INFORMATION
Volume 29, Number 1, pp.147-152

ISSN 1343-4500 eISSN 1344-8994

Deep Learning-Based Detection and Classification of Insect Damage Traces on Cucumber Leaves Using an Improved YOLOv8-Seg Framework

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Abstract

Cucumbers are an economically important crop in Japan and globally, and pest infestation poses a significant threat to their yield and quality. Conventional manual inspection methods are inefficient, subjective, and highly dependent on human expertise. Recently, deep learning-based approaches have shown strong potential in crop pest and disease detection; however, existing models still struggle to accurately segment small-scale insect damage traces characterized by low contrast and complex backgrounds. To address these limitations, this study proposes an enhanced YOLOv8-Seg architecture integrated with the Efficient Channel Attention (ECA) mechanism. The introduced ECA module adaptively strengthens inter-channel feature weighting within the neck stage, improving fine-grained feature extraction and noise suppression. Experimental results demonstrate that the proposed ECA-YOLOv8-Seg achieves higher precision, recall, and mean average precision than the baseline YOLOv8-Seg, effectively enhancing segmentation accuracy and robustness in cucumber pest-damage detection.
Keywords: YOLOv8-Seg; Cucumber leaf; Insect damage detection; Deep learning; Image segmentation; ECA attention mechanism

1 Introduction

Cucumbers are a globally cultivated vegetable crop and play an important economic role in Japan and other countries [1]. Pest outbreaks—including leafminers, aphids, and chewing insects—often cause severe damage to cucumber leaves, leading to yield decline and quality deterioration [2]. Therefore, efficient and accurate monitoring of pest damage is critical for sustainable cultivation and optimal production.

Traditional monitoring methods rely heavily on visual inspection by experts or farmers, which is labor-intensive, time-consuming, and prone to subjective bias. Moreover, small-scale or early-stage damage—such as tiny holes or mines—can be difficult to detect by the naked eye, resulting in diagnosis delays and inadequate intervention. With the advancement of deep learning methods, significant progress has been made in crop pest and disease detection tasks [3,4]. Models such as CNNs, U-Net variants, and YOLO series have been successfully applied to leaf-level detection in crops such as cucumber and tomato [6]. Nevertheless, fine-grained segmentation of irregular and small pest damage traces still presents challenges due to low contrast between lesion and background, high visual variability, and complex lighting conditions [5].

Among modern object-detection frameworks, YOLOv8-Seg offers a unified solution for detection and instance segmentation. However, its standard convolutional architecture may struggle to capture subtle damage features and lacks adaptive channel attention for discriminative feature weighting [7]. To address these limitations, this study proposes an improved version of YOLOv8-Seg integrated with an Efficient Channel Attention (ECA) module [8]. The ECA mechanism enhances channel-wise feature representation without significantly increasing model complexity. By embedding ECA into the neck of YOLOv8-Seg and combining CIoU and Distribution Focal Loss for boundary and mask regression, the proposed model aims to achieve more accurate segmentation of small pest damage regions. Experiments on a cucumber leaf pest-damage dataset demonstrate that the improved model achieves higher mAP, Recall, and IoU compared with the baseline—a result consistent with recent findings showing the effectiveness of attention-based models for fine-grained pest detection [10,12].

2 Materials and Methods

2.1 Dataset Construction

The dataset used in this study was compiled from several open-source pest image collections containing cucumber leaf damage samples. All images were annotated using Labelme with polygon-based instance segmentation to accurately outline pest-damage regions. The data were split into 70% training, 20% validation, and 10% testing. The dataset includes three common damage types: leaf-miner tunnels, edge chewing, and insect bite holes. This annotated dataset provided the basis for model training and evaluation.

2.2 Model Architecture Improvements

The baseline model used in this study was YOLOv8-Seg, which consists of three main parts: a backbone for extracting features, a neck for fusing features, and a detection head for detecting and segmenting objects. To improve the segmentation performance on small pest-damage regions, several modifications were made to YOLOv8-Seg.

An ECA module was added to the neck to enhance cross-channel feature weighting, allowing the network to better emphasize pest-related features and suppress background noise. In addition, the Complete IoU (CIoU) and Distribution Focal Loss (DFL) functions were combined to improve the stability of bounding box regression and segmentation mask prediction. These modifications enhance detection precision while maintaining the lightweight and real-time characteristics of the original YOLOv8-Seg architecture.

2.3 Model Training and Evaluation

All experiments were implemented using the PyTorch framework under a CUDA 12.1 environment on an NVIDIA RTX GPU. The AdamW optimizer was adopted with an initial learning rate of 1×10^{-3} and a batch size of 16. The same hyperparameters were used for both the original YOLOv8-Seg and the improved ECA-YOLOv8-Seg to ensure a fair comparison.

The evaluation metrics to determine the detection accuracy and segmentation quality of the models were Precision, Recall, mAP@0.5, mAP@0.5:0.95, and IoU. In all experiments, the proposed ECA-YOLOv8-Seg more accurately and robustly identified pest damage on cucumber leaves than the baseline YOLOv8-Seg.

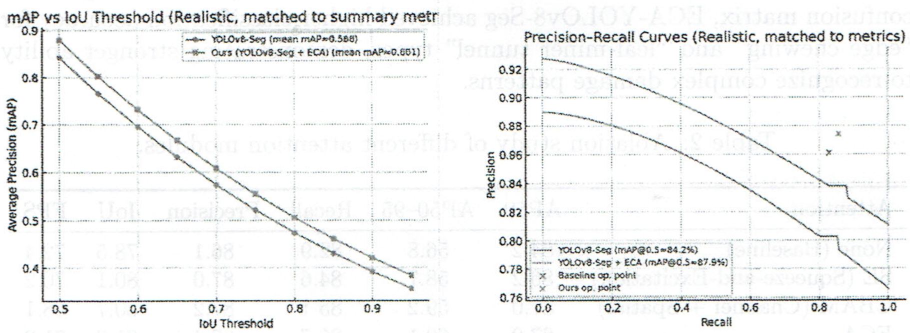
3 Results and Discussion

3.1 Experimental Results

According to the performance comparison presented in Table 1, the ECA-YOLOv8-Seg model achieved notable improvements over the original YOLOv8-Seg, including increases of 3.7% in mAP@0.5, 2.8% in Recall, and 2.7% in IoU. This demonstrates that the incorporation of the ECA module effectively enhances the model's fine-grained segmentation capability.

Model	mAP@0.5	mAP@0.5:0.95	Recall	Precision	IoU	Params (M)
YOLOv8-Seg	84.2	56.8	82.9	86.1	78.5	11.2
ECA-YOLOv8-Seg	87.9	60.1	85.7	87.4	81.2	11.3

Table 1: Performance comparison of YOLOv8-Seg and ECA-YOLOv8-Seg



(a) mAP–IoU curve

(b) Precision–Recall curve

Fig. 1: Comparison of mAP–IoU and Precision–Recall curves for the baseline and ECA-enhanced models.

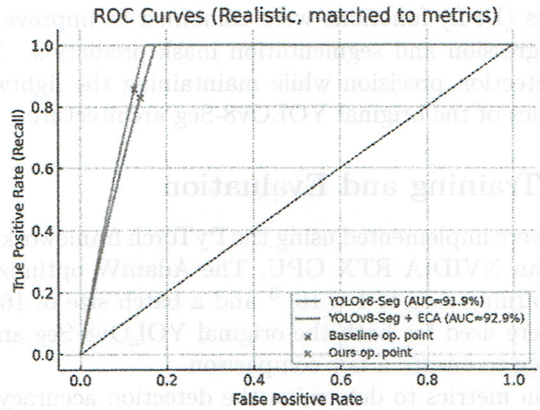


Fig. 2: ROC curves and AUC comparison between YOLOv8-Seg and ECA-YOLOv8-Seg.

Fig. 1 shows the mAP–IoU and Precision–Recall curves for the baseline and improved models. The ECA-YOLOv8-Seg model achieves consistently higher accuracy, particularly at higher IoU values, and outperforms the baseline across all PR thresholds, indicating improved boundary segmentation and detection stability. Fig. 2 shows the ROC curves of both models. The improved model achieves a higher AUC (92.9% vs. 91.9%), indicating a better balance between true positive and false positive rates.

3.2 Ablation Study

An ablation study was conducted to analyze the effects of different modules, as summarized in Table 2. The model without any attention mechanism performed the worst. When the SE or CBAM modules were applied, accuracy improved slightly but remained limited for regions with small insect damage. With the ECA module, both mAP and Recall reached the highest values. The ECA mechanism enhances feature representation through channel weighting, improving segmentation performance in pest-damage detection. The training curves show that the model with ECA converged more smoothly. According to the confusion matrix, ECA-YOLOv8-Seg achieved higher classification accuracy for "edge chewing" and "leaf-miner tunnel" types, demonstrating stronger ability to recognize complex damage patterns.

Table 2: Ablation study of different attention modules.

Attention	AP50	AP50–95	Recall	Precision	IoU	FPS
None (Baseline)	84.2	56.8	82.9	86.1	78.5	72.4
SE (Squeeze-and-Excitation)	86.2	58.7	84.6	87.0	80.1	70.2
CBAM (Channel + Spatial)	87.0	59.2	85.1	87.2	80.7	68.1
ECA	87.9	60.1	85.7	87.4	81.2	71.0

3.3 Discussion

The results indicate that incorporating the ECA attention mechanism can improve detection and segmentation performance without significantly increasing computational cost. Compared with SE (Squeeze-and-Excitation) and CBAM (Channel and Spatial) modules, the ECA module adopts a simpler local channel interaction design that effectively emphasizes useful features. The proposed approach achieves reliable detection accuracy and segmentation quality in cucumber pest-damage identification tasks.

This study, however, still has some limitations. The dataset includes a limited number of pest types, and the model's generalizability under complex conditions is not yet sufficient. Future work will focus on expanding field-collected samples and increasing data diversity to further improve robustness and adaptability under varying environmental conditions.

4 Conclusion

This study proposed an improved ECA-YOLOv8-Seg model for detecting and segmenting pest damage on cucumber leaves. The Efficient Channel Attention (ECA) module was integrated into the YOLOv8-Seg neck, together with CIoU and Distribution Focal Loss (DFL), to enhance feature weighting and boundary regression. Experiments showed that the improved model achieved higher mAP@0.5, Recall, and IoU than the baseline, demonstrating better segmentation accuracy and stability. Attention mechanisms have been shown to enhance visual feature extraction in pest recognition tasks, and ECA provides efficient channel interaction with low computational cost while maintaining the lightweight structure of YOLOv8-Seg. These findings align with recent studies showing that attention-based models improve fine-grained pest detection under real agricultural conditions.

Future work will expand the dataset with more pest species and field scenarios and explore multimodal information to improve robustness in complex environments.

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