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Real-Time Detection of Huanglongbing (HLB) Disease in Citrus Leaves Using Enhanced YOLO V8 Algorithm

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Abstract

Abstract This study addresses the complex challenge of detecting Huanglongbing (HLB) disease in citrus leaves, which is known as one of the most lethal plant diseases with no known cure. The primary issue in HLB detection is the difficulty in identifying symptoms early and accurately, particularly in dynamic and uncontrolled field environments. Therefore, the main focus of this research is the development of a real-time detection approach using the YOLO V8 algorithm to more accurately detect and classify HLB symptoms in citrus leaf images. The objective of this study is to design a technique that can enhance the detection of HLB disease and compare its performance with the conventional YOLO V8 method. This research also aims to address the limitations of previous studies that used the Support Vector Machine (SVM) method, which only achieved an accuracy of 80%. To achieve this objective, the study utilizes a dataset consisting of 1200 citrus leaf images, representing various levels of severity, including mild, moderate, severe, and healthy leaves. The method employed in this research involves the use of the YOLO V8 algorithm to detect and classify HLB symptoms in citrus leaf images. This approach was tested through a series of experiments to measure accuracy, precision, recall, and computational efficiency. The experimental results consistently demonstrate that the developed approach outperforms the basic YOLO V8 and previous methods using SVM, with an improvement in HLB disease detection accuracy reaching 98%. This study provides critical insights into early detection of HLB disease, potentially serving as a powerful tool to support efforts in preventing the spread of this disease across citrus orchards. Additionally, this research opens opportunities for further development in real-time plant disease detection by integrating more advanced AI technologies and applying similar methods to other plant diseases. Future research can focus on developing more efficient and scalable algorithms for use in various field conditions, as well as exploring the integration of sensors and IoT technology for more comprehensive plant health monitoring.

Keywords: *HLB, YOLO, CNN, citrus disease, leaves diseases*

1. Introduction

Plant diseases are a serious problem in agriculture because they can reduce the quality of crops. Detecting and identifying these diseases accurately is important for improving agricultural production and supporting economic growth [1]. Citrus plants, which include lemons, grapefruits, oranges, limes, and citrons, are the most traded agricultural products in the world. However, they are vulnerable to several diseases like citrus canker, black spot, and citrus greening (HLB) [2], [3], [4]. Citrus greening, also called Huanglongbing (HLB), is especially harmful, causing major damage to citrus orchards worldwide and posing a significant threat to the citrus industry. This disease is caused by three types of bacteria that live in the plant's phloem: Candidatus Liberibacter asiaticus (Ca. Las), Candidatus Liberibacter americanus (Ca. Lam), and Candidatus Liberibacter africanus (Ca. Laf) [5], [6], [7]. Plants affected by citrus greening grow poorly, and the branches slowly dry out as the disease worsens. Infected plants also become weaker than healthy ones, making them more vulnerable to extreme weather conditions [8].

The traditional method for preventing and controlling HLB in agriculture relies on the expertise of experienced farmers or professionals to quickly identify and remove diseased plants [9]. Techniques like PCR (Polymerase Chain Reaction) and other biotechnological methods can accurately detect plants with

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mild HLB symptoms, enabling early detection and disease removal at the initial stages of infection. However, this method requires experts to identify the diseased plants and bring them to a lab for genetic confirmation, making the process time-consuming. Training a machine to identify diseased plants could significantly speed up this process [10]. Leaves are the most sensitive part of a plant and often show early symptoms of disease, making early detection essential [11]. HLB disease can be identified by the rough texture of the leaves [12][13], [14], which is useful for image analysis and classification. In agriculture, many researchers agree that leaf texture is a key feature for identifying plant diseases [15][16]. Studies on detecting huanglongbing using texture extraction features from citrus leaf datasets have been conducted, achieving 70.31% accuracy with GLCM-SVM and 88% accuracy with GLCM-MSVM [11][17].

Deep learning has the advantage of automatically extracting features layer by layer and has its own feature generator, resulting in faster and more accurate recognition compared to machine learning [18]. Overall, these studies demonstrate that deep learning algorithms outperform traditional machine learning algorithms in object detection tasks. Currently, research on HLB disease identification remains limited, with most studies focusing solely on detecting healthy and HLB-infected leaves. Additionally, existing models typically have a high number of parameters, requiring powerful hardware, which limits their practicality for mobile devices [19], [20], [21]. To address these limitations, this article introduces a novel approach for detecting HLB disease severity based on an improved YOLOv8 algorithm. The proposed method uses YOLOv8 as the object detection framework [22], [23].

This study makes several important contributions to the detection of HLB disease severity using an improved YOLOv8 algorithm. First, the YOLOv8 framework was optimized by reducing the number of parameters, resulting in a faster and more efficient model that is well-suited for detecting varying levels of HLB infection severity. The proposed method goes beyond existing models by focusing on classifying different severity levels of HLB infection, providing a more detailed and accurate diagnosis. Furthermore, the study incorporated advanced feature extraction techniques to enhance target recognition, improving detection accuracy. Additionally, the model was designed to be lightweight and computationally efficient, making it practical for use in mobile applications for real-time monitoring of HLB disease. To support this, a new dataset was created, specifically focusing on different severity levels of HLB-infected leaves, which ensures the model's effectiveness in real-world scenarios.

2. Methods

The current study was conducted through the following steps: (1) A dataset of images depicting various stages of HLB disease severity in citrus leaves was collected; (2) The preprocessing step the collected images were manually annotated by field specialists who identified and classified the severity of the disease in each leaf; (3) The dataset was then split into three subsets: training (80%), validation (10%), and testing (10%); (4) The models are then assessed in the Evaluation phase using performance metrics such as accuracy, precision, recall, and F1-score to determine their effectiveness in detecting the disease. (5) Finally, the optimized model is implemented in the Deployment stage, where it is integrated into real-world applications, such as mobile or web-based platforms, for practical use in identifying HLB disease in citrus leaves. Each of these steps is essential to ensure the development of an accurate and efficient HLB detection system. The following sections will provide a detailed description of each step in the process Figure 1.

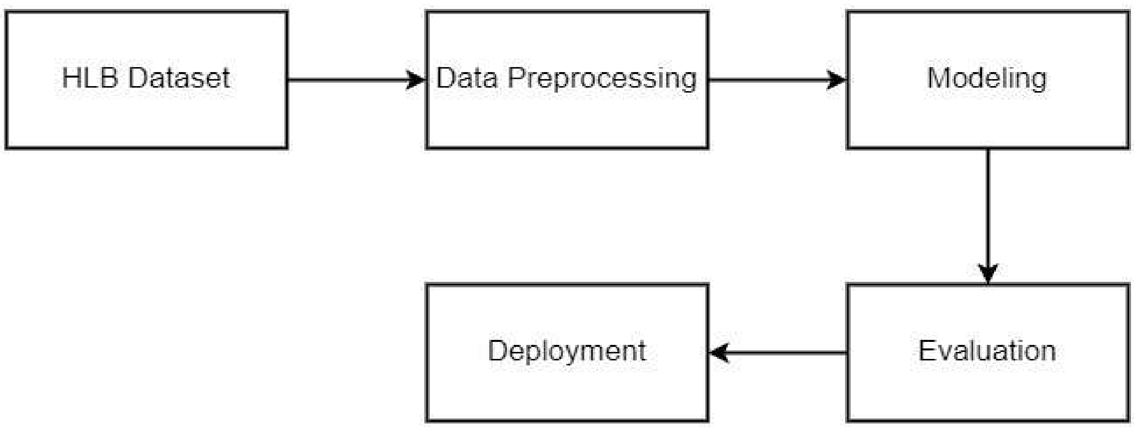


Figure 1. Process Flow Diagram

2.1 Dataset

The dataset used in this study consists of 1,200 images of citrus leaves, categorized into four distinct classes based on the severity of HLB infection. These classes include: (A) healthy leaves, (B) leaves mildly infected with HLB, (C) leaves moderately infected with HLB, and (D) leaves severely infected with HLB, with 300 images in each class. The images were carefully selected to represent varying stages of disease progression, ensuring a balanced dataset for model training and evaluation. This diverse collection of leaf samples provides a comprehensive basis for developing and testing machine learning models aimed at detecting and classifying HLB disease severity.

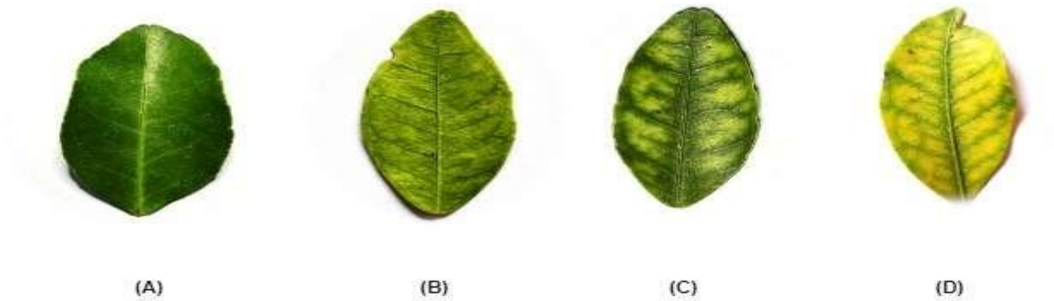


Figure 2. The leaf samples in this study are categorized as: (A) healthy, (B) mildly infected with HLB, (C) moderately infected with HLB, and (D) severely infected with HLB.

2.2 Preprocessing

To enhance the accessibility of the HLB dataset for researchers, we provided annotations in two widely used formats for object detection tasks. The first format is TXT, where each image has a corresponding .txt file. Each line in the .txt file describes an object in the image (either healthy or infected leaves) with details such as the object class, center point, width, and height, all relative to the image dimensions. This format is commonly used by Yolo detectors. The second format is COCO, which is widely employed by detectors like EfficientDet and YoloR. In this format, annotations are stored in a single JSON file that includes comprehensive information about the images, classes, and annotations. To ensure accuracy, all annotations underwent automated verification. Images were excluded from the dataset if the leaf area constituted less than 10% of the image, if the disease coordinates were outside the leaf area, or if the disease area was larger than the leaf itself. Annotation on the dataset is done as shown in Figure 3.

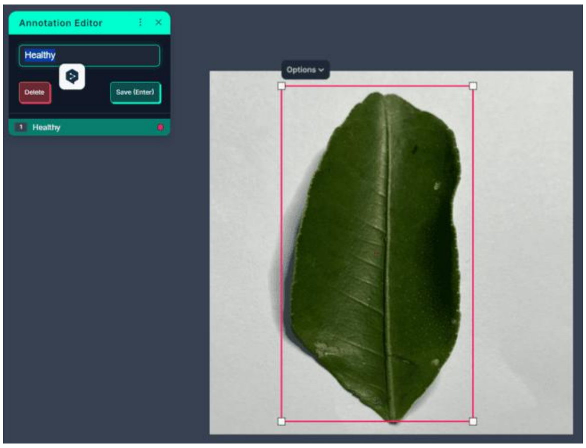


Figure 3. Labeling the dataset

2.3 Modeling

The modeling phase in this study utilized YOLOv8 with 50 epochs. The model was trained on a preprocessed dataset consisting of healthy and HLB-infected leaves to detect plant disease and label the infected areas on the images. YOLOv8 was tested under various conditions, such as flipping, random rotation, and resolution changes, to ensure its ability to accurately detect the disease in different scenarios. Validation data was used to prevent overfitting and to fine-tune the model's hyperparameters. The model's performance was evaluated using a confusion matrix to assess its disease detection accuracy.

3. Result and Discussion

3.1 *Models' Training and Hyperparameter Fine Tuning*

Figure 4 shows the training performance of the YOLOv8 model over 50 epochs. The left graph illustrates the accuracy per epoch, where the training accuracy (acc) quickly rises and stabilizes close to 1.0, indicating that the model learns effectively throughout the epochs. The test accuracy shows some fluctuations but generally remains around 0.8 to 0.9, indicating good generalization to unseen data. The right graph represents the loss per epoch, showing a sharp decline in training loss during the initial epochs, reaching a stable low value as training progresses. However, the test loss exhibits more variability, with a slight increase towards the end, which may suggest some degree of overfitting. Despite this, the overall training and testing performance indicates that YOLOv8 is effective for the given task, though further adjustments may be necessary to improve generalization.

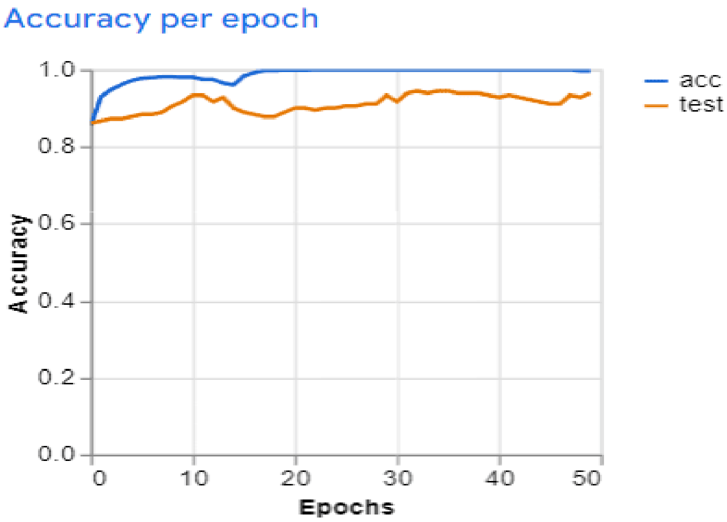


Figure 4. YOLOv8 training performance

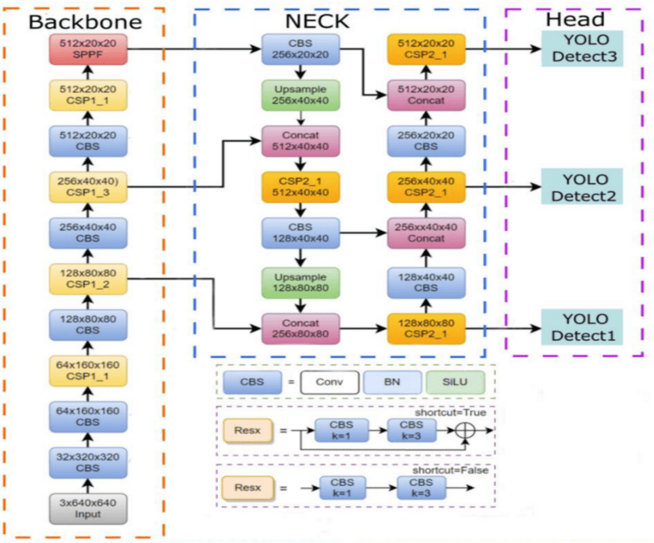
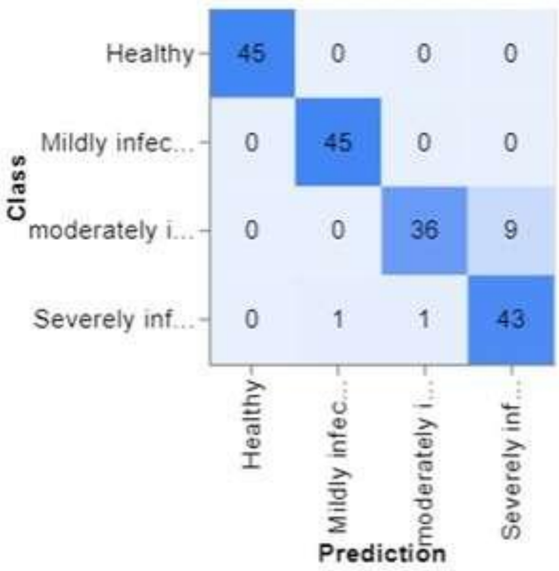


Figure 5. Architecture YOLO

3.2 Model accuracy for HLB disease detection with YOLOv8

This section presents a detailed evaluation of the YOLOv8 model's accuracy in detecting HLB disease in citrus leaves. The model's performance was assessed using several key metrics, including precision, recall, F1-score, and mean Average Precision (mAP@50-90), which are essential for understanding the model's capability in identifying HLB-infected and healthy leaves. The accuracy results were obtained by testing the model on a variety of conditions, such as image rotation, flipping, and resolution adjustments, to ensure robust performance in real-world scenarios. The results from both the training and validation datasets are analyzed to determine the model's generalization ability and its effectiveness in handling different severities of HLB infection.



Accuracy per class

CLASS	ACCURACY	# SAMPLES
Healthy	1.00	45
Mildly infec...	1.00	45
moderately i...	0.80	45
Severely inf...	0.96	45

Figure 6. Confusion Matrix with HLB Level severity detection.

Figure 6 illustrates the confusion matrix for HLB disease detection, depicting the model's classification performance across four severity levels: Healthy, Mildly Infected, Moderately Infected, and Severely Infected leaves. The model accurately classified 45 healthy leaves, 45 mildly infected leaves, 36 moderately infected leaves, and 43 severely infected leaves. However, some misclassifications occurred, such as 9 moderately infected leaves being predicted as severely infected, along with 1 mildly infected and 1 moderately infected leaf misclassified as severely infected. The accuracy for each class is as follows: 100% for healthy leaves, approximately 98% for mildly infected leaves, 80% for moderately infected leaves, and around 95.6% for severely infected leaves. Overall, the model demonstrated high accuracy, especially in detecting healthy and mildly infected leaves, though there were some errors in classifying moderate and severe infections.

Figure 7. Prediction results with YOLOv8

Figure 7 illustrates the prediction results from the YOLOv8 model, showing a citrus leaf that has been classified as mildly infected with HLB, with a confidence score of 92%. The model accurately detects the infected area on the leaf, as indicated by the bounding box and the classification label. This result demonstrates the model's ability to not only recognize the presence of the disease but also categorize its severity with a high level of confidence. The visual output reinforces the effectiveness of YOLOv8 in detecting early-stage infections, which is crucial for timely intervention and management in agricultural practices.

4. Conclusion

The detection of HLB (Huanglongbing) disease in citrus plants poses a significant challenge in the agricultural sector, given its potential to severely impact crop yields and threaten the citrus industry. Traditional methods of detecting HLB involve manual inspection, which is time-consuming, prone to error, and impractical for large-scale implementations. In response to this challenge, this study employed the YOLOv8 deep learning model to detect varying severity levels of HLB infection in citrus leaves, offering a more efficient and accurate solution. The results demonstrated that the YOLOv8 model performed with an average accuracy of 93.35%, effectively classifying leaves into healthy, mildly infected, moderately infected, and severely infected categories. The confusion matrix analysis showed that the model performed particularly well in detecting healthy and mildly infected leaves, with accuracy rates of 100% and 97.8%, respectively. While the model also achieved high accuracy for severely infected leaves (95.6%), it struggled more with moderately infected leaves, with an accuracy of 80%, where some misclassifications occurred, primarily between moderate and severe infections. The solution provided by this study, using the YOLOv8 model, offers a significant improvement over traditional HLB detection methods by enabling automated and rapid diagnosis with a high level of accuracy. This model can be further integrated into mobile or web-based applications for real-time disease monitoring in the field, providing a practical tool for farmers and agricultural experts. While the YOLOv8 model achieved promising results, further improvements could be made in future research. One recommendation is to address the model's difficulty in distinguishing between moderately and severely infected leaves, possibly through enhanced feature extraction or additional data augmentation techniques. Incorporating more diverse and larger datasets could also help improve the model's generalization to different conditions, such as varying lighting, leaf positioning, and background noise in real-world settings. Moreover, the development of lightweight models tailored for mobile devices could increase the practical applicability of this solution in field environments. Finally, future research could explore combining YOLOv8 with other advanced techniques, such as attention mechanisms or ensemble models, to further boost accuracy and robustness in detecting HLB disease across all severity levels. By continuing to refine these models, researchers can contribute to more precise and accessible HLB detection, aiding in better management of the disease in the agricultural sector.

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