that has a high economic value so that it can provide high income for farmers who cultivate it (Wehfany et al., 2022).

Chili is a plant that is needed by the community both as a cooking flavoring, a health plant, and even as a livelihood. Chili also contains nutrients that are very necessary for human health. Chili contains protein, fat, carbohydrates, calcium (Ca), phosphorus (P), iron (Fe), vitamins, and contains alkaloid compounds, such as capsaicin, flavenoids, and essential oils. The spicy taste of chili caused by capsaicin is useful for regulating blood circulation; strengthening the heart, pulse, and nerves; preventing flu and fever; raising spirits in the body (without narcotic effects); and reducing gout and rheumatic pain (Paulus A. & Ellen G., 2016).

Chili peppers have many uses in culinary and economic potential, because they can be processed into various types of chili-based seasonings such as chili paste, raw chili, dabu-dabu, green chili, and fried chili. These processed products are widely consumed and have become an important component in Indonesian cuisine. In addition, chili peppers are commonly used as a complement to various traditional Indonesian dishes, including rendang, fried rice, geprek chicken, fried noodles, soto, rawon, and many other regional spicy dishes throughout the archipelago. These extensive culinary uses highlight the importance of chili peppers not only in terms of agricultural value but also in culture.

Indonesian people are among the biggest chili consumers in the world. According to the Central Statistics Agency (BPS), the production of cayenne pepper in Indonesia was 1.55 million tons in 2022. This number increased by 11.5% compared to the previous year which was 1.39 million tons. From this data, it indicates that there are a lot of people interested in consuming cayenne pepper in Indonesia (Simbolon, n.d.).

The demand for chili for daily needs can fluctuate, which is caused by the rise and fall of chili prices that occur in the retail market. Price fluctuations that occur in the retail market, in addition to being caused by factors that affect the demand side, are also caused by factors that affect the supply side. From the supply side, it shows that the process of providing (production and distribution) chili has not been fully mastered by farmers (Paulus A. & Ellen G., 2016). The factors that cause the production of cayenne pepper plants to decline include low soil fertility, high water evaporation caused by air temperature and attacks by Plant Pest Organisms (Polii et al., 2019).

One of the causes of less than optimal cayenne pepper production is due to plant diseases. Some important diseases that attack chili plants include thrips (*Thrips parvispinus Karny*), fruit flies (*Bactrocera sp*), whiteflies (*Bemisia tabaci*), peach aphids (*Myzus persicae*), aphids (*Aphididae*), and mites (*Polyphagotarsonemus latus and Tetranychus*). Meanwhile, important diseases that attack chili plants include fusarium wilt (*Fusarium oxysporum*), ralstonia bacterial wilt disease (*Ralstonia solanacearum*), anthracnose fruit rot disease (*Collectrotichum gloeospoiroides*), yellow virus disease (*Gemini virus*), and leaf spot disease (*Cercospora sp.*) (Arsi et al., 2020).

Therefore, early detection of leaf diseases in cayenne pepper plants is very important to be carried out so that appropriate and effective control can be carried out. One method that can be used to detect leaf diseases in cayenne pepper is using the image classification method. This image classification method is used to categorize healthy chili leaves with chili leaves that are attacked by disease. From the images taken, one of the algorithms used in this method is YOLO or You Look Only Once.

You Only Look Once (YOLO) algorithm is a real-time object detection algorithm designed to identify and localize objects within images or video frames with high speed and accuracy. Unlike traditional detection methods that rely on sliding windows or region proposals, YOLO employs a single convolutional

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
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neural network (CNN) that simultaneously predicts object classes and bounding box coordinates. The detection system repurposes a classifier or localizer to perform detection by applying the model across various locations and scales within an image. The region with the highest confidence score is identified as the detected object. This unified architecture significantly reduces computation time while maintaining reliable detection performance. Due to its efficiency, YOLO is widely used in various fields, including agriculture, medical imaging, surveillance, and autonomous driving systems (Rachmawati & Widhyaestoeti, 2020).

The You Only Look Once (YOLO) algorithm is among the most widely used methods for object detection. It operates by dividing an image into a grid of smaller regions, where each region is then analyzed and classified into a specific object class. Over time, the YOLO algorithm has evolved through multiple versions, including YOLOv1, YOLOv2 (YOLO9000), YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7, and the most recent, YOLOv8. Each successive version introduces enhancements and optimizations to improve object recognition accuracy and computational speed. YOLOv8, in particular, demonstrates improved performance by delivering higher throughput and more efficient processing capabilities compared to its predecessors (Hussain, 2023).

YOLOv8 includes a new labeling tool called RoboFlow Annotate, which is used for image annotation and object detection tasks in computer vision. RoboFlow Annotate makes it easier to annotate images for training the model and includes several features such as auto labeling, labeling shortcuts, and customizable hotkeys. In contrast, YOLOv5 uses a different labeling tool called LabelImg. LabelImg is an open-source graphical image annotation tool that allows its users to draw bounding boxes around objects of interest in an image, and then export the annotations in the YOLO format for training the model (Reis et al., 2024).

. This research employs the YOLOv8 algorithm to detect and classify leaf diseases in cayenne pepper plants. The dataset used in this study includes multiple disease categories such as leaf spot, yellowing, curling, and healthy leaves which serve as indicators for assessing plant health in agricultural settings. The objective is to evaluate the extent to which the YOLOv8 model can be optimized for real-time object detection applications in this context.

2. Method

The method used is YOLO, (You Only Look Once) is a CNN-based algorithm that uses a single neural network approach to detect objects in images. This network can predict each bounding box using features from all images. It can directly predict the bounding box and probability in a single evaluation. The YOLO architecture is largely influenced by Google's LeNet backbone, which consists of a neural network consisting of 24 convolutional layers to perform feature extraction, followed by 2 FCNs (Fully Connected Layers) to predict bounding box coordinates and object class classification (Redmon et al., 2016).

This study specifically utilizes the YOLOv8 method for detecting and classifying leaf diseases in cayenne pepper plants. The research follows a structured workflow, starting with data acquisition, annotation, and splitting, followed by pre-processing and data augmentation. After these steps, the YOLOv8 model is configured and applied to the dataset. The final phase involves testing scenarios to evaluate the model's performance. This workflow, as illustrated in the diagram below, ensures a systematic approach to optimizing YOLOv8 for object detection.

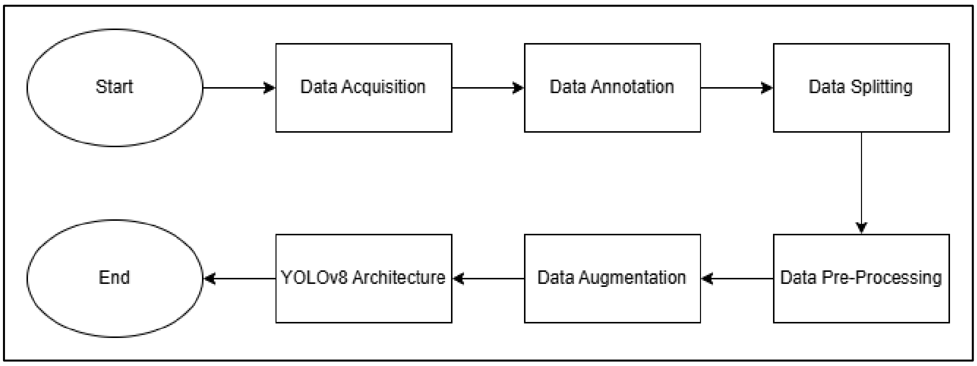


Figure 1. Research Workflow

a. Data Acquisition. The data acquisition process in this study involves obtaining a publicly available dataset sourced from the open-source platform

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
ISSN 2746 8208 (Online) and ISSN 2746 3575 (Print)

Kaggle. The dataset comprises chili leaf images categorized into four distinct classes: healthy, yellowing, curly, and leaf-spot. Each class represents a specific condition of the chili plant leaves, serving as the basis for classification and detection. The dataset is structured to support image-based learning, where each class contains a specific number of image samples, as detailed in the accompanying table or figure below.

Table 1. Number of image datasets

No	Leaf Disease	Amount Dataset
1	Leaf-Spot	120
2	Curly	110
3	Yellowing	140
4	Healthy	120
Total		490

b. Data Annotation. The data annotation process is a critical step in preparing the dataset for object detection tasks. In this study, annotation was carried out using the Roboflow platform, a widely used tool for labeling images in computer vision projects. Through Roboflow, each image was manually annotated by drawing bounding boxes around affected areas of chili leaves and assigning them to one of the predefined classes: healthy, yellowing, curly, or leaf-spot. This labeling process enables the YOLOv8 model to learn not only the class of each image but also the precise location of the diseased regions, which is essential for accurate detection and classification during model training and evaluation.

c. Data Splitting. The data splitting phase is essential to ensure that the model can be trained effectively and evaluated objectively. In this study, the dataset was divided into two main subsets: training data and testing data, with a ratio of 80% for training and 20% for testing. The training data is used to teach the YOLOv8 model to recognize and classify different types of chili leaf conditions, while the testing data is reserved to evaluate the model's performance on unseen images. This proportion is commonly used in machine learning to balance learning accuracy and generalization capability.

d. Data Pre-Processing. The data pre-processing stage in this study focuses on standardizing the image dimensions to ensure consistency during model training. Specifically, all images in the dataset were resized to 512 x 512 pixels. This resizing step is essential to match the input requirements of the YOLOv8 model and to maintain uniformity across the dataset. By using a fixed image size, the model can process data more efficiently and learn features more effectively, which contributes to improved accuracy in object detection and classification.
e. Data Augmentation. The data augmentation process was implemented to increase the diversity and volume of the training dataset, which helps improve the robustness and generalization ability of the YOLOv8 model. In this study, several augmentation techniques were applied, including horizontal and vertical flipping, as well as 90-degree rotations to the right and left. These transformations simulate various real-world conditions in which leaf orientations may vary, enabling the model to better recognize disease patterns under different perspectives. As a result, the total number of training images increased significantly, as shown in the table below, providing a richer dataset for model training.

Table 2. Dataset after Augmentations

No	Data	Before	After Augmentation
1	Train	392	1159
2	Testing	98	98
3	Total	490	1257

f. YOLOv8 Architecture. The architecture of YOLOv8, as illustrated in the diagram below, is composed of four main components: Backbone, Neck, Head, and Non-Maximum Suppression (NMS). The Backbone functions as the feature extractor, capturing essential visual patterns from the input image using deep convolutional layers. These features are then passed to the Neck, which serves to aggregate and refine multi-scale feature maps, enhancing the model’s ability to detect objects of various sizes. The Head processes these refined features to generate final predictions, including object class

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
ISSN 2746 8208 (Online) and ISSN 2746 3575 (Print)

probabilities and bounding box coordinates. Lastly, the NMS algorithm is applied to eliminate redundant or overlapping detections, ensuring that only the most accurate bounding boxes are retained. This modular architecture allows YOLOv8 to achieve high accuracy and real-time performance in object detection tasks.

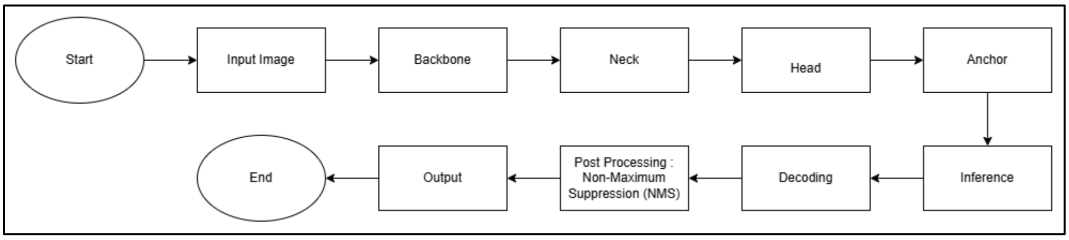


Figure 2. YOLO8 Architecture

In the YOLOv8 architecture, the object detection process begins with the input image, which is a pre-processed image resized to a standardized dimension (e.g., 512 × 512 pixels). This image is passed into the Backbone, a feature extraction network built using the CNN-C2f (Cross Stage Partial with Feedforward) structure. The C2f module enhances feature reuse and gradient flow while maintaining computational efficiency, allowing the model to extract rich and deep feature representations from the input. The extracted features are then forwarded to the Neck, which in YOLOv8 adopts a PAN-FPN (Path Aggregation Network – Feature Pyramid Network) design. This module merges feature maps from different scales, enabling the model to detect objects of varying sizes with improved spatial and semantic information integration. Next, the processed features are passed to the Head, which is responsible for generating detection predictions. It predicts bounding boxes, objectness scores, and class probabilities. YOLOv8 uses an anchor-free approach, eliminating the need for predefined anchor boxes and allowing the model to predict objects directly from feature maps. This contributes to faster computation and greater flexibility across different object types and sizes. During the inference phase, the model processes new, unseen images to produce detection results in real time. This involves decoding the raw outputs of the network into interpretable bounding boxes and class labels. After decoding, Non-Maximum Suppression (NMS) is applied to remove redundant and overlapping bounding boxes by retaining only the highest-confidence predictions. The final output consists of the coordinates of the detected objects, the associated confidence scores, and the predicted class labels such as healthy, yellowing, curly, or leaf-spot.

3. Result and Discussion

This section presents the results of the model training, including the evaluation metrics such as the confusion matrix and F1-score. The training process was conducted using the YOLOv8 model on the augmented dataset, with performance evaluated on the testing set. The confusion matrix provides a detailed breakdown of the model's predictions across the four classes—healthy, yellowing, curly, and leaf-spot—highlighting the number of correct and incorrect classifications for each category. From this matrix, important performance indicators such as precision, recall, and ultimately the F1-score are calculated. The F1-score represents the harmonic mean of precision and recall, offering a balanced measure of the model's accuracy, especially in cases of class imbalance. These metrics serve as a comprehensive evaluation of the model's effectiveness in detecting and classifying chili leaf diseases.

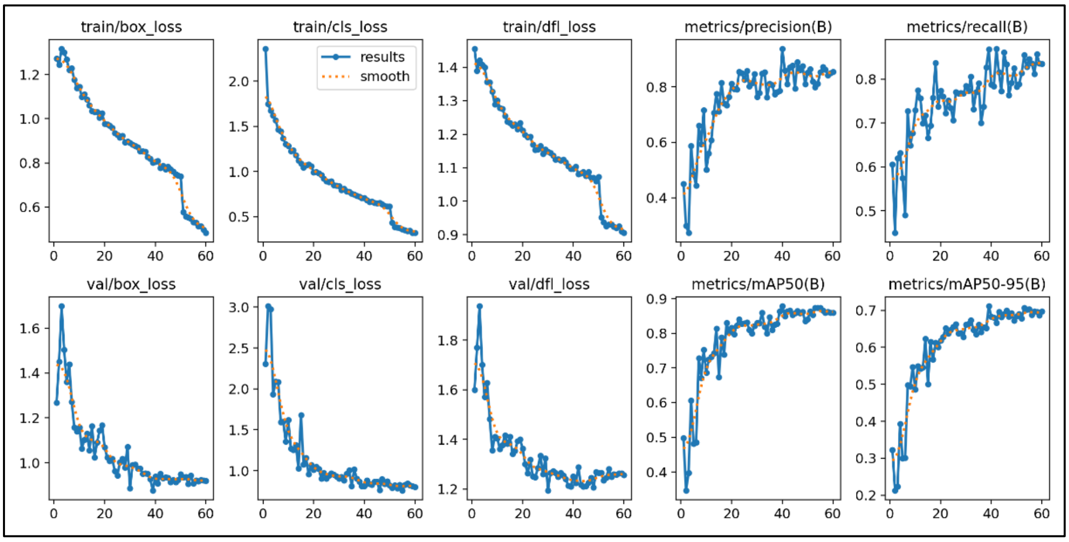


Figure 3. Data Training Result Graph

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
ISSN 2746 8208 (Online) and ISSN 2746 3575 (Print)

The figure above presents the training performance metrics of the YOLOv8 model over 60 epochs. The first row displays the training loss curves, which include box_loss, cls_loss, and dfl_loss. These losses show a consistent downward trend, indicating effective model learning and convergence during training. The same trend is observed in the validation loss plots shown in the second row, where losses also decrease steadily, confirming that the model generalizes well on unseen data.

The right side of the image illustrates the evaluation metrics, such as precision, recall, mAP50, and mAP50–95, which all show significant improvement over time. Precision and recall curves indicate increasing classification accuracy, while the mAP values reflect enhanced overall detection performance. The final metrics reached approximately 0.88 for precision, 0.85 for recall, 0.88 for mAP50, and 0.70 for mAP50–95, suggesting a well-trained and high-performing model.

A detailed summary of these results can also be seen in the table below, which provides numerical insights into the evaluation metrics obtained during the training process.

Table 3. Data Training Result

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
All	74	123	0.858	0.853	0.887	0.721
Leaf-spot	18	19	0.91	1	0.993	0.89
Curly	17	44	0.797	0.682	0.768	0.52
Yellowing	21	27	0.96	0.883	0.949	0.787
Healthy	18	33	0.764	0.848	0.838	0.687

The table above presents a detailed evaluation of the YOLOv8 model's performance in detecting and classifying chili leaf conditions across four classes: Bercak (leaf spot), Keriting (curly), Kuning (yellowing), and Sehat (healthy). Overall, the model achieved a precision of 0.858, recall of 0.853, mAP50 of 0.887, and mAP50–95 of 0.721 across all classes, indicating strong general performance.

Class-specific results show that the Bercak class attained the highest performance, with perfect recall (1.000) and very high precision (0.91), along with a mAP50 of 0.993 and mAP50–95 of 0.89, suggesting highly accurate detection. The Kuning class also performed well, with precision of 0.96, recall of 0.883, and high mAP values (0.949 and 0.787 respectively). In contrast, the Keriting class exhibited the lowest performance, particularly in recall (0.682) and mAP50–95 (0.52), indicating that the model had more difficulty detecting this type of leaf condition. The Sehat class achieved balanced results, with precision and recall values of 0.764 and 0.848, respectively, and a decent mAP50–95 of 0.687. These quantitative metrics provide a general overview of the model's classification performance for each class. To further analyze the distribution of correct and incorrect predictions in more detail, a confusion matrix is used, as it visually represents the model's ability to distinguish between each class.

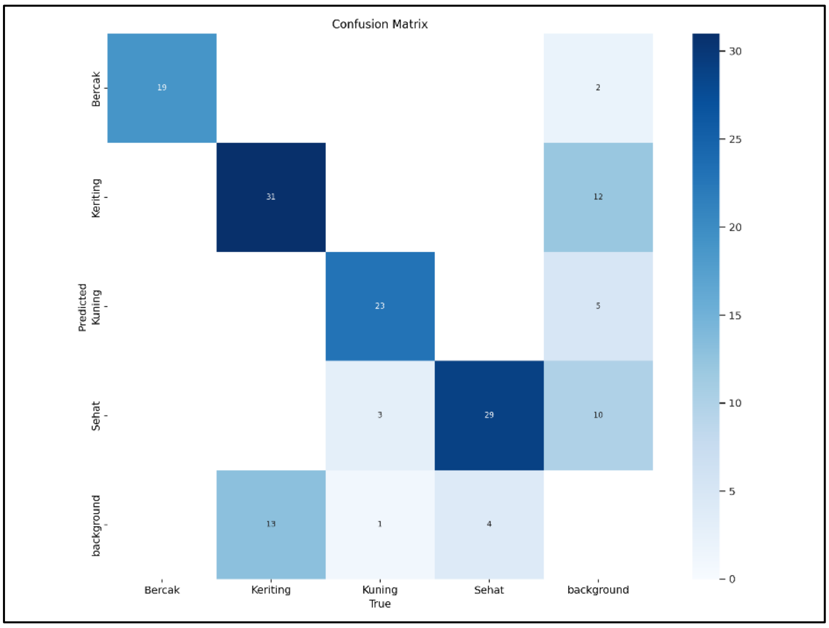


Figure 3. Confussion matrix

The confusion matrix above provides a detailed visualization of the YOLOv8 model's classification performance across the chili leaf disease categories. The diagonal elements represent the number of correct predictions for each class, while the off-diagonal elements indicate misclassifications. The model achieved perfect classification for the Curly class with 31 correct predictions. The Leaf-spot class was also predicted with high accuracy, yielding 19 correct predictions and only 2 misclassified as background.

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
ISSN 2746 8208 (Online) and ISSN 2746 3575 (Print)

For the Yellowing class, 23 instances were correctly identified, but 5 were misclassified as Healthy, showing some level of confusion between these visually similar conditions. The Healthy class had 29 correct predictions, though it also experienced misclassification, particularly with 10 instances predicted as background. Notably, the background class had the highest number of misclassifications into other categories, especially Curly (13 instances), suggesting the model occasionally struggles to distinguish background elements from actual leaf symptoms.

Overall, the confusion matrix reinforces the model's strong ability to identify certain classes while highlighting areas, particularly background separation and subtle symptom differences, where further improvement is needed. To complement the analysis from the confusion matrix, a more comprehensive metric is needed to evaluate the balance between precision and recall across all classes. Therefore, the F1-score is utilized to provide a harmonic mean of both metrics, offering a clearer picture of the model's classification performance.

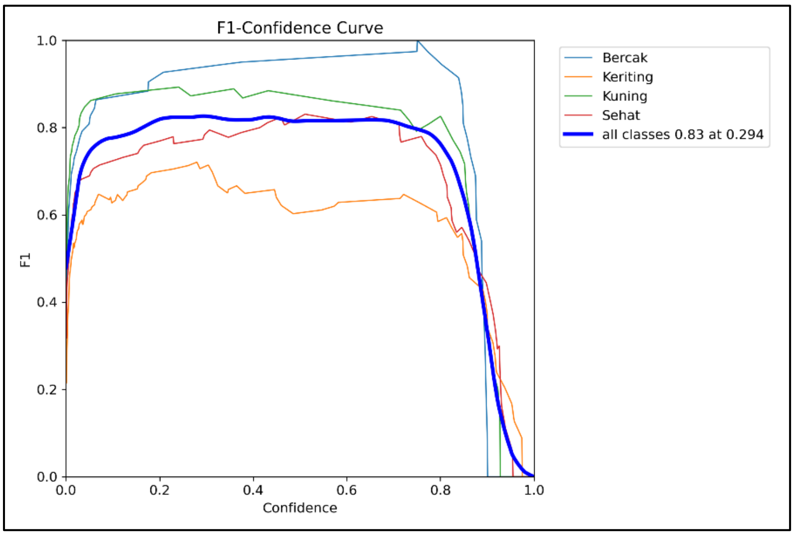
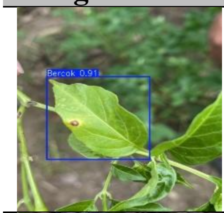
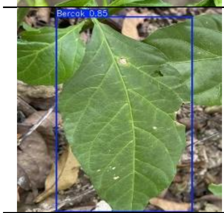
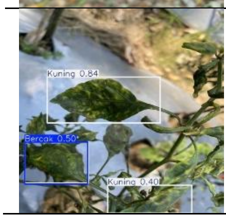


Figure 4. F1-Score

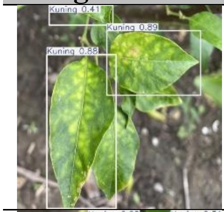
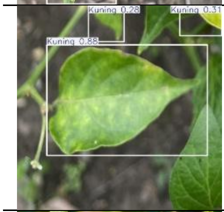
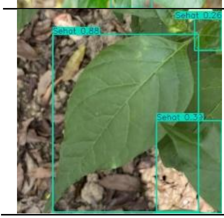
The F1-Confidence Curve shown above illustrates the relationship between the confidence threshold and the F1-score for each class in the chili leaf disease classification. The blue line, which represents the average across all classes, reaches a peak F1-score of 0.83 at a confidence threshold of 0.294, indicating the optimal balance between precision and recall for the overall model. Among the individual classes, the Leaf-spot class (light blue) consistently performs the best, achieving an F1-score close to 1.0 across a wide range of confidence values. The Curly class (orange), however, shows a lower and more fluctuating F1-score, reinforcing previous observations that this class is more challenging to detect accurately. Other classes such as Yellowing (green) and Healthy (red) maintain relatively stable F1-scores above 0.8, showing strong model performance.

These F1-score trends confirm the model's reliability in most categories, though improvements can still be made in handling more complex or ambiguous leaf symptoms. To further illustrate the model's capabilities, the next section will present visual examples of detection results on chili leaf images.

Table 4. Leaf Disease Detection

Image Name	Detected Label	Confidence Score	Real Object
	Leaf-spot	0.91	Leaf-spot
	Leaf-spot	0.85	Leaf-spot
	Leaf-spot	0.90	Leaf-spot
	Yellowing Leaf-spot	0.84 0.50	Yellowing

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
ISSN 2746 8208 (Online) and ISSN 2746 3575 (Print)

Image Name	Detected Label	Confidence Score	Real Object
	Yellowing	0.89	Yellowing
	Yellowing	0.88	Yellowing
	Curly	0.85	Curly
	Curly	0.89	Curly
	Curly	0.88	Curly
	Healthy Leaf-spot	0.73 0.30	Healthy
	Healthy	0.74	Healthy
	Healthy	0.88	Healthy

From a total of 12 test images used to evaluate the performance of the YOLOv8 model, 9 images were accurately detected and classified according to their true leaf condition. These results reflect the model's strong ability to identify various types of cayenne pepper leaf diseases, such as leaf spot, curly, yellowing, and healthy, under different lighting and visual conditions. The accurate detection across most test images confirms the effectiveness of the training process, including data augmentation, annotation, and model optimization.

In addition to those, 2 test images were also correctly classified, but the model predicted more than one class within the same image. Although the correct class was still included in the prediction results, the presence of additional classes indicates the model's sensitivity to visual features that may resemble symptoms from other categories. This could be caused by overlapping features, image noise, or the visual complexity of the leaf structure.

However, the model misclassified 1 image, where a curly leaf was incorrectly identified as healthy with a confidence score of 0.74. This misclassification suggests that in certain cases, especially where disease symptoms are subtle or not well-pronounced, the model may still struggle to distinguish between visually similar classes. These findings highlight the need for further improvements, such as adding more training data with diverse symptom variations or fine-tuning the model using misclassified examples to enhance its precision and robustness.

4. Conclusion

This research has successfully demonstrated the effectiveness of the YOLOv8 algorithm in detecting and classifying leaf diseases in cayenne pepper (Capsicum annuum L.). With Indonesia being one of the largest chili producers and consumers, maintaining the health of chili plants is crucial for food security and economic stability. Leaf diseases such as leaf-spot, yellowing, curly, and healthy conditions were selected as key classification targets, reflecting common challenges faced by farmers in the field.

The research followed a structured methodology involving data acquisition from Kaggle, manual annotation using Roboflow, data augmentation, and training the YOLOv8 model on a well-balanced dataset. The

Literasi Nusantara. vol.5 no. 3, July 2025 – October 2025
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model was evaluated based on metrics such as precision (0.858), recall (0.853), mAP50 (0.887), and mAP50–95 (0.721). The F1-Confidence Curve also highlighted consistent model performance, particularly for leaf-spot and yellowing classes. The confusion matrix further supported these findings, with high classification accuracy across most classes, although the curly class showed slightly lower performance, indicating the need for further refinement.

In the test phase involving 12 chili leaf images, 9 were correctly detected, 2 showed multi-label detections with the correct class included, and 1 image was misclassified. These results affirm the model's robustness and also underline opportunities for improvement, especially in handling visually ambiguous symptoms.

Overall, this research validates YOLOv8 as a powerful and real-time object detection tool for supporting early identification of plant diseases in the agricultural sector. Its integration in smart farming systems can help farmers take prompt action, reduce crop losses, and increase productivity. Future research may explore larger and more diverse datasets, real-field deployments, or the development of mobile applications to bring this solution closer to end-users in agricultural environments.

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