Journal of
Computer & Electrical and Electronics Engineering Sciences
Original Article
DOI: 10.51271/JCEEES-0034

Intelligent diagnosis of tomato leaf diseases using YOLOv8

Hatice Candan*, Hüseyin Aydilek, Mustafa Yasin Erten
Department of Electrical and Electronics Engineering, Faculty of Engineering and Natural Sciences, Kırıkkale University, Kırıkkale, Turkiye

Cite this article as: Candan, H., Aydilek, H. & Erten, M. Y. (2026). Intelligent diagnosis of tomato leaf diseases using YOLOv8. *J Comp Electr Electron Eng Sci, 4*(1), 27-33.

Received: 11.11.2025 ◆ **Accepted**: 01.04.2026 ◆ **Published**: 25.04.2026

ABSTRACT

Tomato is one of the most widely cultivated and consumed vegetables worldwide. However, its production is hindered by various pests and pathogens. Rapid and accurate detection of these diseases is crucial for timely intervention and effective management. This study presents a model that employs YOLOv8n, an advanced object detection algorithm, for the identification of tomato leaf diseases. Experimental evaluations were conducted using 2,000 images selected from the Tomato subset of the CCMT dataset, which comprises 5,435 images categorized into five disease classes. The subset was constructed using a stratified sampling strategy to ensure balanced class representation, while low-quality or ambiguous images were excluded to improve annotation reliability. The results demonstrate that YOLOv8n achieved a mean Average Precision of 0.704, a precision of 0.655, and a recall of 0.721 across all classes. The best performance was observed in the healthy class, with an mAP50 of 0.942, a precision of 0.835, and a recall of 0.944. Overall, the findings indicate that AI-based rapid diagnostic systems can serve as an effective solution for early detection of tomato diseases and the prevention of yield losses in agricultural production.

Keywords: Plant leaf disease, disease detection, tomato leaf disease, YOLOv8, object detection

INTRODUCTION

Tomatoes are among the most consumed and widely cultivated vegetables worldwide. Almost every region with suitable climate conditions grows tomatoes. According to FAO and TEPGE data, while world tomato production was approximately 186 million tons in 2022, Turkiye's 13 million tons of production constituted 7% of the world total, placing the country in third place after China and India (FAO, 2023; TEPGE, 2024). According to TEPGE's 2024 report, tomato production in Turkiye in 2023 was approximately 13.3 million tons, 58.3% of which was table tomatoes and 41.7% was tomato paste. In addition, Turkiye's tomato exports in 2023 amounted to 533 thousand tons and provided foreign exchange income of 459 million dollars (TEPGE, 2024). According to TÜİK balance tables, per capita tomato consumption in Turkiye was 106.4 kg in the 2022/23 period, and the sufficiency level was at 117.5% (TUIK, 2023 ; TEPGE, 2024).

Tomatoes are of great importance to human health due to their nutritional value and antioxidant properties. However, tomato cultivation faces significant challenges from pests and diseases, which negatively affect yield and quality. Farmers need adequate knowledge of tomato diseases to identify and distinguish them manually. Nevertheless, they already encounter numerous difficulties during the cultivation process. Pest attacks and failure to detect diseases on time can lead to significant reductions in yield and quality, causing severe economic losses and potentially resulting in the need to import tomatoes at exorbitant prices. Similar yield-related research highlights the importance of precise agricultural decision-making for enhancing productivity. For example, Karadaş and Bulut (2024) compared multiple predictive algorithms for estimating tomato yield, finding that the MARS algorithm achieved the highest accuracy and identified key agronomic factors influencing yield, such as irrigation frequency, fertilizer amount, and seedling density.

Therefore, it is crucial to identify tomato diseases rapidly and accurately and assess disease severity for timely implementation of preventive and management strategies. Currently, tomato disease detection relies on visual identification by experts using microscopes and similar tools, a process that is both time-consuming and labor-intensive. Additionally, the accuracy of disease identification depends on the expertise of the personnel involved. Since experts cannot always be present in the field and farmers may lack sufficient knowledge to diagnose such diseases, Artificial Intelligence (AI) and computer-aided methods can be employed to detect tomato leaf diseases (Mugithe et al., 2020).

In the literature, deep learning methods such as YOLO, VGG-16, Faster R-CNN, ResNet, AlexNet, CNN, and MobileNet have been widely used for tomato leaf disease detection (Ibáñez and Reyes-Muñoz, 2023; Adhikari et al., 2018; Kılıçarslan and Paçal, 2023; Li and Wang, 2020; Sakkarvarthi et al., 2022; Hong and Huang, 2020). Similar comparative studies on plant leaf disease detection using transfer learning-based CNN models have also been conducted. For instance, Sazak, Balsak, and Badem (2025) evaluated VGG16, VGG19, AlexNet, MobileNetV1, and MobileNetV2, reporting that

Corresponding Author: Hatice Candan, hatcan95@gmail.com

MobileNetV1 achieved the highest accuracy (99.20%) and superior precision, sensitivity, and F1-score across all classes, with the model integrated into a real-time web-based application for practical use in agriculture. In a study conducted by Ibáñez and Reyes-Muñoz, a model based on a Convolutional Neural Network (CNN) was proposed for identifying and classifying tomato leaf diseases, achieving an accuracy of 99% on both training and test datasets (Ibáñez and Reyes-Muñoz, 2023). Adhikari and others (Adhikari et al., 2018) used the PlantVillage dataset to detect three classes of tomato diseases (late blight, gray spot, and bacterial canker) using the YOLO model, reporting a Mean Average Precision (mAP) of 0.76. Kılıçarslan and Paçal (Kılıçarslan and Paçal, 2023) compared DenseNet, ResNet50, and MobileNet deep learning models for distinguishing between healthy and diseased tomato leaves. Their experimental results indicated that the DenseNet model performed best, achieving an error rate of 0.0269 and an accuracy of 99%.

Li and Wang detected tomato diseases and pests using YOLOv3 algorithm. They concluded that YOLOv3 can accurately and quickly detect tomato diseases in real time with a detection time of 20.39 ms and a detection accuracy performance of 92.39% (Li and Wang, 2020). Sakkarvarthi et al. used a CNN-based model with two convolutional and two pooling layers for tomato plant disease detection and classification. Their proposed model outperformed the pre-trained InceptionV3, ResNet152 and VGG19 models by showing a training accuracy performance of 98% (Sakkarvarthi et al., 2022). Hong et al. (Hong and Huang, 2020) evaluated the performance of ResNet50, Xception, MobileNet, ShuffleNet and Densenet121_Xception models on tomato leaf images captured by mobile applications. Among the tested models, DenseNet_Xception achieved the highest detection accuracy of 97.10%, while the lowest accuracy belongs to ShuffleNet with 83.68% accuracy.

The aim of this study is to provide fast and accurate identification of tomato diseases, which are critical factors for tomato production and yield, by employing the YOLOv8 model, a state-of-the-art object detection algorithm. Unlike earlier versions such as YOLOv3 or other CNN-based approaches (e.g., ResNet, MobileNet, DenseNet), YOLOv8 offers significant advantages in terms of real-time performance, computational efficiency, and adaptability to different vision tasks. These characteristics make it highly suitable for practical agricultural applications where timely detection is essential. Experimental studies were conducted using 2,000 selected images from the "Tomato" subset of the CCMT dataset, which contains a total of 5,435 images across five different disease classes. The performance of the YOLOv8 model was then evaluated, and promising results were obtained.

METHODS

Ethics

Ethical approval was not required for this study as it does not involve human participants, animal subjects, or identifiable personal data. All procedures were carried out in accordance with the ethical rules and principles.

Dataset

The dataset used in this study was developed within the scope of the African Food Systems program, supported by the AI4AFS/GR/AFS1233809296 project (Mensah et al., 2023). It comprises images of cashew, cassava, maize, and tomato plants collected from local farms across various regions of Ghana, representing diseased, pest-affected, and healthy samples. The images were captured using a Canon EOS Rebel T7 DSLR camera equipped with an 18–55 mm lens between October and December 2022, during daylight hours, from multiple angles, and under varying lighting conditions and diverse backgrounds, including white, yellow, brown, gray, and natural settings.

A total of 24,881 raw images were initially collected. To enhance the dataset's diversity and generalizability, augmentation techniques such as rotation, brightness adjustment, and scaling were applied, resulting in 102,976 images. All images were labeled by experts in plant virology and pathology, and this labeling process was verified by the authors through manual review and consistency checks. Label accuracy was further validated via cross-validation and consensus meetings among the experts. Samples with inconsistent or ambiguous labels were excluded, and the final dataset was structured to include 22 distinct classes across four plant species.

The images were collected using a high-resolution camera device. The original JPG images have varying dimensions, including 400×400, 487×1080, 1080×518, 3024×4032, and 4032×3024 pixels. The tomato subset of the dataset consists of five categories: healthy leaves, leaf blight, leaf curl, septoria leaf spot, and verticillium wilt, as illustrated in Figure 1 and 2. Each category is represented in both raw and augmented forms, totaling 5,435 raw and 27,178 augmented images in JPG format. The images were captured from both front-facing and 180-degree rotated angles, under various lighting conditions including daylight, shadow, and artificial illumination, and against diverse backgrounds.

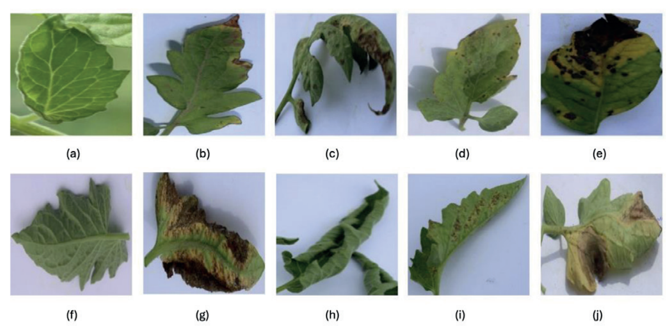

Figure 1. Tomato leaf samples: (a,f) healthy, (b,g) blight, (c,h) curl, (d,i) septoria, (e,j) wilt

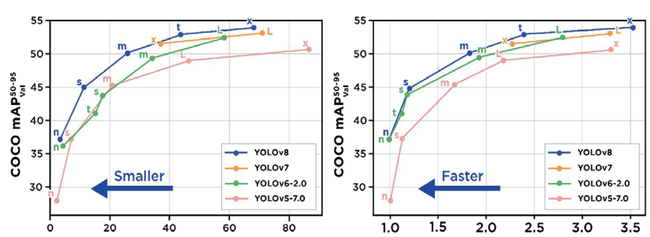

Figure 2. Comparison of YOLOv8 with other YOLO models (Taromi and Haghzad Klidbary, 2025)

Although the tomato subset contains 5,435 raw images, only 2,000 images were used for model training. This decision was made because processing high-resolution images imposes substantial hardware requirements. Considering the limited processing power and memory capacity of the available hardware, the dataset was restricted to 2,000 images in a balanced manner to preserve the representativeness of each class. This selection aimed to reduce computational load and ensure an efficient and stable training process.

Data Preprocessing Procedure

In this study, tomato leaf diseases were identified using the YOLO algorithm, which is widely applied in deep learning-based object detection tasks. Object detection is a branch of computer vision that focuses on identifying and locating objects of interest within an image or video frame. The objective is not only to determine the presence of specific objects but also to localize them precisely by drawing bounding boxes around their regions.

In supervised learning applications such as object detection and recognition with YOLO, labeling constitutes a crucial preprocessing stage. This process involves assigning appropriate labels to objects within each image and defining the region of interest that encompasses the object through bounding boxes.

Manual labeling of extensive datasets and the determination of bounding boxes require considerable time and human effort. Although various software platforms such as Roboflow provide partial automation, the labeling and bounding box annotation steps in this study were manually executed by the authors using a custom-developed labeling tool. A total of 2000 tomato leaf images were annotated into five distinct classes encompassing healthy leaves, leaf blight, leaf curl, septoria leaf spot, and verticillium wilt as presented in **Table 1**. The selection of the 2000-image subset was performed using a stratified sampling approach to ensure balanced class representation. Specifically, images were randomly selected from each class while preserving proportional distribution across all five disease categories. Additionally, images with poor quality, excessive blur, or insufficient visibility of disease symptoms were excluded to improve annotation reliability. This selection strategy aimed to maintain dataset diversity while reducing computational load, ensuring that the model was trained on representative and informative samples.

The labeling process was guided by visual disease characteristics commonly reported in the literature, such as lesion color, shape, and distribution patterns on the leaf surface. Although the annotation was performed by the authors, reference images and publicly available dataset guidelines were used to ensure consistency across all classes. In addition, annotations were reviewed multiple times to minimize labeling errors and improve internal consistency.

However, laboratory-based diagnostic methods such as molecular or microscopic analyses were not applied to validate the labels, and no external expert verification was conducted. Therefore, the labeling process may include a degree of subjectivity, particularly in visually similar disease classes. This limitation is inherent in many image-based agricultural datasets.

The relatively limited size of the annotated subset and the absence of expert-validated labeling constitute important limitations of the present study. Nevertheless, the applied labeling procedure provides sufficiently consistent ground-truth data for model training and evaluation, while highlighting the need for more robust annotation protocols in future research.

YOLO Model

YOLO is a deep learning-based object detection algorithm that employs convolutional neural networks to identify and localize multiple objects within an image. It was first introduced by Redmon et al. (2016) and is designed to perform detection in a single pass through the image, which provides high computational efficiency and strong detection accuracy. Unlike region-based methods that operate in multiple stages, YOLO processes the entire image simultaneously, thereby reducing computational complexity and allowing faster inference. This single-stage approach makes YOLO particularly suitable for real-time applications in which rapid decision-making and efficient computation are essential.

Although newer iterations of the YOLO architecture have been introduced, YOLOv8 was selected for this study because it represents a mature, well-documented, and extensively benchmarked generation that integrates several architectural innovations without the instability or limited community validation often associated with more recent releases. YOLOv8 introduces a fully anchor-free detection mechanism, decoupled classification and regression heads, and a revised feature fusion module that significantly enhance convergence stability, inference speed, and detection accuracy. These advancements collectively provide a robust foundation for real-world applications requiring both precision and computational efficiency. Moreover, YOLOv8 has been widely adopted in various domains such as medical imaging, remote sensing, and agriculture, where it has demonstrated reproducible and verifiable performance across diverse datasets. This makes it particularly suitable for research that demands methodological transparency and replicability.

YOLOv8 employs a convolutional neural network architecture composed of two main components, the backbone and the head. The backbone is based on an enhanced Cross Stage Partial Darknet structure with 53 convolutional blocks, enabling improved information flow between layers. The head comprises several convolutional layers followed by fully connected layers that predict bounding boxes, objectness scores, and class probabilities. A key innovation of YOLOv8 is the integration of a self-attention mechanism within the head, allowing the model to focus on salient regions of the image and refine important features. Furthermore, the use of a feature pyramid network provides strong multi-scale detection capability, enabling the simultaneous recognition of both large and small objects. The schematic diagram of the YOLOv8 architecture is illustrated in **Figure 3**.

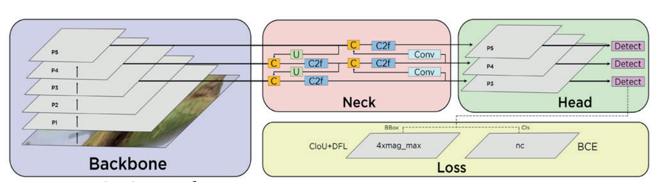

Figure 3. YOLOv8 architecture

Table 1. Number of images per class

Class type	Healthy	Leaf blight	Leaf curl	Septoria leaf spot	Verticillium wilt	Total
		(Alternaria solani)	*(Morbus foliorum tomati incurvation)*	*(Septoria lycopersici)*	*(Verticillium dahliae)*	
Number of images	426	328	433	466	347	2000

Within the YOLOv8 model family, which consists of five variants (n, s, m, l, and x), the YOLOv8n model was deliberately chosen due to its optimal balance between detection accuracy and computational efficiency. Agricultural image datasets often contain high-resolution images with substantial variation in illumination, texture, and background complexity. YOLOv8n effectively addresses these challenges while requiring considerably less processing power and memory. Its lightweight structure allows deployment on standard GPUs and edge devices without significant accuracy loss. Architectural features such as the anchor-free detection head, decoupled classification and regression branches, and adaptive spatial feature fusion further enhance training stability and generalization capability. Although larger models such as YOLOv8l or YOLOv8x offer slightly improved accuracy, their increased computational cost makes them less suitable for real-time or large-scale agricultural analysis.

In addition, although more recent versions such as YOLOv9 have been introduced, these models are relatively new and have not yet been extensively validated across diverse agricultural datasets. The lack of standardized benchmarks and reproducibility studies for these newer versions may introduce uncertainty in performance evaluation. Therefore, YOLOv8 was preferred due to its architectural maturity, extensive documentation, and proven stability in real-world applications.

Furthermore, the selection of YOLOv8n was guided by the need to balance detection accuracy and computational efficiency. In practical agricultural scenarios, models are often required to operate under limited hardware conditions, making lightweight architectures more suitable for deployment. While larger or newer models may provide marginal accuracy improvements, they typically require significantly higher computational resources.

Performance Evaluation Metrics

Standard quantitative metrics are necessary for only evaluation and comparison of object detection models performances. The two most accepted standard metrics used for these kinds of evaluations are IoU and Mean Average Precision (Rizzoli, 2023; Padilla et al, 2020).

Intersection over Union (IoU)

IoU is rather frequently mentioned among the object detection metrics for assessing localization, as well as for errors in localization. The calculation of IoU is performed using the intersection area shared by the two appropriate bounding boxes set for the same object. Next, the total area covered by the two bounding boxes constitutes the 'Union,' and the overlapping occupied by these two bounding boxes works out the 'Intersection.' To get the cover between prediction boxes and ground-truth boxes, the intersection should be divided by the union to create a ratio (**Figure 4**). IoU denotes how well the predicted coordinates of the bounding box overlap with the actual box coordinates. Generally, the higher value of IoU indicates a more accurate prediction. IoU values above 0.5 are treated as positive predictions; below 0.5 are treated as negative.

Mean Average Precision (mAP)

mAP is a well-developed metric for evaluating the performance of various object detection models. To compute average precision, one must take the area under the precision-recall curve mapped over the given set of predictions. The mAP is then calculated by averaging the APs of all classes.

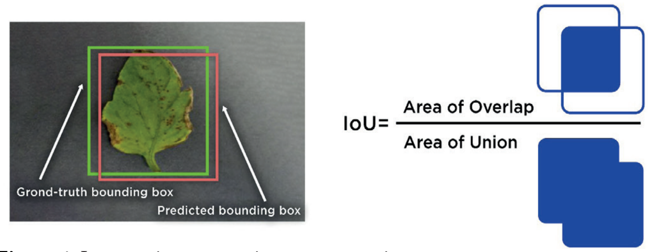

Figure 4. Intersection over union representation

Recall refers to the ratio of correctly predicted instances to the total number of ground truth instances for a class, while precision is the ratio of true positives to the total amount of predictions made by the model. The anomaly of high mAP results from an intelligent object detection model performance.

$$\mathrm{mAP} = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

The formula to compute the mAP is as follows, where ⟦AP⟧_k is the AP of class k and n is the number of classes.

Such terms include true positive (TP), false positive (FP), true negative (TN), and false negative (FN); that are used in the calculation of other important metrics such as accuracy, precision, and recall.

Accuracy is the percentage of correctly classified instances:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision represents the proportion of correctly predicted positive cases:

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

Recall reflects the proportion of positive instances correctly identified by the model:

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

F1 Score, the harmonic mean of precision and recall, ranges between 0 and 1, with 1 indicating perfect precision and recall:

$$f1\ score = 2x * \frac{precision * recall}{precision + recall}$$

RESULTS

After dividing the dataset into training, validation, and test sets, the training set was used to train the YOLOv8n model within the PyCharm IDE. The dataset was split into 80% training, 10% testing, and 10% validation. The trained model was then evaluated on the test dataset using the custom-trained weights. **Figure 5** provides a flowchart summarizing the entire process.

The model aims to classify each image into one of the predefined classes ('healthy', 'leaf blight', 'leaf curl', 'septoria leaf spot', 'verticillium wilt'), effectively identifying tomato leaf diseases. **Table 2** provides details on the hyperparameters used during the training process, while **Table 3** presents the model's evaluation metrics and mAP values for each class.

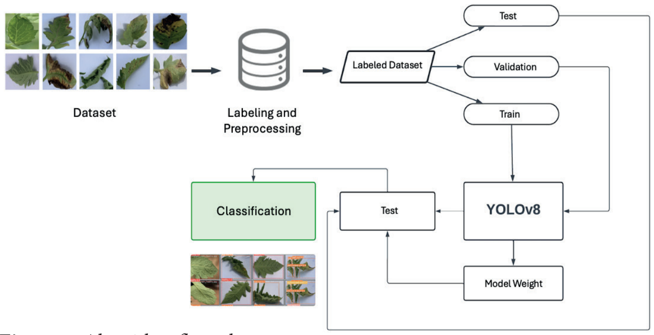

Figure 5. Algorithm flow chart

Table 2. Hyperparameters used in YOLOv8n model training	
Hyperparameter	**Value**
Image size	600x800 pixels
Training time	2282 sec
Epochs	20
Batch size	32
Learning rate	0.01

Table 3. Model performance on the test dataset				
Class	**P**	**R**	**mAP50**	**mAP50-95**
All	0.655	0.721	0.704	0.520
Healthy	0.835	0.944	0.942	0.788
Leaf blight	0.650	0.412	0.503	0.293
Leaf curl	0.710	0.800	0.709	0.440
Septoria leaf spot	0.520	0.636	0.606	0.484
Verticillium wilt	0.560	0.812	0.761	0.597

P: Precision, R: Recall

The model's hyperparameters included a resolution of 600×800 pixels for input images, a total training time of 2282 seconds, and 20 epochs with a batch size of 32. The learning rate was set to 0.01. Due to hardware limitations, the training process was restricted to 20 epochs. Despite the relatively low number of epochs, the training and validation loss curves indicated stable convergence without significant fluctuations.

The results in **Table 3** indicate that the YOLOv8n model performed best in detecting healthy leaf samples, with precision and recall values of 0.835 and 0.944, respectively. However, lower performance metrics for classes such as "leaf blight" and "septoria leaf spot" highlight areas for improvement. The overall mAP50 value of 0.704 and mAP50-95 of 0.520 suggest good general performance, with room for optimization.

Figure 6 provide examples of labeled data and predictions made by the YOLOv8n model. **Figure 7** displays the precision-confidence, recall-confidence, and precision-recall curves, which further demonstrate the model's performance at various thresholds.

Precision-confidence curve: The precision reached a perfect score of 1.0 at a confidence threshold of 0.958.

Recall-confidence curve: Recall was 0.96 even at a confidence threshold of 0.0, indicating robust sensitivity.

Precision-recall curve: The model achieved an average precision score of 0.704 at a 0.5 IoU threshold, indicating effective classification across different classes.

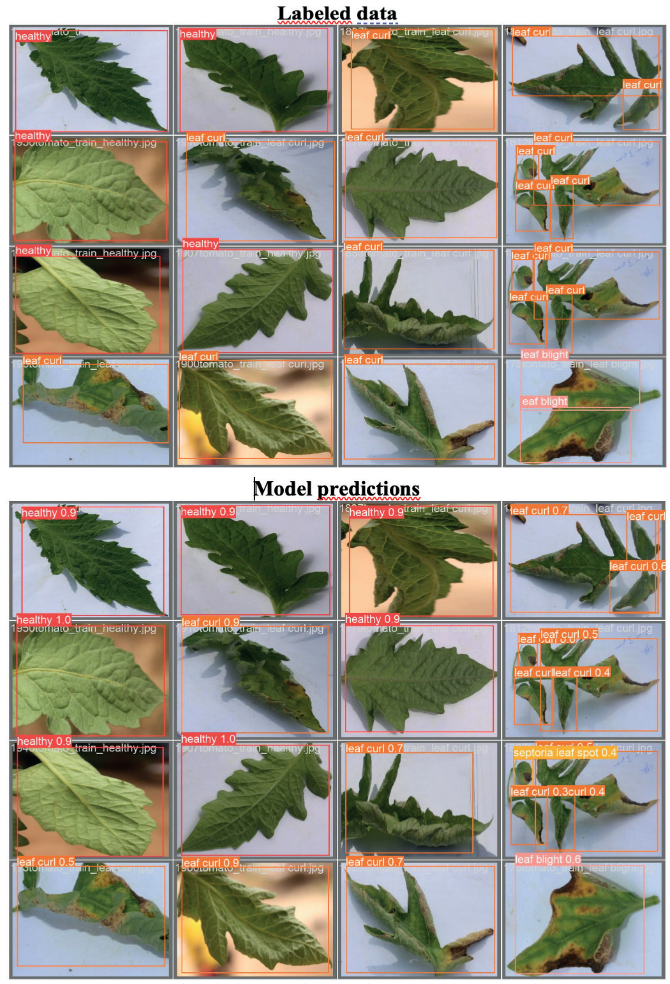

Figure 6. a) Images labeled by us during the model training data preparation process, b) Labels predicted by YOLOv8n model

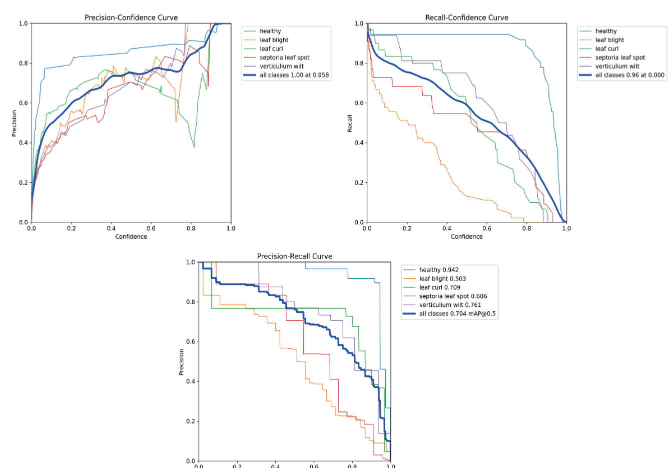

Figure 7. Precision-confidence curve; recall-confidence curve; precision-recall curve, respectively

These findings affirm the model's ability to detect plant diseases while emphasizing specific classes where further refinement is needed. The relatively lower mAP50 value observed in the leaf blight class (0.503) can be explained by several interrelated factors. First, leaf blight shares highly similar visual symptoms with other diseases such as Septoria leaf spot and Verticillium wilt, which increases inter-class confusion even for advanced deep learning models. Second, class imbalance within the dataset-where leaf blight samples are fewer than Septoria leaf spot samples-may have biased the model toward the majority classes. Third, variations in illumination, background texture, and leaf overlap in field images reduce lesion contrast and increase detection difficulty. Moreover, YOLOv8's object-detection-based architecture is inherently more sensitive to labeling inconsistencies and background noise compared to pure classification models. Similar difficulties have also been reported in prior works such as (Durmuş et al. 2017). Therefore, the lower detection performance primarily reflects the natural complexity and heterogeneity of real-world agricultural imagery rather than a shortcoming of the proposed model. Future research will focus on mitigating these challenges by applying class balancing, targeted data augmentation, and attention-based feature enhancement strategies.

Although the YOLOv8n model achieved promising overall results, performance varied across classes. The primary reason for selecting the YOLOv8 model in this study is its real-time detection capability, computational efficiency, and robustness to varying image conditions such as illumination, background clutter, and leaf overlap. Unlike models such as DenseNet or ResNet50, which perform only image-level classification, YOLOv8 is capable of both detecting and localizing diseased regions within the leaf images. This dual functionality makes it more suitable for practical field applications and real-time monitoring systems. Moreover, the models in the literature that report extremely high accuracies typically rely on cropped, segmented, or laboratory-captured images under controlled lighting conditions, whereas the YOLOv8 model in this study was trained and tested on unsegmented, natural field images containing greater variability and noise. Therefore, the overall mAP50 value of 0.704 represents a reasonable performance level for a more complex and realistic detection task. This discussion strengthens the justification for model selection and clarifies the contextual differences between the proposed model and previous benchmark studies. The lowest performance was achieved, particularly in the Leaf Blight class, with a recall value of 0.412 and an mAP50 value of 0.503. The Septoria Leaf Spot class remained relatively low, with a precision of 0.520 and an mAP50 value of 0.606. hese lower scores may be attributed to several factors. Firstly, there is an imbalance between classes in the dataset; having fewer images in some classes (leaf blight and verticillium wilt classes have fewer images than others) may reduce the generalization ability of the model. Second, leaf blight, Septoria leaf spot, and verticillium wilt share similar visual symptoms, which can lead to misclassifications. Finally, variations in image quality and background conditions introduced additional noise into the model, making it difficult to accurately detect disease-specific patterns. Another important limitation of this study lies in its single-label classification framework, which assumes that each image corresponds to only one disease category. However, in real agricultural environments, multiple diseases or abiotic stress factors may coexist on the same leaf, forming what is known as a "disease complex." In such cases, a single-label detection model like YOLOv8 tends to identify the most dominant visible symptom, potentially overlooking secondary infections. The timing of image capture also plays a crucial role, as disease symptoms evolve over time-early and late infection stages exhibit different color, texture, and lesion characteristics that significantly influence visual diagnosis and model predictions. Although the present framework defines five disease classes and one "healthy" class for academic clarity, real-world implementations would benefit from a hierarchical multi-label structure that first distinguishes between "healthy" and "diseased" conditions and then differentiates co-occurring disease types. The model's higher accuracy in the "healthy" class further supports this interpretation, suggesting that YOLOv8 is more proficient at detecting the presence of anomalies than distinguishing between visually similar disease categories. Future work will therefore focus on extending the framework to multi-label learning, temporal disease modeling, and stage-aware dataset collection to improve its practical utility under real field conditions.

Unlike previous studies that reported higher accuracy values using larger datasets and heavier models such as DenseNet, ResNet50, or MobileNetV2 (Ibáñez & Reyes-Muñoz, 2023; Kılıçarslan & Paçal, 2023), the proposed approach in this study focuses on achieving a balance between accuracy and computational efficiency. Specifically, the YOLOv8n model-a lightweight and real-time variant of the YOLO family-was intentionally selected to enable practical deployment under limited hardware conditions. While the mean Average Precision (mAP50) of 0.704 is relatively lower than those obtained by more complex architectures trained on larger or augmented datasets, it demonstrates that reliable tomato disease detection can still be achieved with reduced computational cost. This makes the proposed method particularly valuable for resource-constrained environments such as small-scale farms, mobile applications, or edge-based agricultural monitoring systems. Therefore, the novelty of this work lies not in surpassing existing models in raw performance metrics but in providing a feasible, efficient, and transparent framework adaptable to real-world agricultural contexts.

Limitations

In addition, a limitation of this study is that only a single detection model (YOLOv8n) was employed. Ablation studies or experiments with alternative models and hyperparameter settings could provide deeper insights and potentially improve performance. Another practical limitation is that, under real field conditions, multiple diseases or stresses may co-occur on the same leaf, whereas this study assumed a single-label classification approach. This gap may reduce the applicability of the model in complex real-world scenarios.

CONCLUSION

In this study, a YOLOv8n-based deep learning model was successfully developed and tested for tomato leaf disease detection. Utilizing a subset of 2,000 manually annotated images selected from the 5,435-image "Tomato" dataset categorized into five distinct disease classes, the model achieved a promising overall mean Average Precision (mAP50) of 0.704. The highest detection performance was recorded for the healthy class, confirming the model's strong capability in accurately identifying disease-free tomato leaves. The notably higher performance in the healthy class suggests that the model more easily distinguishes between healthy and diseased leaves, while finer discrimination among visually similar disease categories such as leaf blight and septoria leaf spot remains more challenging.

The main contribution of this study lies in demonstrating that a lightweight YOLOv8n model can provide reliable and efficient tomato disease detection, even with a relatively small manually annotated subset. This shows the potential of integrating real-time AI solutions into agricultural practice to support farmers in early diagnosis and reduce yield losses.

However, the lower detection metrics observed in specific disease categories highlight areas for refinement. Future research could focus on: (i) expanding the labeled dataset to reduce class imbalance, (ii) employing advanced data augmentation techniques, (iii) experimenting with different versions of YOLOv8 (s, m, l, x) and alternative models such as EfficientNet, DenseNet, or ResNet for comparative analysis, (iv) conducting ablation studies on hyperparameters and feature selection, and (v) extending the framework to handle multi-label classification, where multiple diseases may occur on the same leaf under real field conditions.

Overall, this study emphasizes the potential of advanced AI-based solutions like YOLOv8n to improve agricultural practices by enabling rapid and accurate disease detection. By bridging the gap between laboratory-level image datasets and real-world agricultural needs, the proposed approach contributes to more sustainable tomato production and enhanced food security.

ETHICAL DECLARATIONS

Ethics Committee Approval

Ethical approval was not required for this study as it does not involve human participants, animal subjects, or identifiable personal data.

Peer Review Process

This manuscript was subject to external peer review.

Conflict of Interest

The authors declare no conflicts of interest related to this study.

Financial Disclosure

The authors received no financial support for the conduct or publication of this research.

Author Contributions

Concept: HC, HA, MYE; Design: HC, HA, MYE; Control: HC, HA, MYE; Resources: HC, HA, MYE; Materials: HC, HA, MYE; Data Collection and/or Processing: HC, HA, MYE; Analysis and/or Interpretation: HC, HA, MYE; Literature Review: HC, HA, MYE; Writing the Article: HC, HA, MYE; Critical Review: HC, HA, MYE.

REFERENCES

Adhikari, S., Shrestha, B., & Baiju, B. (2018, September). *Tomato plant diseases detection system*. In *Proceedings of the 1st KEC Conference* (Vol. 1, pp. 81-86). Kathmandu Engineering College.

Durmuş, H., Güneş, E. O., & Kırcı, M. (2017, August). *Disease detection on the leaves of the tomato plants by using deep learning*. In *2017 6th International Conference on Agro-Geoinformatics* (pp. 1-5). IEEE. https://doi.org/10.1109/Agro-Geoinformatics.2017.8047016

Food and Agriculture Organization of the United Nations. (2023). *FAOSTAT: crops and livestock products*. FAO. https://openknowledge.fao.org/server/api/core/bitstreams/6e04f2b4-82fc-4740-8cd5-9b66f5335239/content

Hong, H., Lin, J., & Huang, F. (2020). *Tomato disease detection and classification by deep learning*. In *Proceedings of the 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)* (pp. 25–29). IEEE. https://doi.org/10.1109/ICBAIE49996.2020.00012

Ibáñez, J. A. G., & Reyes-Muñoz, A. (2023). Monitoring tomato leaf disease through convolutional neural networks. *Electronics, 12*(1), 229. https://doi.org/10.3390/electronics12010229

Jocher, G., Qiu, J., & Chaurasia, A. (2023). *Ultralytics YOLO (Version 8.0.0)* [Computer software]. Ultralytics. https://github.com/ultralytics/ultralytics

Karadaş, K., & Bulut, O. D. (2024). Comparison of predictive performance of data mining algorithms in predicting tomato yield: a case study in Iğdır. *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 27*(2), 443-452. https://doi.org/10.18016/ksutarimdoga.vi.121585

Kılıçarslan, S., & Paçal, İ. (2023). Domates yapraklarında hastalık tespiti için transfer öğrenme metotlarının kullanılması. *Mühendislik Bilimleri ve Araştırmaları Dergisi, 5*(2), 215-222. https://doi.org/10.46387/bjesr.1273729

Li, J., & Wang, X. (2020). Tomato diseases and pests detection based on improved YOLOv3 convolutional neural network. *Frontiers in Plant Science, 11*, 898. https://doi.org/10.3389/fpls.2020.00898

Mensah, K. P., Akoto-Adjepong, V., Adu, K., Abra Ayidzoe, M., Asare Bediako, E., Nyarko-Boateng, O., & Opoku, M. (2023). *Dataset for crop pest and disease detection* [Data set]. Mendeley Data. https://doi.org/10.17632/bwh3zbpkpv.1

Mugithe, P. K., Mudunuri, R. V., Rajasekar, B., & Karthikeyan, S. (2020). *Image processing technique for automatic detection of plant diseases and alerting system in agricultural farms*. In *Proceedings of the 2020 International Conference on Communication and Signal Processing (ICCSP)* (pp. 1603–1607). IEEE. https://doi.org/10.1109/ICCSP48568.2020.9182281

Padilla, R., Netto, S. L., & da Silva, E. A. (2020). *A survey on performance metrics for object-detection algorithms*. In *Proceedings of the 2020 International Conference on Systems, Signals and Image Processing (IWSSIP)* (pp. 237-242). IEEE. https://doi.org/10.1109/IWSSIP48289.2020.9145130

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 779-788). IEEE. https://doi.org/10.1109/CVPR.2016.91

Rizzoli, A. (2023, April 24). *The ultimate guide to object detection*. V7 Labs Blog. https://www.v7labs.com/blog/object-detection-guide

Sakkarvarthi, G., Sathianesan, G. W., Murugan, V. S., Reddy, A. J., Jayagopal, P., & Elsisi, M. (2022). Detection and classification of tomato crop disease using convolutional neural network. *Electronics, 11*(21), 3618. https://doi.org/10.3390/electronics11213618

Sazak, S., Balsak, S. C., & Badem, H. (2025). Transfer öğrenme temelli bitki yaprak hastalıklarının tespiti için karşılaştırmalı bir çalışma. *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 28*(1), 154–170. https://doi.org/10.18016/ksutarimdoga.vi.1571202

Taromi, A. D., & Klidbary, S. H. (2025). A novel data-driven algorithm for object detection, tracking, distance estimation, and size measurement in stereo vision systems. *Multimedia Tools and Applications, 84*(12), 11041-11061.

Tarım Ekonomisi ve Politika Geliştirme Enstitüsü. (2024). *Domates ürün raporu 2024* (Yayın No: 396). T.C. Tarım ve Orman Bakanlığı.

Türkiye İstatistik Kurumu. (2023). *Bitkisel üretim istatistikleri 2023*. https://data.tuik.gov.tr