



Real-Time Detection and Segmentation of Tomato Pests with YOLOv8

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ABSTRACT

Tomato (*Solanum lycopersicum* L.) is vital for global nutrition and economic stability, yet it is threatened by pests such as *Tuta absoluta*, *Helicoverpa armigera*, and *Bemisia tabaci*. Effective pest management is crucial to prevent significant crop losses. Traditional pest detection methods relying on human observation are labor-intensive, time-consuming, and prone to errors. In contrast, artificial intelligence (AI)-based models such as YOLO provide timely and accurate pest identification, enhancing pest management practices. In this study, images captured throughout the tomato plant's development, from seedling to fruit stage, were used for model training. The capabilities of the YOLOv8 model in detecting and segmenting tomato pests were evaluated. The results demonstrated significant improvements in both detection and segmentation tasks, with precision and recall reaching 98.91% and 98.98% for detection, and 97.47% and 98.81% for

segmentation, respectively. These findings underscore the accuracy and robustness of the YOLOv8 model in monitoring diverse pest species, highlighting its potential to improve agricultural pest management practices. Although YOLO-based detectors have recently been tested on a limited set of pest species, comprehensive field-scale evaluations remain scarce. By assessing YOLOv8 across eleven pest taxa under commercial field conditions, this study delivers among the more comprehensive practice-oriented benchmarks to date for multi-species pest monitoring. This research suggests that integrating AI models like YOLOv8 into pest monitoring systems can contribute to more efficient and sustainable agricultural practices by minimizing human error and labor demands. Furthermore, future applications could extend this approach to other crops and pest species, validating the model's versatility and supporting long-term farming sustainability.

Keywords: *Solanum lycopersicum*, Artificial intelligence, YOLO, Pest detection, Image processing, Precision agriculture

1. Introduction

Tomato (*Solanum lycopersicum* L.) is one of the most significant vegetable crops globally, crucial for both nutrition and economic stability. The cultivation of tomatoes is threatened by various pests. Chief among these are the tomato leaf miner *Tuta absoluta* (Lepidoptera: Gelechiidae), the cotton bollworm *Helicoverpa armigera* (Lepidoptera: Noctuidae), the Colorado potato beetle *Leptinotarsa decemlineata* (Coleoptera: Chrysomelidae), the sweet potato whitefly *Bemisia tabaci* (Hemiptera: Aleyrodidae) and the green peach aphid *Myzus persicae* (Hemiptera: Aphididae). In addition, several other taxa inflict notable damage, including the harlequin bug *Dolycoris baccarum* (Hemiptera: Pentatomidae), flea beetles of the genus *Phyllotreta* (Coleoptera: Chrysomelidae), the southern green stink bug *Nezara viridula* (Hemiptera: Pentatomidae), the two-spotted spider mite *Tetranychus urticae* (Trombidiformes: Tetranychidae) and the western flower thrips *Frankliniella occidentalis* (Thysanoptera: Thripidae) (Pereyra & Sánchez 2006; Garzia et al. 2012; Shaltiel-Harpaz et al. 2015; Sylla et al. 2017; Oliveira et al. 2017).

Accurate and rapid identification of pest infestations is fundamental to preserving plant health and maximizing crop yields. Traditional field scouting, however, is labour-intensive, slow, and prone to observer bias. Convolutional neural networks (CNNs)—including Mask R-CNN, Faster R-CNN, Single-Shot MultiBox Detector (SSD), and especially YOLO—automate this process, enabling high-throughput analysis while markedly reducing human workload and improving diagnostic consistency (Ranger et al. 2009; Şahin & Topal 2018; Chen et al. 2020; Raikov & Abrosimov 2022; Leybourne et al. 2024). YOLO, in particular, delivers real-time inference with minimal latency and excels at detecting small, densely clustered arthropods (Redmon & Farhadi 2018; Yuan et al. 2025). Thanks to its multi-scale feature-fusion backbone, YOLO strikes an optimal balance between speed and accuracy, achieving state-of-the-art mean Average Precision (mAP) in both object-detection and instance-segmentation benchmarks (Liu & Wang 2020; Wen et al. 2022); this makes it particularly adept at tracking multiple pest species that differ vastly in size and morphology.

Successive iterations have strengthened both speed and accuracy. Global-Lightweight Upsampling YOLOv8 (GLU-YOLOv8) boosts mean average precision at 0.50 IoU (mAP@0.50) for small objects by 8.2% without sacrificing throughput (Yue et al. 2024), while the parameter-efficient YOLO-Pest cuts model size by 45% yet maintains >94% mAP on the 102-class insect-pest dataset (Xiang et al. 2023). In field trials, YOLOv5 and YOLOv8 achieve >93% accuracy for tomato-pest detection (Bellout et al. 2024), and models trained on in-situ imagery generalize better than those trained on controlled datasets such as PlantVillage (Jelali 2024). Further, YOLOv8 attains an mAP@0.50 of 96.7% across diverse pest taxa (Vilar-Andreu et al. 2024), edge-optimized YOLO-PPLCBot sustains 95.3% mAP with 1.7 ms inference time (Xu et al. 2023), and dense-detection Pest-YOLO improves mAP by 5.3% over YOLOv4 for occluded species (Wen et al. 2022). Collectively, these advances position the most recent YOLO variants as versatile, high-performance backbones for real-time pest surveillance in complex field environments.

This study evaluates the accuracy of a lightweight YOLOv8 architecture for simultaneous detection and instance-level segmentation of eleven key tomato pests: *D. baccarum*, *Phyllotreta* spp., *M. persicae*, *B. tabaci*, *L. decemlineata*, *T. absoluta*, *N. viridula*, *T. urticae*, *H. armigera*, *F. occidentalis*, and *T. absoluta*. Model training and validation relied on a year-long series of high-resolution images captured under commercial greenhouse conditions, covering different phenological stages and documenting both insects and their characteristic damage. By encompassing this full temporal and morphological spectrum, the dataset provides a realistic benchmark for field-level variability. The resulting YOLOv8 model demonstrated real-time, multi-species performance in situ, offering a practical tool for data-driven, integrated pest-management workflows while reducing scouting labour and observer bias. Consequently, the work supplies a comparative reference point for future research on deep-learning-based crop protection and highlights the feasibility of deploying a single, resource-efficient model across a broad pest assemblage under production conditions.

2. Material and Methods

Rather than proposing a novel detection architecture, this study evaluates the practical applicability of the off-the-shelf YOLOv8 framework for real-time, multi-species pest monitoring under commercial greenhouse conditions.

2.1. Overview of the experimental site and dataset composition

Turkey ranks among the world's five largest producers of *Solanum lycopersicum* L. (tomato), with approximately 10% of the country's output generated in the Bursa province. In 2020, Bursa alone yielded 13.2 million t of tomato fruit, making it the region's leading horticultural crop (Kumbasaroğlu et al. 2021). This study is based on a curated image dataset collected under glasshouse conditions in Çeltikçi village, Yenişehir district, northwestern Türkiye. The photographs document all phenological stages—from cotyledon emergence and vegetative growth through flowering and fruit set—and capture occurrences of key arthropod pests as well as the characteristic feeding damage and symptom expression on tomato foliage and fruit. One of the photo locations in Çeltikçi village is situated at coordinates 40°13'36.25"N latitude and 29°32'17.74"E longitude. Taxonomic determination of the pests depicted in the field photographs was performed by applying established morphological diagnostic keys from the literature (Blackman & Eastop 2000; Hoebeke & Carter 2003; Desneux et al. 2010; Ashbrook et al. 2022; Li et al. 2023).

Object detection architectures routinely achieve accurate pest presence confirmation and spatial localization, enabling rapid throughput in large-scale surveys (Barbedo 2016). However, when precise contour delineation of individual insects or a pixel-level atlas of foliar damage is required, semantic segmentation methods are preferable (Arockia et al. 2023). The YOLOv8 family integrates both modalities: the yolov8s.pt checkpoint was applied for bounding-box detection, while yolov8n-seg.pt was employed for mask-based segmentation. In simple terms, detection surrounds the object with a rectangular bounding box, whereas segmentation traces the object's exact outline like a map. The image collections used to train the detection networks are summarized in Table 1, whereas those used for segmentation training appear in Table 2. Between March 2023 and March 2024, pictorial records of pest infestations on tomato foliage were acquired under greenhouse conditions at a fixed frame size of 768 × 1024 pixels. Imaging devices of identical make and resolution were deployed to ensure uniform data quality. Two working distances—approximately 1 m for whole-plant context and 0.2 m for detailed lesion capture—were systematically used, with varying camera orientations to cover different pest postures and damage patterns (Yong et al. 2020). For each target arthropod species, more than 1 000 images displaying a range of angles and symptomatic presentations were collated. The complete dataset was partitioned into training (80 %), validation (18 %), and test (2%) subsets, as detailed in Table 3. Consistent with standard object-detection practice (Everingham et al. 2015), a generic “other” class was not introduced: any organism outside the eleven focal pests was left unannotated and thus learned as background. This avoids label noise that could blur class boundaries, while the held-out validation and test splits still provide an unbiased measure of the network's ability both to ignore non-target arthropods and to discriminate among the target taxa.

Table 1 - Pests images used for training the detection models

Adults	<i>Myzus persicae</i> (Hemiptera: Aphididae)
	<i>Tuta absoluta</i> (Lepidoptera: Gelechiidae)
	<i>Bemisia tabaci</i> (Hemiptera: Aleyrodidae)
	<i>Dolycoris baccarum</i> (Hemiptera: Pentatomidae)
	<i>Phyllotreta</i> spp. (Coleoptera: Chrysomelidae)
	<i>Leptinotarsa decemlineata</i> (Coleoptera: Chrysomelidae)
	<i>Nezara viridula</i> (Hemiptera: Pentatomidae)
Nymphs	<i>Nezara viridula</i> (Hemiptera: Pentatomidae)
	<i>Leptinotarsa decemlineata</i> (Coleoptera: Chrysomelidae)
Larvae	<i>Helicoverpa armigera</i> (Lepidoptera: Noctuidae)
	<i>Tuta absoluta</i> (Lepidoptera: Gelechiidae)

Table 2 – Pest images used for training the segmentation models

Tomato leaf images	Tomato fruit images
<i>Liriomyza bryoniae</i> (Diptera: Agromyzidae) damage	<i>Helicoverpa armigera</i> (Lepidoptera: Noctuidae) damage
<i>Tuta absoluta</i> (Lepidoptera: Gelechiidae)	<i>Tuta absoluta</i> (Lepidoptera: Gelechiidae) damage
<i>Frankliniella occidentalis</i> (Thysanoptera: Thripidae) damage	<i>Tetranychus urticae</i> (Trombidiformes: Tetranychidae) damage
<i>Tetranychus urticae</i> (Trombidiformes: Tetranychidae) damage	

Table 3 - Distribution of the image dataset for model training

Dataset Split	Image Category	Total Images	Training (80 %)	Validation (18 %)	Testing (2 %)
Detection	Adult insects	7 000	5 600	1 260	140
	Nymph-stage insects	2 000	1 600	360	40
	Larval-stage insects	2 000	1 600	360	40
	Subtotal	11 000	8 800	1 980	220
Segmentation	Tomato leaf samples	5 000	4 000	900	100
	Tomato fruit samples	4 000	3 200	720	80
	Subtotal	9 000	7 200	1 620	180

2.2. Techniques for data preprocessing and their practical applications

Data preprocessing encompasses a sequence of preparatory operations applied to raw datasets to rectify missing values, eliminate noise, and resolve inconsistencies, thereby rendering the data amenable to downstream analysis and modelling in fields such as machine learning and statistical inference (Şahin & Topal 2016; Atalan et al. 2022; Baştürk & Şahin 2022; Bütüner et al. 2024). In the context of image-based pest recognition, three principal preprocessing stages were implemented: annotation, geometric normalization, and synthetic augmentation. Annotation was carried out using the LabelMe platform, employing both axis-aligned rectangles for coarse object localization and free-form polygons for precise boundary delineation (Figure 1). For detection network training, eleven distinct classes were delineated via rectangular bounding boxes; for segmentation tasks, eight classes were defined through pixel-accurate masks (Table 4). Images were standardized to a common resolution to ensure uniform input dimensions, and augmentation techniques —such as random rotations, flips, scaling operations, and color perturbations— were applied to expand the effective dataset size, mitigate overfitting, and enhance model robustness to unseen variations (Redmon & Farhadi 2018; Rubanga et al. 2020; Güven & Şahin 2022). All pre-processing routines were scripted in Python 3.11.8 within the Spyder integrated development environment (Anaconda distribution), leveraging its comprehensive scientific computing libraries for efficient data handling and transformation (Şahin et al. 2020; Yılmaz et al. 2021).

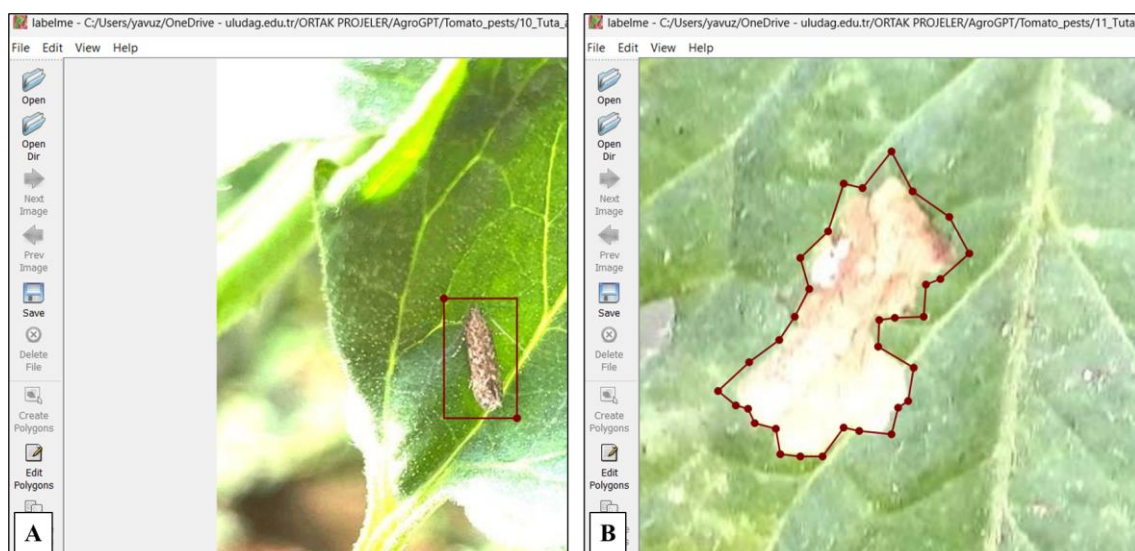


Figure 1 - Image Labelling Methods with LabelMe: A) Rectangle Bounding, B) Polygonal Segmentation

Table 4- Label Names for Detection and Segmentation Models

Detection Model Label Names	
1	<i>Dolycoris baccarum</i> adult
2	<i>Phyllotreta</i> spp.
3	<i>Nezara viridula</i> adult
4	<i>Myzus persicae</i>
5	<i>Bemisia tabaci</i> adult
6	<i>Leptinotarsa decemlineata</i> adult
7	<i>Tuta absoluta</i> adult
8	<i>Nezara viridula</i> nymph
9	<i>Leptinotarsa decemlineata</i> nymph
10	<i>Helicoverpa armigera</i> larvae
11	<i>Tuta absoluta</i> larvae

Segmentation Model Label Names	
1	<i>Liriomyza bryoniae</i> damage
2	<i>Tuta absoluta</i> damage
3	<i>Myzus persicae</i> damage
4	<i>Tetranychus urticae</i> damage
5	Healthy tomato leaves
6	Healthy tomato fruits
7	<i>Helicoverpa armigera</i> damage
8	<i>Tuta absoluta</i> damage

2.3. Model setup and training

The YOLOv8 architecture was trained using the Ultralytics library for model instantiation and optimization, while Google Colaboratory's Drive mounting functionality was employed to access the image dataset. Training was performed for over 100 000 epochs with an early-stopping patience of 50 to prevent overfitting, a batch size of 16, and input images scaled to 640×640 pixels. The computational environment consisted of an Intel Xeon CPU with 12.68 GB of RAM and an NVIDIA Tesla K80 GPU within Colaboratory. Both object-detection and instance-segmentation variants were trained in Python on a custom collection of tomato pest images. Instance segmentation was selected to enable discrimination of individual pest specimens within aggregated infestations, thereby facilitating precise quantification of foliar and fruit damage caused by co-occurring pest species (Mirhaji et al. 2021; Zhang et al. 2023a; Zhang et al. 2023b). The dataset preparation scripts and model training configurations have been made publicly available via the GitHub repository `yolo_colab`, under the username `@yavuzxyz`, to facilitate reproducibility and encourage further research (https://github.com/yavuzxyz/yolo_colab).

2.4. Procedures employed for model evaluation and testing

The model's generalization was assessed on a reserved dataset partitioned into 80% training, 18% validation and 2% testing subsets. During training, precision, recall, $\text{mAP}@0.5$ and $\text{mAP}@[0.5-0.95]$ were computed on both the training and validation splits to track convergence and overfitting. Detection and instance-segmentation performance were evaluated at multiple IOU thresholds by computing precision (P), recall (R) and mean average precision (mAP), with $\text{mAP}@0.5$ and $\text{mAP}@[0.5-0.95]$ providing insights into accuracy across object scales and degrees of overlap (Li et al. 2020; Arfan et al. 2023). The loss components—bounding-box regression loss (box_loss), classification loss (cls_loss) and Distribution Focal Loss (dfl_loss)—were inspected to identify dominant error sources. A confusion matrix was constructed to summarize per-class prediction outcomes, distinguishing true positives, false positives and false negatives for each pest category. This suite of metrics furnished a detailed profile of the model's predictive strengths and shortcomings. The formal definitions of P, R, $\text{mAP}@0.5$ and $\text{mAP}@[0.5-0.95]$ are given in Equations 1-4, where TP, FP and FN denote true positives, false positives and false negatives, respectively; Q is the number of recall thresholds; and $P(R_q)$ represents the interpolated precision at recall level R_q . Specifically, Precision (Eq. 1) expresses the proportion of correct model detections, Recall (Eq. 2) measures the proportion of ground-truth

pest instances that are successfully retrieved, AP@0.5 (Eq. 3) is the area under the precision–recall curve computed at an IoU threshold of 0.50, and mAP@[0.5:0.95] (Eq. 4) averages AP over ten equidistant IoU thresholds from 0.50 to 0.95 and serves as the primary summary metric for overall detection performance.

$$P = \frac{TP}{(TP + FP)} \quad [1]$$

$$R = \frac{TP}{(TP + FN)} \quad [2]$$

$$AP = \frac{1}{Q} \sum_{q=1}^Q P(Rq) \quad [3]$$

$$mAP = \frac{1}{Q} \sum_{i=1}^{95} P(Rq) \frac{1}{Q_i} \sum_{q=1}^{Q_i} P(Rq, i) \quad [4]$$

3. Results

In agricultural pest detection, accurately identifying the exact locations, numbers, and spatial relationships of individual pests on a single leaf is crucial. Unlike semantic segmentation, which classifies every pixel but cannot differentiate between objects of the same class, instance segmentation provides separate segmentation for each object. This precision is essential for detecting pest density, implementing precision agriculture, and analyzing pest life stages. Therefore, instance segmentation models were preferred (Redmon et al. 2016; Hariharan et al. 2015). Statistical analyses were necessary to objectively evaluate model efficiency and success. Training and Validation Loss graphs were used to identify overfitting or underfitting, while Performance Evaluation Metrics (Recall, Precision, mAP) assessed detection and segmentation accuracy. Confusion Matrix Analysis examined classification errors and correct detections, providing critical insights into the model's reliability and applicability.

3.1. Training and validation loss graphs

‘Train Loss Over Epoch’ was employed to quantify the reduction in error on the training dataset at each epoch, whereas ‘Validation Loss Over Epoch’ was used to assess generalization performance on unseen data. Declines in these loss curves were interpreted as evidence of effective learning and prevention of overfitting. In this work, loss profiles were computed for each candidate detection architecture to enable an objective comparison and support the selection of the most robust model. The box_loss term evaluated the precision of bounding-box localization and scaling, cls_loss quantified categorical discrimination among pest species, and dfl_loss measured the accuracy of shape-deformation predictions via distribution focal outputs. An epoch was defined as a single full pass through the training dataset. During YOLOv8’s pest detection training, the training set’s box_loss was reduced from 1.84 to 0.54, cls_loss from 3.48 to 0.37, and dfl_loss from 1.54 to 0.86. Corresponding validation losses also declined box_loss from 1.38 to 0.53, cls_loss from 3.45 to 0.31, and dfl_loss from 1.30 to 0.90. Automatic early stopping was triggered at 749 epochs to prevent overfitting, thereby confirming the effectiveness of the training protocol (Figure 2). Furthermore, the YOLO-Dense model was proposed by Liu & Wang (2020) for the detection of tomato anomalies in greenhouse environments; dense-connection modules and k-means–optimized anchor boxes were integrated to accelerate inference. A mean average precision (mAP) of 0.9641 and an inference latency of 20.28 ms per image were achieved, outperforming SSD, Faster R-CNN and the original YOLOv3 in complex settings.

Significant reductions in both training and validation loss metrics were recorded for the segmentation-based YOLOv8 pest detection model. During training, the bounding-box regression error (train/box_loss) was reduced from 1.97 to 0.57, denoting more precise spatial localization of larvae and adults. The classification loss (train/cls_loss) fell from 4.04 to 0.37, reflecting enhanced differentiation among pest species, and the distribution focal loss (train/dfl_loss) decreased from 1.56 to 0.86, indicating improved estimation of irregular body contours. Validation losses likewise declined—from 1.99 to 0.74 for box_loss, from 2.65 to 0.37 for cls_loss, and from 1.45 to 0.92 for dfl_loss—before automatic early stopping was invoked at 372 epochs to avert overfitting, thereby confirming strong generalization on unseen greenhouse imagery (Figure 2). Yang et al. (2024) further advanced the YOLOv8 architecture for tomato canopy monitoring by integrating depthwise separable convolutions (DSConv) to reduce computational overhead, dual-path attention gates (DPAG) for more robust contextual feature fusion, and a feature enhancement module (FEM) to emphasize fine-scale lesion and pest morphology. The resulting model achieved higher precision, recall, and mean average precision (mAP) across varied environmental conditions, underscoring the value of tailored deep-learning enhancements in automated plant-protection systems (Bütüner et al. 2024).

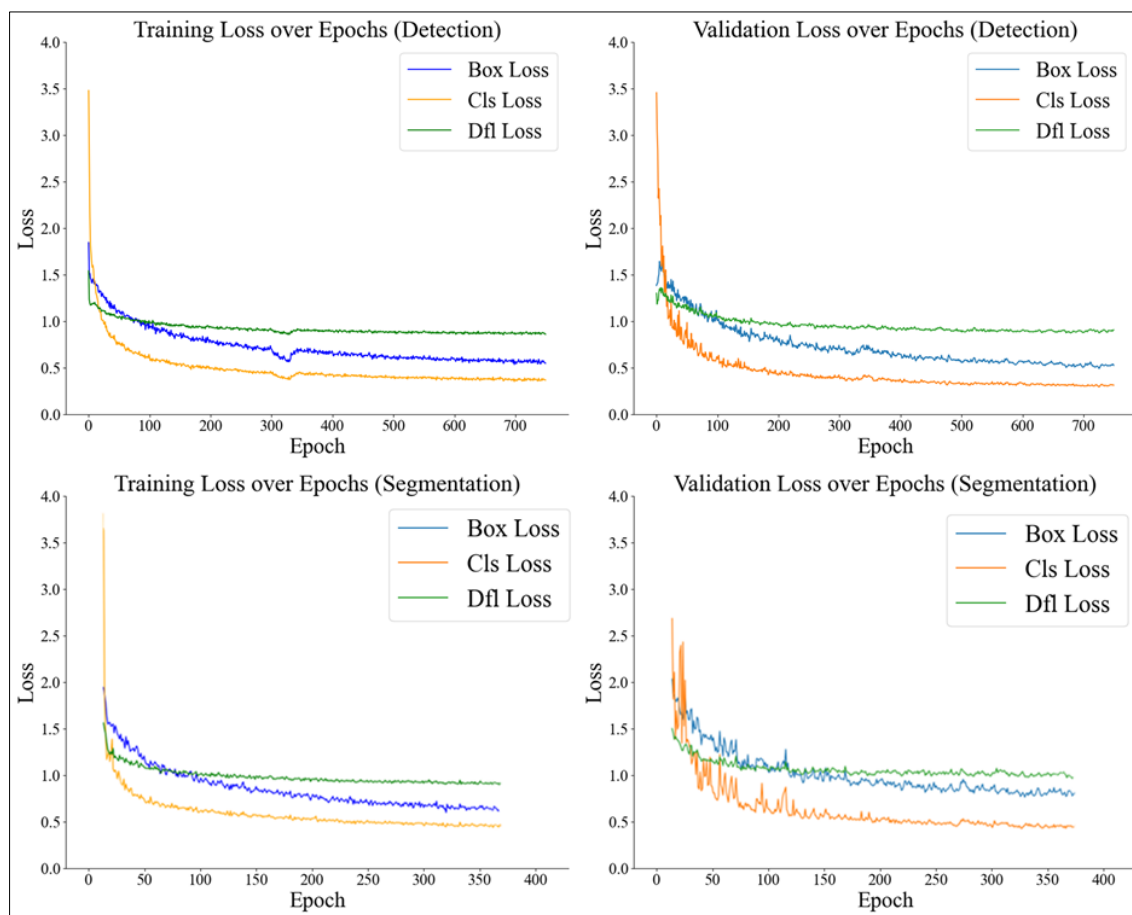


Figure 2 - Tracking of training and validation loss over successive epochs for the YOLOv8 model applied to pest detection and instance segmentation

3.2. Performance evaluation metrics

Mean average precision (mAP) metrics, notably mAP 50 and mAP 50–95, are employed to summarize detection performance at varying Intersection over Union (IoU) thresholds, with mAP50–95 offering a cross-threshold evaluation of model robustness. During the detection training of the YOLOv8 architecture, precision was increased from 0.0 to 0.9891, recall from 0.0 to 0.9898, mAP50 from 0.0 to 0.9875, and mAP50–95 from 0.0 to 0.9772. Early stopping was automatically triggered at 749 epochs to prevent overfitting, thereby validating the model's high-fidelity pest localisation and classification (Figure 3A). An improved YOLOv8s variant was subsequently introduced by Yang et al. (2023), in which depthwise separable convolutions (DSConv) and a dual-path attention gate (DPAG) were incorporated to enhance contextual feature aggregation under greenhouse lighting and occlusion conditions; this configuration attained an overall mAP of 0.934, outperforming earlier single-stage detectors. In parallel, segmentation training of the YOLOv8 model yielded marked gains: precision rose from 0.0 to 0.9747, recall from 0.0 to 0.9881, mAP50 from 0.0 to 0.9938, and mAP50–95 from 0.0 to 0.9599. Automatic cessation at 372 epochs ensured generalization, confirming accurate instance delineation across IoU criteria (Figure 3B). Complementary findings by Ahmad et al. (2022) demonstrated that the YOLOv5x model, when applied to the IP-23 insect pest dataset, achieved an average precision of 0.983, precision of 0.945, and recall of 0.978, thereby underscoring the efficacy of deep-learning-based object detectors in entomological surveillance for plant protection.

The YOLOv8 model in this study achieved 98.91% precision and 98.98% recall. These values exceed those reported for several other deep-learning detectors used in agriculture. For example, an R-CNN variant tested by Jiao et al. (2022) reached 77% accuracy on the AgriPest21 dataset, while Faster R-CNN obtained 74.77% mAP in Arun & Umamaheswari (2022). Optimised SSD implementations have approached 96.89% mAP for small objects (insects) (Lyu et al. 2021), and EfficientDet has reported around 94.29% mAP in forestry and fruit-detection tasks (Yang et al. 2024). Although comparisons should be made cautiously because datasets and evaluation protocols differ, the present results suggest that YOLOv8 provides competitive—and in many cases higher—performance for real-time, multi-species pest monitoring under commercial growing conditions.

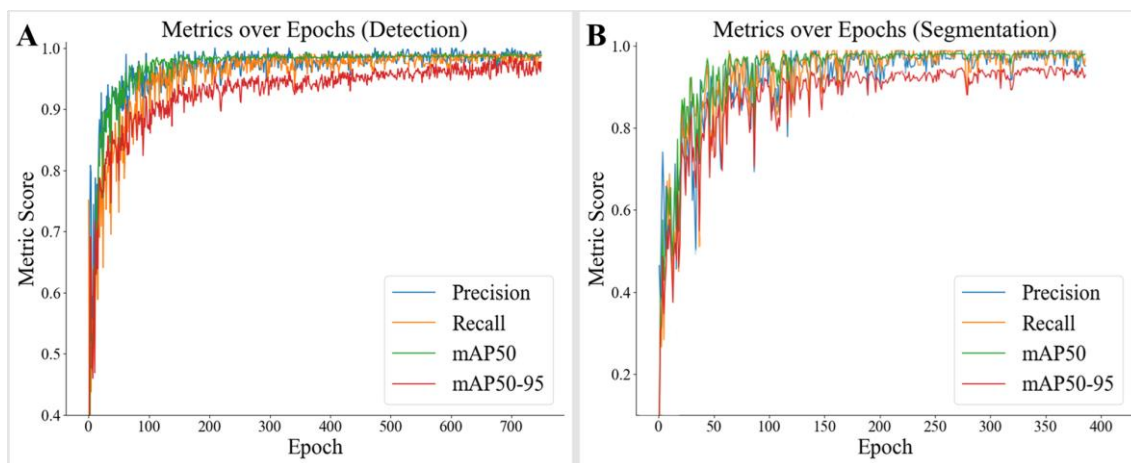


Figure 3 - Evolution of quantitative performance metrics recorded during YOLOv8 model training, with (A) object detection metrics and (B) instance segmentation metrics shown

3.3. Confusion matrix analysis

A comprehensive confusion matrix was constructed to reveal classification accuracies, mislabel patterns, and avenues for model optimization (Jensen et al. 2017). An image repository of 11 000 specimens was partitioned into training (80%), validation (18%), and testing (2%) subsets. The testing cohort—comprising adult imagoes, nymphs and larvae across eleven pest classes—was employed to compute the confusion matrix. High detection consistency was achieved: *Dolycoris baccarum* adults were accurately detected in 890 cases, with 15 misclassifications; *Nezara viridula* adults were correctly recognized in 695 instances, alongside 15 errors; and aphid adults were correctly classified in 998 occurrences. Comparable performance was observed for other taxa, with *Bemisia tabaci* adults detected correctly 1 025 times and *Leptinotarsa decemlineata* adults identified without error in 666 instances (Figure 4). These findings corroborate the model’s precision in entomological monitoring. Parallel investigations by Golatkar et al. (2020) and Yuan et al. (2024) have likewise highlighted the transformative impact of deep-learning frameworks on agricultural pest detection.

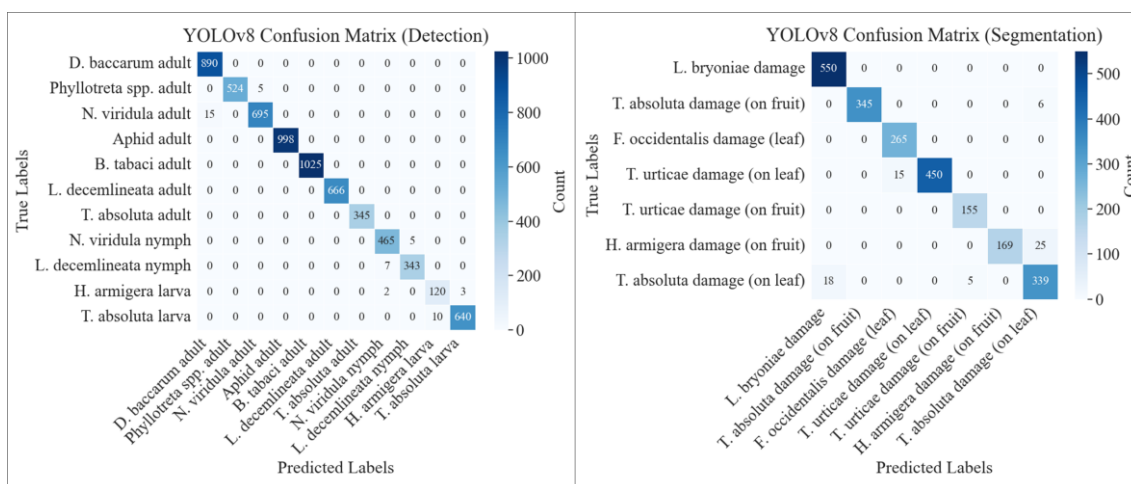


Figure 4 - The confusion matrices for the YOLOv8 model, illustrate detection performance across eleven pest classes and segmentation performance across seven classes

A dataset comprising 9 000 high-resolution images of tomato foliage and fruit, annotated across eight classes representing disease-free tissue and various pest-induced lesions, was employed to train YOLOv8 instance segmentation models. On the independent test subset, 550 instances of *Liriomyza bryoniae*-induced leaf mines were correctly segmented, 345 necrotic lesions on fruit caused by *Tuta absoluta* were accurately delineated, 450 *Tetranychus urticae* feeding scars on foliage were precisely segmented, and 565 regions of healthy leaf tissue were correctly identified (Figure 4). These results highlight the effectiveness of YOLO models in early pest detection, enhancing tomato production efficiency and sustainability. Studies like Wen et al. (2022) and Khalid et al. (2023) underscore the significance of advanced AI and deep learning techniques, such as YOLO, in agricultural pest detection and management. The YOLOv8 detection model, trained on pest images, was evaluated using a dataset where 2% was allocated for testing. The model accurately identified pests in specific test images with the following accuracy rates: *T. absoluta* adult at 0.98, *D. baccarum* adult at 0.92, *Phyllotreta* spp. adult at 0.89, *N. viridula* adult at 0.85, *T. absoluta* larvae at 0.93, *H. armigera* larvae at 0.87, *M. persicae* adult at 0.98, *L. decemlineata* adult at 0.95, *B. tabaci* adult at 0.89, *N.*

viridula nymph at 0.82, and *L. decemlineata* nymph at 0.88 (Figure 5). These results highlight the model's high accuracy in detecting various pest species on tomato plants, demonstrating the effectiveness of YOLOv8 for pest detection and management.

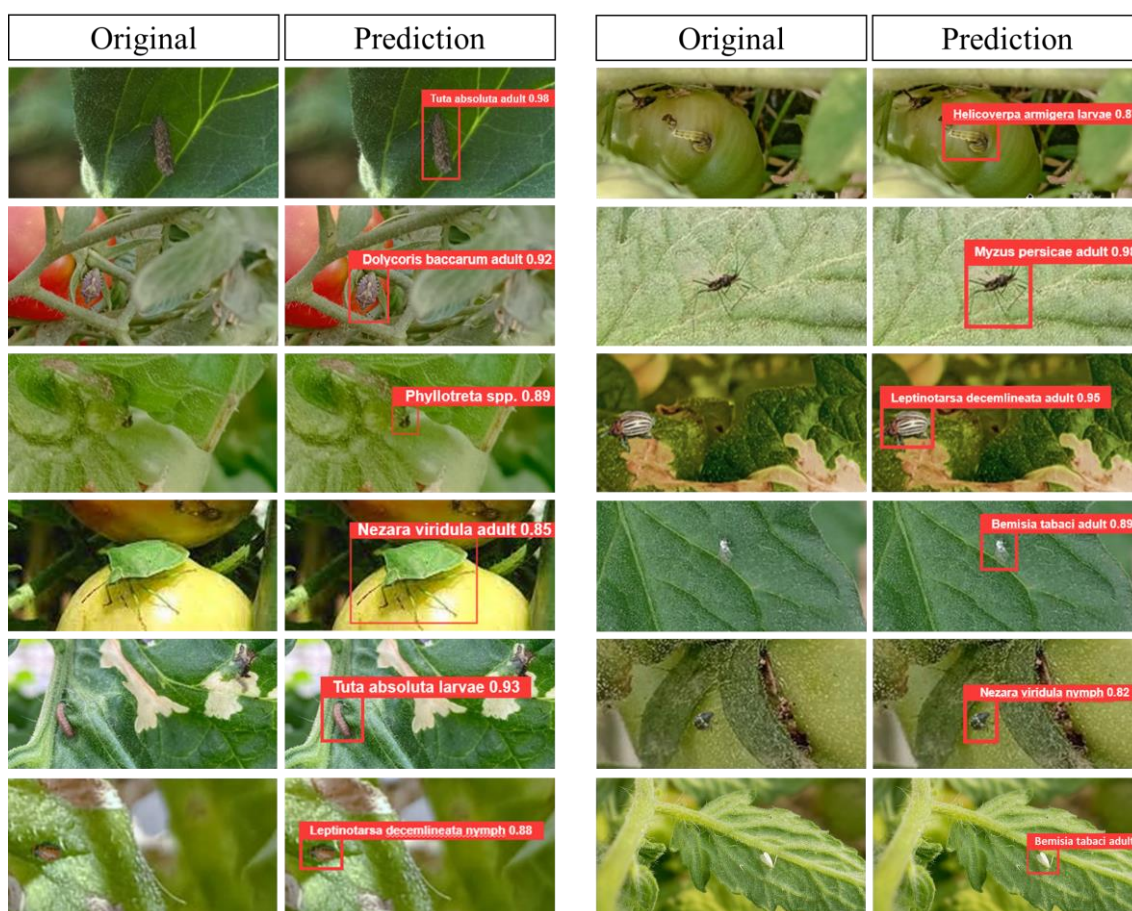


Figure 5 - Detections produced by the YOLOv8 model (yolov8s.pt) on the test dataset

The YOLOv8 model trained for segmentation was evaluated using a specific test dataset. The model achieved the following accuracy rates: *H. armigera* damage at 0.88, *F. occidentalis* damage at 0.82, *T. urticae* damage at 0.96, *T. absoluta* damage on fruit at 0.92, *L. bryoniae* damage at 0.88, and *T. absoluta* damage on leaf at 0.92 (Figure 6). These results demonstrate the model's effectiveness in accurately segmenting various types of pest damage on tomato plants.

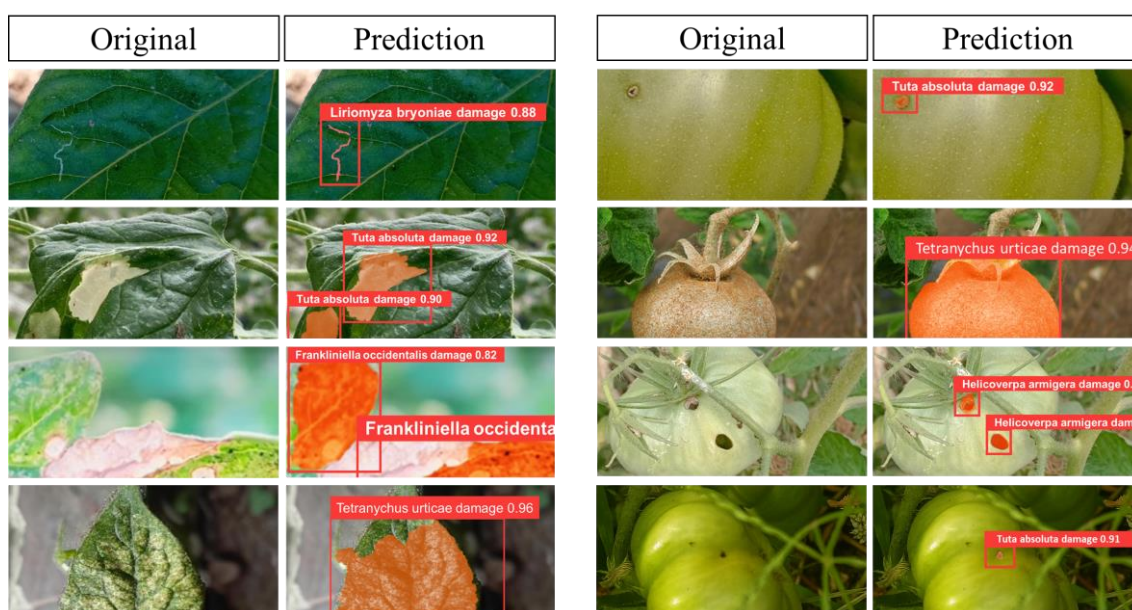


Figure 6 - Segmentations produced by the YOLOv8 model (yolov8n-seg.pt) on the test dataset

4. Discussion

The findings of the study using the YOLOv8 model demonstrate significant advancements in both the detection and segmentation of tomato pests. Precision, recall, and mean Average Precision (mAP) metrics showed notable improvements, with precision for detection reaching 0.9891 and segmentation achieving 0.9747. These results highlight the efficacy of YOLO-based models in agricultural pest detection, consistent with other studies in the field. Liu and Wang (2020) showed that an improved YOLO V3 model for tomato pest detection could effectively simplify the recognition process and achieve high accuracy in identifying pests and diseases. This study emphasizes the time-saving benefits and real-time judgment capabilities of deep learning models. Similarly, Wen et al. (2022) developed the Pest-YOLO model, which achieved mAP scores of 0.6959 for multi-class pest detection by addressing occlusion and low discrimination features. Rajamohanam & Latha (2023) utilized an optimized YOLO v5 model for classifying tomato leaf diseases, achieving a 0.93 accuracy rate on a field dataset, underscoring the model's robustness in real-time applications. Şahin et al. (2023) applied the YOLOv5 algorithm to detect *Tuta absoluta* larvae on tomato plants, achieving high accuracy in both categorization and damage detection.

Detection outcomes demonstrated marked enhancements, with object detection precision rising to 0.9891, recall to 0.9898, mAP 50 to 0.9875, and mAP 50–95 to 0.9772. Instance segmentation performance likewise improved, achieving precision of 0.9747, recall of 0.9881, mAP50 of 0.9938, and mAP50–95 of 0.9599. These findings are in concordance with earlier investigations: the Pest-YOLO framework reported an mAP of 0.6959 alongside a recall of 0.7771; a YOLOv8-based approach for small pest detection in field crops achieved an mAP of 0.847 (Khalid et al. 2023); and a segmentation-driven study on strawberry pest identification attained a detection rate of 0.9193 with 0.8341 reliability (Choi et al. 2022).

Overall, the results of this study validate the effectiveness of YOLOv8 in practical agricultural scenarios, highlighting its potential for enhancing pest detection and management in tomato production. A key contribution of this study is the model's ability to maintain high accuracy despite the increased number of labels (Wen et al. 2022; Xu et al. 2023; Kang et al. 2023). This underscores the model's robustness in learning and detecting multiple pest species with diverse morphologies. Typically, as the number of labels increases, the quality of training can decrease (Dong et al. 2022; Wang et al. 2022); however, this study shows that YOLOv8 can effectively manage this complexity. These results summarize the effectiveness of YOLOv8 in practical agricultural scenarios, highlighting its potential for enhancing pest detection and management in tomato production.

5. Conclusions

YOLOv8 model's ability to effectively manage this complexity suggests its potential to enhance pest detection and management in tomato production, contributing to more efficient and sustainable agricultural practices. This study exemplifies how artificial intelligence models can replace human labor-intensive, time-consuming, and error-prone observations (Chen et al. 2020; Raikov & Abrosimov 2022) with stable and rapid outputs, which are essential for sustainable agriculture. Future work could explore the model's application to other crops and pest species, further validating its versatility and utility in broader agricultural contexts. The implementation of such AI models in agriculture could revolutionize pest management, ensuring higher productivity and stability in outputs, thus supporting the long-term sustainability of farming practices.

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