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Application of Yolov11 for Corn Plant Disease Detection Based on Leaf Images

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ABSTRACT

This study develops a corn leaf disease detection system using the YOLOv11 algorithm to overcome the limitations of manual identification, which is often subjective and slow. The dataset from Roboflow was converted to the object detection format with four classes (Leaf Spot, Blight, Rust, Healthy), annotated with bounding boxes, split in a 70:20:10 proportion, and optimized through preprocessing and data augmentation. The model was trained for 150 epochs, yielding an average precision of 0.785, a recall of 0.662, and an mAP@0.5 of 0.717 from 80 test images. The Healthy class performed superiorly (mAP 0.988), while the Leaf Spot class was the lowest (mAP 0.471) due to the variation of complex lesions. The confusion matrix confirmed prediction consistency. The main advantage is the detection of specific disease locations via bounding boxes, complementing previous classification approaches. This system has the potential to support automatic diagnosis and effective precision agriculture management.

Keywords: *YOLOv11, Corn Disease Detection, Computer Vision, Bounding Box, Precision, Recall, mAP@0.5*

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INTRODUCTION

Corn (*Zea mays L.*) is an agricultural commodity that plays a vital role in national food security and the Indonesian economy. As the second staple food crop after rice, corn not only serves as a primary carbohydrate source but is also an essential component in the animal feed industry and various processed food products (Hamsinar et al., 2019). The vast area of corn planting, spanning from lowlands to highlands, demonstrates the plant's adaptability to various agroecological conditions (Karim et al., 2020). Nevertheless, the potential productivity of corn, which should reach 8–12 tons per hectare, is often unmet (Statistik, 2025). This is mainly due to various biotic constraints, such as pathogenic disease attacks on the leaf organs, which are the center of photosynthetic activity. Agronomic challenges such as climate change and agricultural intensification also increasingly affect the stability of national corn production (Widianto et al., 2023). Despite these constraints, the latest data in 2025 shows an increase in the national corn harvest area to approximately 2.79 million hectares with a production potential of 16.55 million tons, an increase of about 9.34 percent compared to the previous year (HumasLIP, 2025).

Diseases in corn plants are one of the main factors hindering the achievement of optimal productivity (Wahyudi et al., 2025). Several important diseases such as leaf blight (*Bipolaris maydis*), leaf rust (*Puccinia polysora*), and leaf spot (*Cercospora zeae-maydis*) attack the leaf organs, which are the center of photosynthetic activity (Hendrayana et al., 2020). These attacks can significantly reduce the plant's ability to produce the energy needed for growth and development (Kurniawan et al., 2025). Disease attacks that are undetected or delayed in their handling can cause production losses of up to tens of percent, and may even trigger crop failure (Septian et al., 2021). Environmental factors and climate change support micro-conditions that are more suitable for pathogen growth and spread, making fast and accurate control very crucial (Wahyudi et al., 2025).

In conventional cultivation practices, the early identification of these important diseases still heavily relies on the visual ability and subjective experience of farmers or field officers (Widianto et al., 2023). This manual approach requires a relatively long time for diagnosis and is prone to identification errors. The limitation of competent human resources in central corn production areas often leads to delays in taking appropriate control actions (Yusuf et al., 2024).

In facing these challenges, the system is designed with YOLOv11. YOLOv11 is the latest evolution in the You Only Look Once (YOLO) framework, continuing the legacy started by YOLOv1. Formally introduced at the YOLOVision 2024 Conference (YV24), this model marks a significant advancement in real-time object detection technology. YOLOv11 specifically expands and refines the established architecture of YOLOv8 and YOLOv5 by introducing significant parameter optimization and architectural innovations. Its key features include the integration of highly advanced feature extraction techniques, which provide more detailed vision for diverse computer vision (CV) tasks. Furthermore, YOLOv11 has successfully achieved a substantial increase in processing speed, further enhancing its performance capabilities in real-time scenarios. The details of the key architectural modifications applied to YOLOv11 will be elaborated in the subsequent sections (Tappi & Dewi, 2025).

The purpose of this research is to develop and evaluate a YOLOv11-based model for detecting major corn leaf diseases to support precision agriculture. This system is designed to provide rapid, accurate, and efficient disease diagnosis by utilizing computer vision technology. Furthermore, this research aims to analyze the performance of the YOLOv11 model in terms of detection accuracy, data processing speed, and detection effectiveness under real-world field conditions. By achieving these goals, the ability to identify diseases is expected to become more objective, faster, and more accurate, supporting optimal and sustainable agricultural management.

METHOD

The research methodology is systematically structured to develop a plant disease detection model using the YOLO algorithm, covering stages from data collection to the implementation of the detection application. This research aims to provide an automatic and accurate solution for disease identification by leveraging the sophistication of deep learning methods. Each stage is carried out sequentially with a focus on data quality and model performance optimization so that the results obtained can be effectively applied in the field.

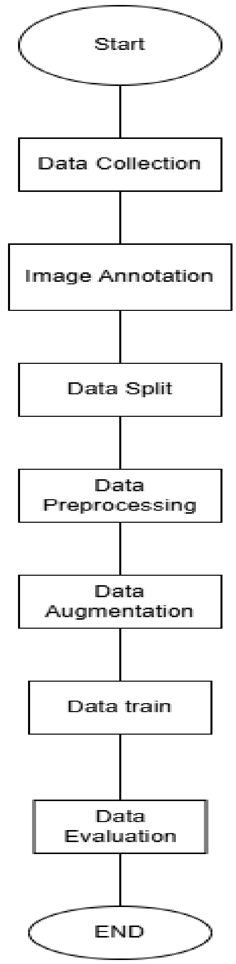

Figure 1 Flowchart System

A. Data Collection
   The corn leaf image dataset was obtained from the Roboflow platform, which provides data in the image classification format, where each image is placed in a folder based on its class, such as leaf spot, blight, rust, and healthy. To convert the classification format to the YOLOv11 object detection format, an automatic conversion was performed using a Python script that copies the images into a new directory structure and creates .txt label file for each image with the bounding box format. The final result is a dataset with an images/ and labels/ structure ready for use in object detection model training.
B. Image Annotation
   The image annotation stage involved giving labels and bounding boxes according to the type of disease in each image. Labeling was performed using Roboflow tools

during the image annotation stage. This process aims for the model to accurately understand the location and classification of the disease from the provided training data.

C. Splitting Data

In this stage, the annotated dataset is divided into three groups: training data, validation data, and testing data. The dataset splitting uses a 70:20:10 proportion.

D. Preprocessing Data

This stage includes resizing to 1024x1024, auto-contrast, and image orientation adjustment to ensure data consistency during training.

E. Augmentation Data

This stage aims to increase dataset variation so that the model can recognize diseases under different conditions and angles. The augmentations performed are image rotation, horizontal flipping, saturation, brightness, exposure, and noise.

F. Model Creation

The YOLO model creation is done by inputting the training data into the chosen YOLO architecture, YOLOv11. The model is trained using the backpropagation method with hyperparameter optimization for the learning rate, batch size, and epoch, which are set to obtain the best performance. During training, validation data is used to avoid overfitting and assess training progress. Hyperparameter tuning is performed iteratively to find the optimal configuration.

G. Model Evaluation

The evaluation stage is carried out to measure how well the model recognizes and detects diseases accurately. Evaluation is conducted using several key metrics, namely precision, recall, and mean average precision (mAP), and is analyzed using a confusion matrix to obtain a comprehensive picture of the model's performance.

Precision or exactness is calculated using the formula:

$$Precision = \frac{TP}{TP + FP}$$

where TP (True Positives) is the number of correct positive predictions by the model (disease correctly detected), while FP (False Positives) is the number of incorrect positive predictions by the model (the model flags a disease, but none exists). Precision measures the proportion of correct positive predictions out of all positive predictions made by the model. A high precision value indicates that the model rarely makes positive errors (false alarms)(A, Annisa Mustika; H, Teguh Iman; N, 2025).

Recall or sensitivity is calculated using the formula:

$$Recall = \frac{TP}{TP + FN}$$

where FN (False Negatives) is the number of false negative predictions (the model fails to detect a disease that is actually present). Recall describes the model's ability to capture all occurrences of the disease. A high recall value indicates that the model is able to detect most appearing diseases without omission (A, Annisa Mustika; H, Teguh Iman; N, 2025).

Mean Average Precision (mAP) is a metric that calculates the average precision across all classes and at various Intersection over Union (IoU). In this study, is used. mAP50 considers a prediction correct if the overlap between the predicted bounding box and the ground truth is at least 50%.

The formula for mAP at threshold t is:

$$mAP@t = \frac{1}{N}\sum_{i=1}^{N} \quad AP_i$$

where AP_i is the average precision for the i-th class dan N adalah jumlah kelas.

is the number of classes. Model evaluation is usually performed by plotting the precision-recall curve at various confidence thresholds and calculating the area under the curve for each class. With mAP50, the model is tested under minimal overlap conditions, providing a comprehensive view of the model's quality, which is more demanding and realistic for real-world applications (A, Annisa Mustika; H, Teguh Iman; N, 2025).

H. Implementation

In this stage, the plant disease detection application displays a simple interface with two main buttons and an image preview area using the tkinter library. When the user selects an image and presses the detection button, the program displays the analysis results in the form of an image with disease bounding boxes, the detected disease name, and the accuracy percentage. The display is clear and informative, showing the image filename and the detection confidence score, making it easy for users to visually and quantitatively understand the plant disease diagnosis results.

FINDING AND DISCUSSION

RESEARCH RESULT

The evaluation results of the plant disease detection model using YOLOv11 show that the model is capable of identifying four classes: Leaf Spot, Blight, Rust, and Healthy. With dataset containing 952 images The testing was conducted for 150 epochs. Overall, the model yielded an average precision of 0.785, a recall of 0.662, and an mAP50 value of 0.717. These findings indicate that the model has been able to recognize plant disease objects with a satisfactory level of success in most classes.

Table 1: Evaluation Results of Detection Model Performance for Each Class

Class	Precision	Recall	mAP50
Bercak	0.578	0.503	0.471
Hawar	0.765	0.591	0.702

Karat	0.839	0.615	0.706
Sehat	0.958	0.938	0.988
All	0.785	0.662	0.717

Based on the test results, the Healthy class is the best-performing class, with a precision value of 0.958, a recall of 0.938, and an mAP50 of 0.988. This indicates that the model is highly consistent in detecting healthy leaves. Meanwhile, the Leaf Spot class has the lowest performance value, namely a precision of 0.578, a recall of 0.503, and an mAP50 of 0.471. This difference illustrates the variation in visual characteristics between disease types that affect the model's ability to differentiate information patterns in each class. These results are consistent with previous research stating that variations in lesion texture and size are common challenges in plant leaf disease detection systems

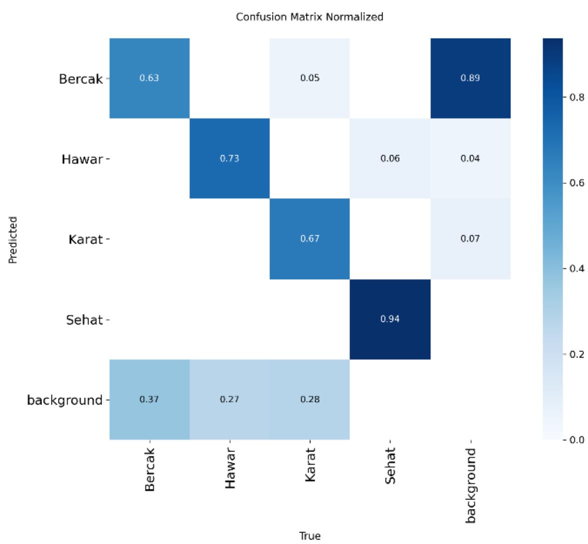

Figure 2 Confusion Matrix

The resulting confusion matrix shows the distribution of the model's predictions for all classes. In the normalized matrix version, the dominant diagonal pattern indicates that most instances have been correctly predicted by the model. The highest percentage is in the Healthy class, while most prediction errors occur in the Leaf Spot class. This information provides a more detailed picture of the model's classification patterns and can be used for further analysis related to the need for improvements, such as dataset balancing or the addition of specific augmentation for certain classes.

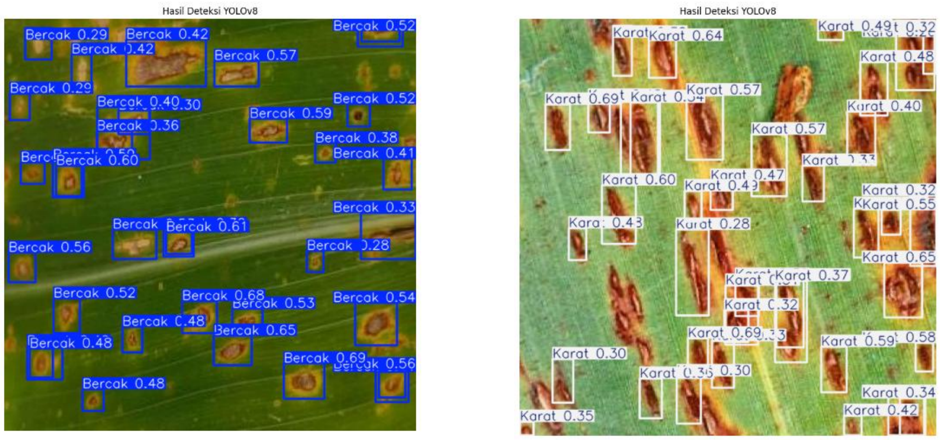

Figure 3 Evaluation Results

Overall, these findings indicate that the YOLOv11 model trained in this study has been able to perform leaf disease detection effectively and specifically with competitive mAP values. The visualization of the detection results on the test images also shows that the model can provide bounding boxes along with the appropriate labels. The results obtained support the use of the YOLO-based object detection model as a potential approach to support an automated plant disease diagnosis system.

DISCUSSION

The evaluation results of the corn leaf disease detection model using YOLOv11 show good identification capability for the four main classes: Leaf Spot, Blight, Rust, and Healthy. The average precision value of 0.785, recall of 0.662, and mAP50 of 0.717 indicate that the model is quite effective in classifying and detecting the specific presence of the disease in the infected leaf area. The best performance in the Healthy class shows the model is highly consistent in recognizing uninfected leaves, while the lower performance in the Leaf Spot class suggests that the visual pattern is more complex for this type. The specific location of the disease successfully detected with bounding boxes by the model allows for targeted control actions, increasing efficiency in optimal plant disease management.(Daffa Nazmi Alwan et al., 2024)

This research contributes to the development of a corn plant disease detection system with an approach that not only classifies the type of disease but is also able to identify the specific location of the infection on the leaf. Several previous studies, such as those conducted by (Sulistiyana & Anardani, 2023) focused more on disease classification without including information about the position of the lesion on the leaf, thus being limited to the recognition of the overall infected condition. The research by (Daffa Nazmi Alwan et al., 2024) achieved a high accuracy of 93%, but the ability to detect the location of the disease was not specifically optimized. Meanwhile, the study by (Yusuf et al., 2024) was also effective in distinguishing between infected and healthy conditions, but did not complement it with spatial information regarding the location of the disease. Thus, this research attempts to complement these approaches by adding a precise disease location detection feature using YOLOv11, which is expected to provide additional benefits in more focused and efficient plant disease management applications in the field.

This research has successfully developed and evaluated a YOLOv11-based corn leaf disease detection model with promising results; however, there are several limitations that need to be considered. Firstly, model testing was carried out on a relatively limited dataset with controlled image acquisition conditions, thus the variability of field environments such as changing lighting, diverse camera angles, and extreme weather conditions were not fully covered. Secondly, although the model is capable of detecting four main disease classes, the detection capability for disease symptoms at very early stages or for very small lesions can still be improved. Thirdly, this study has not conducted extensive validation on different local corn varieties across various regions in Indonesia, which may affect the model's generalization. Fourthly, real-time evaluation on mobile devices or edge devices in the field has not been thoroughly performed, so the model's performance in practical use conditions by farmers still requires further testing. These limitations form an important basis for future research development so that the system can be applied more widely and reliably.

The success of specific corn leaf disease location detection with YOLOv11 opens a real opportunity for the development of computer vision-based mobile applications that can be used directly by farmers in the field for fast and targeted diagnosis. Recommendations for disease control based on spatial data can increase the efficiency of pesticide use, reduce production costs, and significantly increase yield productivity. Further research is recommended to enhance model robustness through more diverse data augmentation and the integration of multispectral imaging technology to detect disease symptoms at very early stages. On the other hand, collaboration with agricultural agencies and drone technology providers can accelerate the implementation of automatic corn area surveillance systems on a large scale, which has the potential to enhance national food security and support sustainable agriculture (Mohti et al., 2024)

CONCLUSION

Based on the research results, the YOLOv11 model successfully detected and localized four corn leaf conditions (Leaf Spot, Blight, Rust, and Healthy) with competitive performance. The mAP50 value of 0.717 indicates the model's ability to balance classification accuracy and localization precision at an IoU threshold of 50%. The model showed the highest consistency in identifying healthy leaves (high precision), but faced challenges in the Leaf Spot class, which has more complex and varied visual characteristics. The primary strength of this research lies in its ability to generate bounding boxes that precisely delineate the specific location of the disease on the corn leaves. This feature overcomes the limitations of traditional classification approaches, which merely identify the presence of the disease without providing spatial location information. The high accuracy of the bounding boxes directly enables the implementation of localized pesticide or fungicide application (spot treatment) . By applying chemical inputs only to the detected diseased areas, the system effectively reduces overall agricultural chemical usage, minimizes operational costs, and supports more environmentally friendly and sustainable farming practices.

Suggestions for further development, especially for improving model performance in the Leaf Spot class, include the enrichment of the dataset with more varied examples of leaf spot symptoms at different developmental stages, including early, vague symptoms. Exploration of specific data augmentation techniques such as simulating extreme lighting changes, adding noise resembling water splashes or dust, and geometric transformations that mimic camera angles in the field can increase model robustness. Additionally, fine-tuning hyperparameters with a focus on optimizing anchor boxes suitable for the relatively small size of leaf spot lesions has the potential to increase recall.

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