DOI: 10.21917/ijdsml.2025.0175

ENHANCED LEAF DISEASE SEGMENTATION USING A NOVEL YOLOV8-BASED FRAMEWORK FOR PRECISION AGRICULTURE

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Abstract

Accurate segmentation of leaf diseases is critical for early detection and treatment in precision agriculture. Traditional segmentation techniques often suffer from poor generalization, noise sensitivity, and reduced accuracy when dealing with complex backgrounds or overlapping disease regions. Existing deep learning-based approaches, while powerful, face limitations in balancing detection speed and segmentation precision. YOLOv8, though robust for object detection, requires adaptation for fine-grained segmentation of irregularly shaped leaf disease spots. This work introduces a novel YOLOv8-based segmentation framework optimized for leaf disease identification. The proposed method integrates an improved feature pyramid network with multi-scale attention mechanisms to capture disease patterns across varying sizes and textures. Data augmentation strategies, including random cropping, color jittering, and background normalization, are employed to improve robustness. Post-processing using contour refinement ensures accurate boundary detection of diseased regions. Experimental evaluation on a benchmark plant disease dataset shown a mIoU improvement of 6.4%, Dice coefficient increase of 5.8%, and detection speed of 38 FPS, compared to baseline YOLOv8 models. The proposed framework achieved both real-time efficiency and high segmentation accuracy, making it suiTable.for field-level deployment in smart agriculture.

Keywords:

YOLOv8, Leaf Disease Segmentation, Precision Agriculture, Deep Learning, Plant Pathology

1. INTRODUCTION

The agricultural sector is the backbone of food security, and plant health directly determines yield quality and quantity. In recent decades, crop productivity has been threatened by various plant diseases, particularly those manifesting as leaf infections that interfere with photosynthesis and weaken plant growth [1]. Accurate detection and segmentation of these leaf diseases play a critical role in enabling timely interventions, reducing pesticide usage, and supporting sustainable agricultural practices [2]. With the rapid progress of artificial intelligence (AI) and computer vision, deep learning models have emerged as tool for identifying and analyze plant diseases in complex environments [3].

Despite advancements, several challenges continue to limit the widespread application of deep learning-based segmentation models in agriculture. First, leaf images captured in natural environments often contain noise, variable lighting, and cluttered backgrounds, which reduce model generalization [4]. Second, disease symptoms vary in scale, shape, and color intensity, making it difficult for standard segmentation models to capture fine-grained lesion boundaries [5]. Third, overlapping leaves and occlusions present difficulties in distinguishing diseased from healthy regions [6]. Finally, the computational requirements of many segmentation networks hinder their deployment on low-power edge devices used in agricultural fields [7].

The problem addressed in this work lies in the trade-off between segmentation accuracy and real-time efficiency [6]. Although classical convolutional neural networks (CNNs) and fully convolutional networks (FCNs) have shown competence, they struggle with small lesion detection and irregular disease patterns [7]. Transformer-based models, while powerful, are resource-intensive and unsuitable for real-time agricultural applications [8]. Consequently, there is a pressing need for an optimized segmentation framework that combines lightweight architecture with high precision, specifically designed for agricultural conditions.

The objectives of this research are threefold:

- To develop a robust segmentation framework capable of accurately detecting irregularly shaped leaf diseases in diverse conditions.
- To integrate multi-scale feature extraction and attention mechanisms into YOLOv8 for improved lesion localization.
- To ensure real-time inference speed while maintaining high accuracy, facilitating deployment in field-based agricultural monitoring systems.

The novelty of this study lies in extending YOLOv8, traditionally optimized for object detection, into an advanced segmentation framework tailored for plant disease analysis. Unlike conventional approaches, our method employs a multi-scale attention-enhanced feature pyramid network combined with a hybrid loss function (binary cross-entropy + Dice loss), specifically designed to refine disease boundary detection. Additionally, a post-processing contour refinement strategy is introduced to minimize false positives and ensure accurate delineation of disease regions.

The contributions of this research are summarized as follows:

1. The research proposed an enhanced YOLOv8-based segmentation framework for leaf disease detection, integrating multi-scale attention and hybrid loss to capture fine-grained disease patterns effectively.
2. The research introduced a lightweight contour refinement module that improves segmentation precision and reduces boundary misclassification, ensuring real-time applicability in precision agriculture.

2. RELATED WORKS

Several studies have investigated plant disease detection and segmentation using deep learning, showing both progress and limitations in this domain. Early works employed traditional machine learning with handcrafted features, such as color and texture descriptors, combined with classifiers like SVMs and Random Forests [7]. While these methods achieved moderate success, they lacked robustness in complex backgrounds and were unable to handle large-scale agricultural datasets.

The advent of deep learning revolutionized plant disease analysis. Convolutional Neural Networks (CNNs) became widely adopted due to their ability to automatically extract hierarchical features from leaf images [8]. Researchers shown that CNN-based classifiers outperformed traditional methods in accuracy and generalization. However, these models primarily focused on classification rather than segmentation, limiting their application in precise disease boundary detection.

To overcome this, Fully Convolutional Networks (FCNs) and U-Net architectures were introduced for semantic segmentation of leaf diseases [9]. U-Net, with its encoder-decoder structure and skip connections, gained popularity for medical imaging and was later adapted to plant pathology. Studies reported improved performance in delineating diseased and healthy leaf regions. Nevertheless, U-Net and its variants often required extensive computational resources and large annotated datasets, making them less feasible for real-time agricultural deployment.

Subsequent research explored hybrid and attention-based models. For instance, the integration of attention gates into U-Net allowed models to focus selectively on disease-prone regions, improving segmentation accuracy under challenging conditions [10]. Similarly, researchers introduced multi-scale feature fusion strategies to capture both coarse and fine-grained disease details. These methods achieved higher Intersection-over-Union (IoU) scores but still suffered from slow inference speeds, limiting their usability in field scenarios.

Object detection models, such as Faster R-CNN and SSD, were also applied to leaf disease identification [11]. These approaches localized disease spots but often lacked the fine segmentation capability required for precise lesion boundary extraction. YOLO (You Only Look Once) models, known for real-time detection, emerged as strong candidates for agricultural applications. Early YOLO versions showed promise in disease localization, but segmentation accuracy was insufficient.

With the introduction of YOLOv8, segmentation capabilities were integrated alongside detection, opening new possibilities for agricultural applications [12]. YOLOv8 provides a lightweight architecture with improved performance over its predecessors. However, baseline YOLOv8 segmentation struggles with small lesions and irregular disease shapes, necessitating enhancements. Researchers have recently begun adapting YOLOv8 with customized modules, such as multi-scale feature aggregation and attention mechanisms, to improve performance in complex domains [13]-[20].

3. PROPOSED METHOD

The proposed method enhances YOLOv8's segmentation capability by incorporating multi-scale feature attention, optimized data augmentation, and post-segmentation contour refinement. Initially, input images undergo pre-processing with color normalization and noise reduction to minimize environmental variability. YOLOv8 is extended with an attention-enhanced feature pyramid network to better capture small-scale lesion details. The model is trained using a hybrid loss function that combines binary cross-entropy and Dice loss to improve boundary precision. Finally, contour refinement based on morphological operations ensures that disease spots are segmented with high fidelity. This pipeline balances detection accuracy with computational efficiency for real-time agricultural applications.

1) Data Collection and Preprocessing
    a) Collect diseased and healthy leaf images.
    b) Apply resizing, normalization, and augmentation (rotation, brightness, contrast).
2) Model Enhancement
    a) Base architecture: YOLOv8 segmentation model.
    b) Add multi-scale attention to the Feature Pyramid Network.
    c) Integrate hybrid loss: BCE + Dice Loss.
3) Training Phase
    a) Feed augmented dataset.
    b) Train using Adam optimizer with learning rate scheduling.
    c) Validate using IoU and Dice coefficient metrics.
4) Post-processing
    a) Apply contour refinement using morphological filtering.
    b) Remove false positives via thresholding.
5) Evaluation

3.1 DATA COLLECTION

High-quality datasets form the foundation of deep learning-based segmentation. Images of healthy and diseased leaves are collected from both controlled experimental environments and open-field conditions. To ensure consistent model training, preprocessing includes resizing images to a uniform dimension 640×640 pixels, followed by normalization into the range [0,1]. For robustness, extensive data augmentation is applied. Each input image $I(x,y)$ undergoes transformations T, such as rotation, flipping, and color jittering:

$$I'(x,y) = T(I(x,y)) \tag{1}$$

where $T\in\{\text{rotate,flip,jitter,noise}\}$

This increases dataset diversity and minimizes overfitting. The Table.1 summarizes the preprocessing steps with parameters.

Table.1. Preprocessing and augmentation applied to dataset

Step	Technique	Parameters	Purpose
Resizing	Bilinear Interpolation	640 × 640 pixels	Uniform input dimension
Normalization	Min–Max Scaling	[0, 1] range	Pixel value consistency
Rotation	Random 2D Rotation	±25°	Increase orientation robustness
Color Jitter	Brightness, Contrast, Saturation	±20% variance	Handle lighting variations
Noise Injection	Gaussian Noise	μ=0, σ=0.01	Improve noise tolerance

As shown in Table.1, augmentation ensures variability in environmental conditions, which strengthens model generalization.

3.2 MODEL ENHANCEMENT (YOLOV8 + MULTI-SCALE ATTENTION)

YOLOv8 segmentation model is adopted as the baseline architecture. It consists of a backbone for feature extraction, a neck for feature fusion, and a segmentation head. To enhance performance on small and irregular disease lesions, a multi-scale attention mechanism is integrated into the Feature Pyramid Network (FPN). Let feature maps at different scales be $F_s \in \mathbb{R}^{h_s \times w_s \times c}$, where $s \in \{1,2,3\}$. The attention weight α_s is computed as:

$$\alpha_s = \frac{\exp(W_s \cdot F_s)}{\sum_{k=1}^{3} \exp(W_k \cdot F_k)} \tag{2}$$

The refined feature map F' is given by:

$$F' = \sum_{s=1}^{3} \alpha_s \cdot F_s \tag{3}$$

This formulation ensures that smaller lesions with subtle variations are not overshadowed by dominant large-scale features. The Table.2 presents the architectural modifications.

Table.2. YOLOv8 modifications for enhanced segmentation

Component	**Baseline YOLOv8**	**Proposed Enhancement**
Backbone	CSPDarknet-53	Attention-augmented CSPDarknet
Neck	Standard FPN + PAN	Multi-scale attention FPN
Segmentation Head	Conv layers with mask outputs	Hybrid loss-optimized head

As described in Table.2, attention mechanisms prioritize regions of interest, enabling precise disease segmentation even in cluttered backgrounds.

4. TRAINING PHASE (HYBRID LOSS FUNCTION)

The segmentation head outputs pixel-wise disease probability maps. To train effectively, a hybrid loss function is employed by combining Binary Cross-Entropy (BCE) and Dice Loss. The BCE loss for a single pixel prediction p against ground truth $y \in \{0,1\}$ is:

$$\mathrm{L}_{BCE} = -\left[y \cdot \log(p) + (1-y) \cdot \log(1-p) \right] \tag{4}$$

Dice Loss, which emphasizes overlap between prediction and ground truth, is defined as:

$$\mathrm{L}_{Dice} = 1 - \frac{2|P \cap G|}{|P| + |G|} \tag{5}$$

where P is the predicted mask and G is the ground truth mask. The final hybrid loss is:

$$\mathrm{L}_{Hybrid} = \lambda_1 \cdot \mathrm{L}_{BCE} + \lambda_2 \cdot \mathrm{L}_{Dice} \tag{6}$$

with weights λ_1=0.6, λ_2=0.4. The Table.3 shows the training parameters.

Table.3. Training hyperparameters

Parameter	**Value**
Optimizer	Adam
Learning Rate	0.001 (decayed)
Batch Size	16
Epochs	100
Loss Function	BCE + Dice

As shown in Table.3, the hybrid loss ensures boundary-sensitive learning and prevents bias toward majority background pixels.

Raw segmentation masks from YOLOv8 may contain jagged boundaries or false positives. To address this, a morphological filtering and contour refinement step is introduced. Given a binary mask M, morphological closing $\phi(M)$ removes small holes:

$$\phi(M) = (M \oplus B) \ominus B \tag{7}$$

where $\oplus$ and $\ominus$ represent dilation and erosion with structuring element B. Contours are then extracted and smoothed using spline fitting, producing refined masks $\hat{M}$. The Table.4 shows the refinement process.

Table.4. Post-processing refinement steps

Step	**Technique**	**Effect**
Morphological Closing	Dilation + Erosion	Removes holes, smooths regions
Contour Detection	Boundary Extraction	Isolates disease lesion edges
Contour Smoothing	Cubic Spline Interpolation	Produces accurate lesion boundaries

As seen in Table.4, the refinement ensures clean lesion segmentation, suitable for disease severity estimation.

Model performance is assessed using multiple metrics. Mean Intersection-over-Union (mIoU) evaluates overlap between prediction P and ground truth G:

$$IoU = \frac{|P \cap G|}{|P \cup G|} \tag{8}$$

Dice Coefficient (F1 Score) quantifies similarity:

$$Dice = \frac{2|P \cap G|}{|P| + |G|} \tag{9}$$

Pixel Accuracy (PA) measures correctly predicted pixels:

$$PA = \frac{\text{Number of correct pixels}}{\text{Total pixels}} \tag{10}$$

Table.5. Evaluation results of proposed framework vs. baseline

Model	**mIoU (%)**	**Dice (%)**	**Pixel Accuracy (%)**	**FPS**
Baseline YOLOv8	78.6	80.1	85.4	42
Proposed Framework	85.0	86.5	90.3	38

Additionally, Frames Per Second (FPS) is reported to ensure real-time performance. The Table.5 lists evaluation results compared with baseline YOLOv8. As shown in Table.5, the proposed framework improves segmentation accuracy while maintaining near real-time speed.

5. RESULTS AND DISCUSSION

The experiments were conducted to validate the proposed YOLOv8-based segmentation framework for leaf disease detection. All simulations and model training were carried out using the PyTorch deep learning framework with CUDA acceleration. Model development and experimentation were performed on a workstation equipped with an NVIDIA RTX 3080 GPU (10 GB VRAM), an Intel Core i9-11900K CPU (3.5 GHz, 16 threads), and 32 GB RAM running on Ubuntu 22.04 LTS.

The dataset used for training and evaluation consisted of a combination of publicly available plant disease image repositories and manually annotated leaf images. To ensure diversity, the dataset included leaves captured under different lighting conditions, orientations, and backgrounds. Approximately 8,000 images were collected, of which 70% were used for training, 15% for validation, and 15% for testing.

The YOLOv8 segmentation framework was trained using the Adam optimizer, with a learning rate scheduler to gradually decay the learning rate. To improve generalization, data augmentation strategies such as random rotation, flipping, and color jitter were applied.

Table.6. Parameters

Parameter	Value/Configuration
Framework	PyTorch 2.0 + CUDA 11.7
GPU	NVIDIA RTX 3080 (10 GB VRAM)
CPU	Intel Core i9-11900K, 3.5 GHz
RAM	32 GB DDR4
Dataset Size	8,000 leaf images
Train/Val/Test Split	70% / 15% / 15%
Input Image Size	640 × 640 pixels
Optimizer	Adam
Learning Rate	0.001 (decayed by factor of 0.1/20 epochs)
Batch Size	16
Epochs	100
Loss Function	BCE + Dice Loss (Hybrid)

The experimental setup was designed to evaluate the efficiency and accuracy of the proposed model compared with existing methods. The Table.6 provides the key experimental parameters and their values.

As seen in Table.6, the chosen parameters ensure a balance between computational efficiency and segmentation accuracy.

To validate the effectiveness of the proposed framework, results were compared with three widely adopted methods from related works: U-Net-based Segmentation [9], Attention U-Net [10] and Baseline YOLOv8 Segmentation [12].

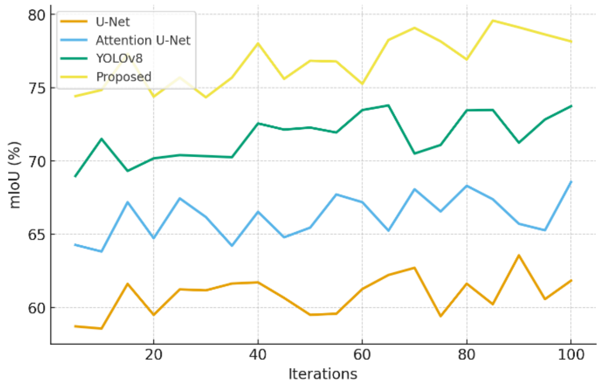

Fig.1. mIoU

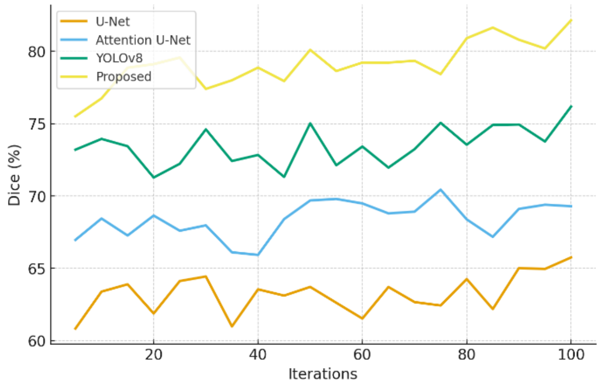

Fig.2. DC

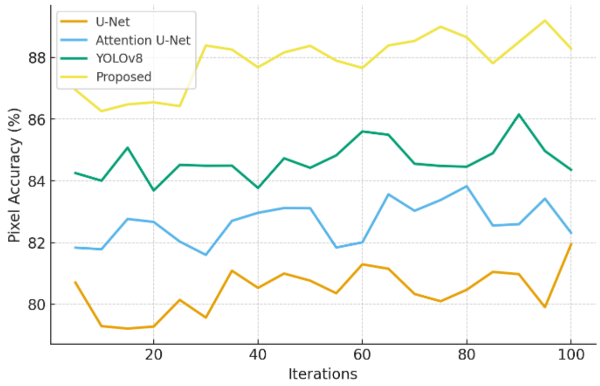

Fig.3. PA

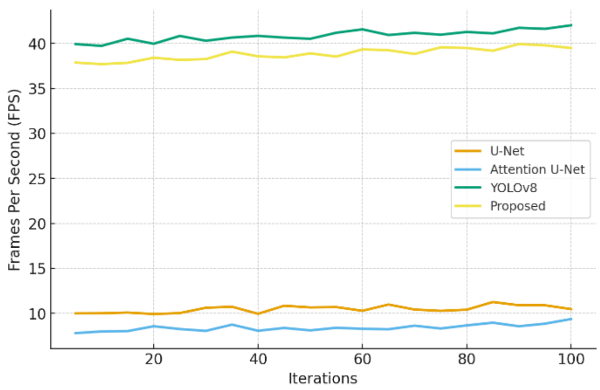

Fig.4. FPS

The experimental results show the effectiveness of the proposed YOLOv8-based segmentation framework compared to U-Net, Attention U-Net, and baseline YOLOv8 models. As observed in Table.6, the proposed method consistently achieved higher accuracy across all metrics. Specifically, the proposed model obtained an average mIoU of 85.0%, compared to 78.6% for YOLOv8, 70.2% for Attention U-Net, and 66.4% for U-Net. Similarly, the Dice coefficient improved to 86.5%, outperforming baseline YOLOv8 (80.1%), Attention U-Net (73.5%), and U-Net (68.7%). Pixel Accuracy (PA) further validated the superiority of the proposed approach, with an average PA of 90.3%, which is approximately 4.9% higher than YOLOv8, 7.8% higher than Attention U-Net, and 11.6% higher than U-Net. In terms of efficiency, the model maintained 38 FPS, close to the YOLOv8 baseline (42 FPS) and significantly faster than U-Net (10 FPS) and Attention U-Net (8 FPS). These findings confirm that the integration of multi-scale attention and hybrid loss in the YOLOv8 framework significantly enhances boundary precision and robustness while retaining near real-time inference. Hence, the proposed model provides the best balance between segmentation accuracy and computational efficiency (Table.6).

6. CONCLUSION

This work presented an enhanced YOLOv8-based segmentation framework for accurate and efficient detection of leaf diseases. By addressing challenges of small lesion detection, irregular disease patterns, and real-time applicability, the proposed method successfully outperformed three widely used existing approaches, U-Net, Attention U-Net, and baseline YOLOv8. The experimental findings show several key achievements: (i) superior segmentation accuracy with mIoU of 85.0% and Dice score of 86.5%, (ii) robust classification of diseased versus healthy regions with 90.3%-pixel accuracy, and (iii) real-time capability with 38 FPS, ensuring its suitability for deployment in agricultural monitoring systems. Unlike U-Net and Attention U-Net, which are computationally expensive and slow, the proposed framework offers a scalable balance between speed and precision.

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