



EVALUATION OF THE PERFORMANCE OF COMPUTER VISION MODELS IN THE DETECTION AND COUNTING OF TOMATE PLANTS INFECTED BY SPOTTED WILT VIRUS (TSWV)

Pinto, L. S.^{1*}; Valdes Fernandez, G.¹; Ciscato, M.¹; Lacerda da Silveira, G.¹; Costa Barboza, T. O.¹; Medeiros, M.¹; Azevedo, S.¹; Felipe dos Santos, A.¹

¹Department of Agriculture, Federal University of Lavras (UFLA), Lavras, Minas Gerais, Brazil.

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ABSTRACT

Tomato (*Solanum lycopersicum* L.) is a crop of high economic importance; however, its production can be severely affected by viral diseases, such as *Tomato spotted wilt virus* (TSWV), whose occurrence makes phytosanitary management more difficult and may cause significant losses. The rapid identification of symptomatic plants is essential to reduce disease spread in the field. In this context, the use of aerial images acquired by unmanned aerial vehicles (UAVs), combined with computer vision models, has potential to automate plant detection, classification, and counting in agricultural areas. Therefore, this study aimed to evaluate the performance of the YOLOv12 Large and RT-DETR models in detecting, classifying, and counting healthy tomato plants and plants showing symptoms associated with TSWV, using RGB images acquired by UAV.

The experiment was conducted at the Center for Development and Technology Transfer (CDTT) of the Federal University of Lavras (UFLA), in Ijaci, Minas Gerais, Brazil. Before the flight, symptomatic plants were visually identified in the field and marked with visual markers to assist the annotation stage. Images were acquired using a DJI Mavic 3M UAV at a flight altitude of 40 m, with 75% frontal and lateral overlap. The images were then processed in Pix4D software to generate the orthomosaic, which was divided into 640 × 640 pixel tiles. The images were annotated on the Roboflow platform, considering two classes: healthy plants and symptomatic plants. The dataset was divided into training, validation, and test sets at proportions of 70%, 20%, and 10%, respectively. The models were trained using Python in the Visual Studio Code environment, with acceleration provided by an NVIDIA GeForce RTX 5070 Ti GPU, using the same hyperparameters for both architectures.

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The results showed that both models achieved performance greater than 90% in the general identification and counting of plants, regardless of phytosanitary condition. RT-DETR showed the best performance in automatic counting, with a coefficient of determination ($R^2 = 0.95$) between automatic and manual counts. For class classification, YOLOv12 Large outperformed RT-DETR, especially for healthy plants. However, both models showed limited performance in identifying infected plants, possibly due to class imbalance, the low number of symptomatic samples, and the subtlety of TSWV symptoms in RGB images acquired at 40 m altitude. It is concluded that object detection models have potential for automatic tomato plant counting under field conditions, but the classification of TSWV symptoms still requires more balanced datasets, a larger number of infected samples, and possibly images with higher spatial resolution or complementary spectral sensors.

Keywords: RT-DETR, YOLOv12 Large, TSWV, UA, computer vision.

INTRODUCTION

Tomato (*Solanum lycopersicum* L.) is one of the most economically important vegetable crops worldwide, playing a fundamental role in food security and agricultural production systems. However, tomato productivity is frequently threatened by biotic stresses, particularly viral diseases that can cause significant yield losses and compromise fruit quality. Among these diseases, Tomato Spotted Wilt Virus (TSWV) is considered one of the most destructive pathogens affecting tomato crops (Tiberini et al., 2025) causing symptoms such as plant wilting, shoot dieback, chlorosis, stunting, and fruit deformities (Fontana et al., 2020). Early identification of infected plants is essential for implementing effective management strategies and reducing the spread of the disease within production areas.

Traditionally, disease monitoring in tomato fields relies on visual scouting performed by trained personnel. Although this approach can provide satisfactory results, it is labor-intensive, time-consuming, and subject to human error, especially in large production areas. Furthermore, symptom expression may vary according to plant developmental stage, environmental conditions, and disease severity, making the identification process even more challenging (Tiberini et al., 2025). These limitations have stimulated the development of automated monitoring approaches capable of increasing efficiency and reducing operational costs.

Recent advances in unmanned aerial vehicles (UAVs) and artificial intelligence have created new opportunities for agricultural monitoring. UAVs equipped with RGB cameras enable rapid acquisition of high-resolution imagery over large areas, while deep learning algorithms have demonstrated remarkable capabilities in object detection, classification, and counting tasks (Agrawal and Arafat, 2024). In agriculture, convolutional neural networks and transformer-based architectures have been successfully applied to crop monitoring, plant detection, disease assessment, yield estimation, and phenotyping applications (Liu et al., 2021). Among the most promising object detection approaches are the YOLO family of models and the Real-Time Detection Transformer (RT-DETR), which combine high detection accuracy with operational efficiency. While YOLO architectures are recognized for their speed and robustness in real-time applications, RT-DETR has emerged as a competitive alternative by incorporating transformer-based mechanisms capable of capturing global contextual information from images.

Despite the growing number of studies involving UAV imagery and deep learning, the detection of virus-infected tomato plants under field conditions remains a significant challenge. Disease symptoms are often subtle, heterogeneous, and restricted to specific portions of the canopy, which may limit the ability of object detection models to accurately discriminate infected plants from healthy individuals, particularly when images are acquired at operational flight altitudes. Moreover, few studies have compared the performance of CNN-based and transformer-based object detection architectures for the simultaneous tasks of plant detection, counting, and disease classification in commercial tomato production systems.

Therefore, the objective of this study was to evaluate and compare the performance of YOLO and RT-DETR models for the detection, counting, and classification of healthy and TSWV-infected tomato plants using RGB images acquired by UAVs. Specifically, we investigated the ability of both architectures to identify individual plants, estimate plant populations, and discriminate infected plants under realistic field conditions.

MATERIALS E METHODS

Study Location and Description

The experiment was conducted at the Center for Development and Technology Transfer (CDTT) of the Federal University of Lavras (UFLA), located in Ijaci, Minas Gerais, Brazil (21°09' S, 44°54' W). The climate of the region is classified as Cwa according to Köppen, characterized by dry winters and rainy summers.

The experimental area consisted of tomato progenies evaluated in a genetic breeding program. The crop was established in beds covered with mulching, with a spacing of 0.70 m between plants and 1.20 m between rows. The plants were trained with two stems, supported by twines, and irrigated using a drip irrigation system.



Figure1: Location of the experimental area at the Center for Development and Technology Transfer (CDTT), in Ijaci, Minas Gerais, Brazil.

Image Acquisition and Processing

Before the flight, a visual inspection of the experimental area was carried out to identify plants showing symptoms associated with infection by *Tomato spotted wilt virus* (TSWV). The symptomatic plants were marked in the field with visual markers, allowing their location in the aerial images and assisting in the subsequent labeling stage.



Figure 2: Visual marking of symptomatic plants in the field.

Image acquisition was performed during the reproductive stage of the crop using an unmanned aerial vehicle (UAV), DJI Mavic 3M model (SZ DJI Technology Co., Shenzhen, China). The equipment was connected to a high-precision DJI D-RTK 2® GNSS mobile station (DJI, Shenzhen, China), used to provide real-time differential corrections and improve the positional accuracy of the acquired images. The flight plan was executed in automatic mode at an altitude of 40 m, with 75% frontal and lateral overlap, resulting in a spatial resolution of 8.0501 cm pixel⁻¹. The images were acquired between 10:00 a.m. and 11:00 a.m., under favorable weather conditions and partially clear skies, in order to minimize interference caused by shadows, wind, and variations in illumination.

Image processing was performed using Pix4D® software (Pix4D S.A., Lausanne, Switzerland), applying the high-quality processing settings. At this stage, the necessary geometric and radiometric corrections were carried out, resulting in the generation of the orthomosaic of the experimental area. Subsequently, the orthomosaic was divided into 640 × 640 pixel images using a code developed in Python in Visual Studio Code, in order to proceed with the annotation process.



Figure 3: Orthomosaic tiles used in the training stage.

Subsequently, the images were annotated on the Roboflow platform, considering two classes of interest: “T”, corresponding to healthy tomato plants, and “I”, corresponding to plants showing symptoms associated with infection by *Tomato spotted wilt virus* (TSWV).

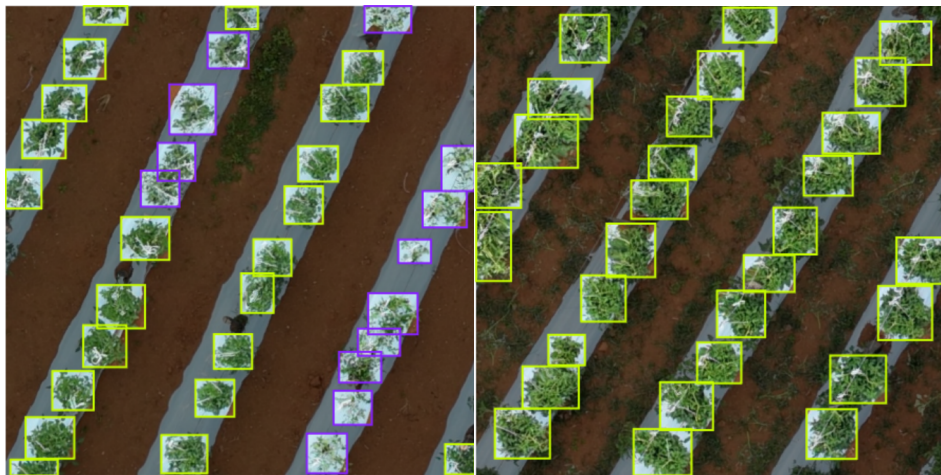


Figure 4: Example of image annotation on the Roboflow platform. The purple annotations correspond to class I, associated with plants showing symptoms of TSWV, while the yellow annotations correspond to class T, referring to healthy plants.

The dataset was divided into three subsets: training, validation, and testing, corresponding to 70%, 20%, and 10% of the images, respectively, ensuring that the final evaluation was performed on data not used during model adjustment. To increase the variability of the samples used for model training, data augmentation techniques were applied exclusively to the training set. The transformations employed included brightness adjustment, blur, flipping, and noise addition.

Model training

After annotation and dataset splitting, the processing workflow was organized into two main stages. The first stage consisted of training and validating the YOLOv12 Large and RT-DETR architectures, aiming to compare two distinct approaches for automatic plant detection in

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the evaluated images. The second stage was dedicated to plant quantification based on the predictions generated by the models.

YOLOv12 Large belongs to the family of one-stage detectors, in which object localization and classification are performed in a single step. This characteristic favors higher inference speed, making the architecture suitable for applications that require fast image processing.

RT-DETR, in turn, is a transformer-based architecture that uses attention mechanisms to represent spatial relationships among the elements present in the scene. This approach can contribute to the identification of visual patterns in more complex situations, such as variations in plant appearance, object overlap, and subtle differences between the evaluated categories.

The training procedures were conducted using codes developed in Python, with structuring, adjustments, and execution performed in the Visual Studio Code environment. Processing was carried out with acceleration using an NVIDIA GeForce RTX 5070 Ti GPU (16 GB VRAM), aiming to reduce computational time and make the training stage more efficient.

The same hyperparameters were adopted for training both models in order to maintain standardization between the evaluated architectures.

Hyperparameters	Value
Input Size	640 x 640 pixels
Batch Size	16
Workers	8
Epochs	500
Early Stopping	50

Tabela 1: Hyperparameters used for training the YOLOv12 Large and RT-DETR models.

After training, the counting stage was performed using the best saved weight from each model, referred to as best. This weight was applied to the test set to perform automatic plant detection and classification. Based on the predictions obtained, plants belonging to each class were counted separately, in addition to the total number of plants detected per image.

Model metrics and performance evaluation

The performance of the models was evaluated using the metrics precision (Equation 1), recall (Equation 2), F1-score (Equation 3), mean average precision with an IoU threshold of 50% (mAP50) (Equation 4), and mean average precision considering IoU thresholds ranging from 50% to 95% (mAP50-95) (Equation 5).

The Precision metric indicates the proportion of correct detections in relation to the total number of detections made by the model. Thus, high Precision values indicate a lower occurrence of false positives.

(1)

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

The Recall metric indicates the model's ability to correctly identify the objects actually present in the images. High Recall values indicate a lower occurrence of false negatives, that is, a smaller number of undetected objects.

(2)

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

The F1-score corresponds to the harmonic mean between Precision and Recall and is used to evaluate the balance between these two metrics. This measure is especially useful when simultaneously considering the occurrence of false detections and unidentified objects.

(3)

$$\text{F1-score} = \frac{2 * (\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

The mAP50 metric represents the average precision calculated at an IoU threshold of 0.50. N refers to the number of evaluated samples, and AP represents the average precision values obtained by the model.

(4)

$$mAP50 = \frac{1}{N} \sum_{i=1}^N AP_i$$

The mAP50-95 metric corresponds to the mean average precision calculated across multiple IoU thresholds, ranging from 0.50 to 0.95. In this equation, N refers to the number of AP values considered, and AP represents the average precision values obtained by the model.

(5)

$$mAP50 - 95 = \frac{1}{N} \sum_{i=1}^N AP_i$$

To complement the evaluation of the models, the loss curves generated during training were analyzed, considering GIoU loss, classification loss, and L1 loss for the training and validation sets. This analysis made it possible to monitor the evolution of the learning process over the epochs, as well as to identify reductions, oscillations, or possible instabilities in the model adjustment process.

Validation of Plant Counts

The quality of the automatic plant counting was evaluated through simple linear regression analysis between the values estimated by the models and the reference values obtained from the images. For this purpose, the coefficient of determination R^2 (Equation 6) was used to verify the degree of association between the predicted and observed counts. R^2 values closer to 1 indicate a better fit between the counts estimated by the model and the reference values.

(6)

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

RESULTS AND DISCUSSION

The YOLO model outperformed RT-DETR in the detection of healthy tomato plants, achieving higher precision, F1-score, mAP50, and mAP50-90 values. Although RT-DETR presented a higher recall for healthy plants, this gain was accompanied by a reduction in precision, indicating a larger number of false positive detections. For infected plants, both models showed limited performance, with F1-scores below 0.30 and mAP50 values below 0.20. These results suggest that disease symptoms were not sufficiently distinguishable in the acquired images, possibly due to early symptom development, symptom variability, or class imbalance within the dataset. Previous studies have demonstrated the potential of YOLO-based architectures for plant disease detection under controlled imaging conditions. For instance, Chitrasingh et al. reported mAP50 and

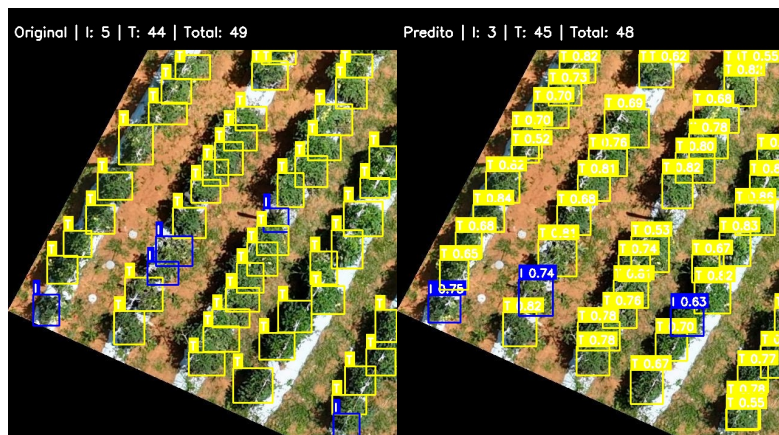
mAP50-95 values of 0.965 and 0.727, respectively, when applying YOLOv8 to classify corn leaf diseases. The substantially higher performance observed in their study may be associated with the nature of the dataset, in which disease symptoms were directly visible on leaves and constituted the primary target of the classification task.

YOLOv12l					
Classes	Precision	Recall	F1-score	mAP50	mAP50-90
Infected	0.2566	0.3589	0.2993	0.1897	0.0865
Healthy	0.8355	0.8215	0.8284	0.8865	0.5182
RT-DETR					
Infected	0.34340	0.1538	0.2125	0.1654	0.0813
Healthy	0.6854	0.8786	0.7701	0.8415	0.4780

Tabela 2: Performance metrics of the YOLOv12 Large and RT-DETR models for the infected and healthy classes.

An additional factor that may have influenced the classification performance was the unequal distribution between healthy and infected plants in the dataset (Figure 5). The predominance of healthy plants reflected the actual field conditions during image acquisition and therefore represents a realistic operational scenario for disease monitoring. Under such conditions, deep learning models tend to learn the characteristics of the majority class more effectively, which may partially explain the lower recall and F1-score obtained for infected plants. Nevertheless, the observed performance should not be interpreted solely as a consequence of class distribution, as the visual characteristics of TSWV symptoms, combined with the spatial resolution of RGB imagery acquired at 40 m altitude, also likely contributed to the difficulty in distinguishing infected plants. Therefore, the results provide valuable insights into the challenges of disease detection under practical field conditions rather than under artificially balanced datasets.

(A)



(B)



(A)

(B)

Figure 5 : Comparison of class identification performed by the RT-DETR (A) and YOLO (B) models, showing differences in the number of detected classes.

The continuous decrease in training classification loss, accompanied by a relatively stable validation loss, indicates that the YOLO model successfully converged during training (Figure 6). However, the limited reduction in validation loss suggests that the discrimination between healthy and TSWV-infected plants remained challenging, likely due to the similarity of visual symptoms under UAV RGB imagery.

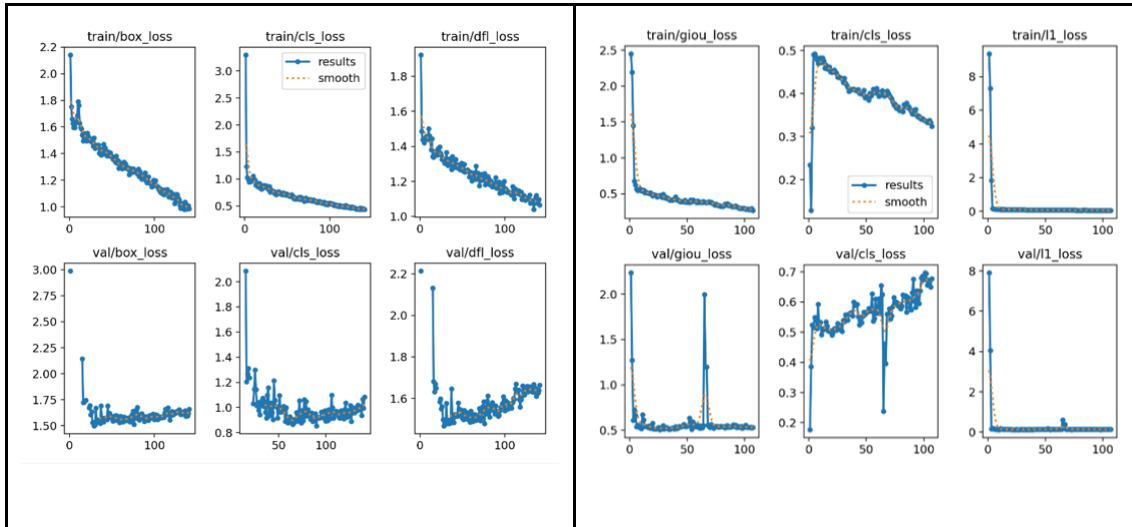


Figure 6: Training loss curves (Train Cls Loss) and validation loss curves (Val Cls Loss) for the YOLOv12 (A) and RT-DETR (B) models in the detection of tomato plants with and without TSWV symptoms.

The low detection performance observed for infected plants is likely associated with the spatial resolution of the RGB imagery acquired at 40 m altitude and the nature of TSWV symptoms (Figure 7). Since the disease primarily induces apical wilting and shoot dieback, the symptomatic regions occupy only a small fraction of the plant canopy, making them difficult to distinguish from healthy plants at the image resolution used. Furthermore, the imbalance between healthy and infected plants may have biased the models toward the majority class, resulting in substantially lower recall values for infected plants.



Figure 7: Orthomosaic of the tomato experimental area obtained from aerial images acquired at a flight altitude of 40 m.

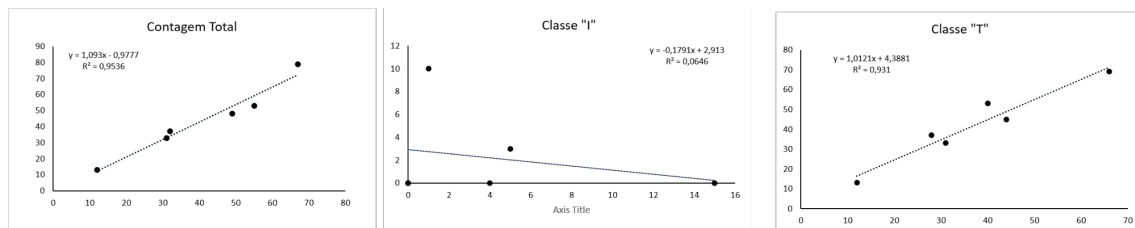


Figure 8: Relação entre as contagens observadas e preditas pelo modelo RT-DETR.

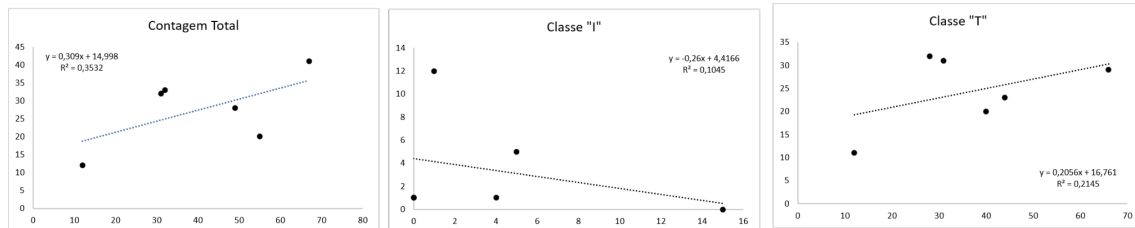


Figure 9: Relação entre as contagens observadas e preditas pelo modelo YOLOv12l.

The validation results show a clear distinction between the tasks of plant detection and disease classification (Figure 8). Although both YOLO and RT-DETR exhibited limited performance in discriminating between healthy and TSWV-infected tomato plants, particularly for the infected class, both models were effective in detecting individual plants within the field. Notably, RT-DETR achieved an R^2 value of 0.95 in the validation dataset for plant counting, demonstrating a strong agreement between automatic and manual counts. This finding indicates that the model was able to accurately locate tomato plants despite difficulties in assigning the correct phytosanitary status.

The lower performance observed for the infected class is likely associated with the characteristics of TSWV symptoms and the image acquisition conditions. Symptoms such as shoot dieback and plant wilting often affect only a portion of the canopy and may not produce sufficiently distinctive visual patterns when RGB images are acquired at 40 m altitude. Consequently, while the overall plant architecture remained detectable, the visual differences between healthy and infected plants were often subtle, increasing the complexity of the classification task. The influence of image spatial resolution on disease classification performance has been reported in previous studies. For example, researchers evaluating soybean leaf diseases using UAV imagery acquired at only 2 m above the canopy reported classification accuracies exceeding 99% when deep learning models were applied after a leaf segmentation procedure (Tetila et al., 2020).

Furthermore, the imbalance between healthy and infected plants may have contributed to the reduced recall and F1-score for the infected class, as the models tended to favor the majority class during training. These findings suggest that the primary challenge was not the identification of tomato plants themselves, but rather the recognition of disease symptoms under operational UAV imaging conditions. The challenges observed in the present study are consistent with previous reports on disease detection under field conditions. Soeb et al. (demonstrated that YOLOv7 was capable of rapidly detecting tea leaf diseases; however, the model became more susceptible to false detections when exposed to complex backgrounds. Similarly, Zhang et al. (2026) proposed the FCHE-YOLO architecture to improve disease recognition in UAV imagery, reporting increases in mAP and detection speed while reducing missed detections in complex environments. These studies highlight that disease detection performance is strongly influenced

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not only by the architecture of the deep learning model but also by the complexity of the scene and the visibility of disease symptoms.

However, it's important to highlight that studies have reported extremely high object detection performance when class differences are visually distinct in UAV imagery. For example, an automated oil palm monitoring system based on YOLOv8 achieved a mAP of 0.990 for the detection and classification of healthy, yellow, small, and dead palms (Thappa et. al., 2025). Similarly, the authors reported that YOLOv8 outperformed several state-of-the-art architectures, including YOLOv9, YOLOv10, DETR, and RTMDet. Such results demonstrate the strong capability of modern object detection models when target classes exhibit pronounced spectral, structural, or morphological differences. In contrast, the classification task addressed in the present study involved the discrimination of healthy and TSWV-infected tomato plants, in which symptoms were often subtle, heterogeneous, and restricted to specific portions of the canopy. Unlike dead or severely stressed trees, infected tomato plants frequently retained much of their original canopy structure, reducing the visual contrast between classes. Consequently, the lower F1-score and mAP values observed for the infected class likely reflect the intrinsic complexity of symptom recognition under field conditions rather than limitations of the detection architectures themselves.

CONCLUSION

This study demonstrated the potential of deep learning-based object detection models for tomato plant monitoring using RGB UAV imagery. Both RT-DETR and YOLOv12l achieved detection efficiencies greater than 90% for tomato plant identification and counting, regardless of plant health status, highlighting their applicability for automated stand assessment and crop monitoring. In particular, RT-DETR showed excellent counting performance, achieving a coefficient of determination (R^2) of 0.95 between automated and manual counts.

For the classification task, YOLOv12l outperformed RT-DETR in distinguishing healthy and TSWV-infected tomato plants, indicating greater robustness for phytosanitary assessment under the evaluated conditions. However, both models exhibited limited performance in the identification of infected plants, suggesting that disease discrimination remains a challenging task when using RGB imagery acquired at operational UAV flight altitudes.

The reduced classification performance observed for infected plants may be associated with the predominance of healthy plants in the dataset, the limited number of infected samples, and the characteristics of TSWV symptoms, which were often restricted to specific portions of the canopy and therefore difficult to distinguish at the spatial resolution employed. Overall, the results indicate that the main challenge was not the detection of tomato plants themselves, but rather the reliable recognition of TSWV symptoms under realistic field conditions.

Future studies should investigate the use of larger and more balanced datasets, lower flight altitudes, and alternative sensing approaches, such as multispectral and hyperspectral imagery, to improve disease detection performance.

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REFERENCES

Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture: 13-15 July, 2026, Porto Alegre, Brazil

LIU, J.; XIANG, J.; JIN, Y.; LIU, R.; YAN, J.; WANG, L. Boost Precision Agriculture with Unmanned Aerial Vehicle Remote Sensing and Edge Intelligence: A Survey. *Remote Sensing*, v. 13, n. 21, art. 4387, 2021. DOI: 10.3390/rs13214387.

FONTANA, A.; ALBANESE, G.; MANGILI, A.; TOMASSOLI, L.; TIBERINI, A. Phylogenetic analysis based on full genome sequencing of Italian tomato spotted wilt virus isolates identified in 'Roggianese' sweet pepper and chilli pepper. *Annals of Applied Biology*, v. 176, n. 2, p. 170–179, 2020. DOI: 10.1111/aab.12566.

TIBERINI, A.; CILLO, F.; GENTILI, A.; BERTIN, S. Tomato spotted wilt virus (*Orthotospovirus tomatomaculæ*), a cyclically occurring threat to crop production worldwide. *Annals of Applied Biology*, v. 186, n. 2, p. 93–114, 2025. DOI: 10.1111/aab.12977.

AGRAWAL, J.; ARAFAT, M. Y. Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture. *Drones*, v. 8, n. 11, art. 664, 2024. DOI: 10.3390/drones8110664.

TIAN, Y.; YE, Q.; DOERMANN, D. YOLO12: Attention-Centric Real-Time Object Detectors. *arXiv preprint arXiv:2502.12524*, 2025.

FILHO, Mario. Precisão, Recall e F1 Score em Machine Learning. Mario Filho, 3 jan. 2023. Disponível em: <https://mariofilho.com/precisao-recall-e-f1-score-em-machine-learning/>. Acesso em: 3 jun. 2026.

LV, W.; XU, S.; ZHAO, Y.; WANG, G.; WEI, J.; CUI, C.; DU, Y.; DANG, Q.; LIU, Y. DETRs Beat YOLOs on Real-time Object Detection. *arXiv preprint arXiv:2304.08069*, 2023.

ZHANG, Y.; WU, G.; SHEN, J. Precise tea leaf disease detection using UAV low-altitude remote sensing and optimized YOLO11 model. *PLOS ONE*, v. 21, n. 2, e0342545, 2026. DOI: 10.1371/journal.pone.0342545.

CHITRANINGRUM, Nidya; BANOWATI, Lies; HERDIANA, Dina; MULYATI, Budi; SAKTI, Indra; FUDHOLI, Ahmad; SAPUTRA, Huzair; FARISHI, Salman; MUCHTAR, Kahlil; ANDRIA, Agus. Comparison study of corn leaf disease detection based on deep learning YOLO-v5 and YOLO-v8. *Journal of Engineering and Technological Sciences*, v. 56, n. 1, p. 61–70, 2024. DOI: 10.5614/j.eng.technol.sci.2024.56.1.5.

TETILA, Everton Castelhão; MACHADO, Bruno Brandoli; MENEZES, Gabriel Kirsten; OLIVEIRA JÚNIOR, Adair da Silva; ALVAREZ, Marco; AMORIM, Willian Paraguassu; BELETE, Nicolas Alessandro de Souza; SILVA, Gercina Gonçalves da; PISTORI, Hemerson. Automatic recognition of soybean leaf diseases using UAV images and deep convolutional neural networks. *IEEE Geoscience and Remote Sensing Letters*, v. 17, n. 5, p. 903–907, 2020. DOI: 10.1109/LGRS.2019.2932385.

