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Research Article

ROI – Enhancing Detection of Citrus Disease Based on YOLOv10

Raya N. Ismail[1,*], Armaneesa Naaman Hasoon[1], Israa Rafaa Abdulqader[1], Salwa Khalid Abdulateef[1]

[1] *Computer Science Department, Computer science and Mathematics College, Tikrit University, Tikrit, Iraq*

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ABSTRACT

One of the most important fruit crops in the world is citrus. However, some citrus diseases spread rapidly, which is why early detection at an accurate stage is important for timely intervention. YOLO-based object detection models, such as the latest YOLOv10, where small lesions are difficult to identify among noisy backgrounds, have recently been developed, yet their accuracy tends to degrade. Therefore, we proposed a citrus disease detection model by integrating the region of interest (ROI) for object segmentation with the YOLOv10 model, thus addressing the issues of low detection accuracy and slow inference time. The proposed model was trained on an annotated dataset of three major citrus pathologies: anthracnose, citrus canker, and leaf miner infestation. Results showed significant improvements in the performance of our proposed model, which incorporates the ROI mechanism into YOLOv10. Specifically, the ROI-YOLOv10 model achieved high mAP scores, reaching 0.99 and 0.985 during training and validation, respectively, and maintaining high generalization capabilities with a test mAP of 0.984. Precision and recall metrics similarly underline the enhanced accuracy and robustness of ROI-YOLOv10. Compared with previous YOLO-based studies, our model exhibits enhanced accuracy and faster inference times. The incorporation of ROI techniques into the YOLOv10 framework is a highly effective approach for improving agricultural productivity by facilitating early and precise detection of plant disease.

1. INTRODUCTION

Citrus is one of the major fruit crops globally, grown in more than 140 countries, with oranges accounting for more than half of world citrus production and being the most widely traded citrus fruit [1]. Citrus fruits are rich in vitamin C, proteins, and essential minerals, and they constitute a large proportion of global agricultural production. However, threats of diseases and pests that affect the quality and productivity of citrus fruits may result in substantial economic losses [2].

Numerous infections affect citrus plants, including cankers, melanoses, scabs, greening, and black spots. Among these, citrus canker is highly contagious, primarily damaging the leaves and fruit. According to reports on kinnow, approximately 22% of the crop is lost, 25%–40% in sweet oranges, 15% in grapefruit, 10% in sweet limes, and 2% in lemons because of such a disease. Additionally, a substantial share of high-quality export-grade citrus fruits is often rejected due to disease symptoms or failure to meet stringent international quality standards, thus highlighting the need for early detection and intervention [3]. Accurate identification of citrus diseases is crucial to minimizing damage, reducing costs, and improving product quality [4].

Various citrus diseases, including citrus yellow shoot disease, have emerged as particularly severe threats, characterized by yellowing of shoots, leaf chlorosis, and gradual tree decline, affecting global crop quality and yield productivity losses [5]-[6]. Automated farming or smart farming is the newest data-driven paradigm of farming [7]. Thus, citrus diseases are diagnosed and classified by researchers who have developed automated techniques for such processes. Different methodologies are used in experiments, including citrus detection, image processing, preprocessing, and deep learning methods, for diagnosing plant diseases [8].

*Corresponding author. Email: Raya_computer@tu.edu.iq

Deep learning models have demonstrated a strong ability to capture spatial hierarchies and contextual features in complex tasks such as disease detection, pattern recognition, and natural language processing. Their hierarchical feature extraction capabilities and scalability make them particularly effective in analyzing large and unstructured datasets [9].

Traditionally, expert assessment for diagnosing citrus diseases is time consuming and requires extensive knowledge of the relevant domain. However, enhancements in deep learning and computer vision have revolutionized disease classification and detection. Existing models face challenges despite their success due to environmental conditions and variations in symptoms that reduce the ability to detect citrus leaf diseases. Therefore, developing lightweight and highly accurate models for detection is necessary to improve adaptability and recognition accuracy [10]-[11].

To achieve real-time detection a series of You Only Look Once (YOLO) has become the best solution . which can identify the positions of objects and categories simultaneously through a unified processing step, by offering an efficient trade-off between computational speed and detection accuracy. The latest addition to the YOLO family, YOLOv10 was unveiled in May 2024, introducing additional advances in architecture over previous versions. Particularly, it jointly reduces the computational cost by minimizes the number of parameters without losing detection accuracy. Because of this optimizations, YOLOv10 is highly efficient and scalable, offering high performance in both resource-constrained edge devices and cloud-based systems . In agricultural applications YOLOv10 has a high potential specially in plant diseases detection , where monitoring of diseases needs precise localization of lesions in complex field [12].

Image processing and segmentation are commonly used techniques to identify objects within images. Image segmentation is the process of keeping useful portions or areas, and this can include deleting certain image elements that are not important to the analysis of the original picture. The performance of image segmentation techniques is dependent on the features of the picture under consideration. One such technique is region of interest (ROI) pooling, where fixed-size feature maps for each region are selected from the original feature maps, speeding up computations significantly [13], [10].

The process of citrus leaf detection is a timely problem in current agricultural practice because citrus leaf diseases affect the production amount and product quality considerably. Images in orchards are highly complex and include overlapping leaves, branches, soil textures, and dynamic lighting conditions that present a real-world challenge. All these elements usually mask or distort visual symptoms of the disease. Despite recent improvements in deep learning, e.g., the current family of YOLOs, there are limitations to the direct use of object recognition in agricultural contexts as with citrus diseases and individuals such as YOLOv10. Particularly, some circumstances can affect the detection process, such as the size of diseased areas, irregular shape, or visual similarity to healthy ones. Moreover, inference speed is hampered by the network's need to process whole raw images without prior filtering [14].

Through ROI segmentation, the model is set to concentrate on the most pertinent leaves surfaces to downplay the effects of the unnecessary background. This selective approach has a number of beneficial implications: It processes symptomatic areas better and returns them with increased accuracy. Moreover, it lowers false positive results and minimizes redundancy, thus increasing inference speed. In addition, the model is robust to environmental variations of orchard conditions due to improved ROI integration. This approach can be scaled up to be transferable to disease detection in crops other than citrus in the larger discipline of precision agriculture [15].

To address existing challenges in citrus disease detection, we introduced a citrus disease detection model that uses ROI to segment citrus disease and then applied YOLOv10 in object detection. The proposed approach effectively identifies infected citrus plants from field images, segmenting diseased and healthy leaves with the assistance of a plant pathologist. This study's contributions include the following:

- Citrus plant illness was detected using a combination of ROI segmentation and YOLOv10.
- The proposed model was evaluated on a sizable dataset.

The remainder of this paper is organized as follows: Section 2 presents the related work, while Section 3 provides a review of the YOLOv10 architecture. Section 4 outlines the proposed methodology, and Section 5 details the experimental results and discussion. Finally, Section 6 concludes the paper and outlines directions for future research.

2. RELATED WORK

Plant disease detection has redefined by deep learning it enabled scalable, real-time, , and highly accurate diagnostic solutions through varied agricultural settings. Application of object detection and classification frameworks has been explored by numerous studies, particularly those use the YOLO architecture, to identify diseases in citrus crops under field conditions.

Xin et al. [16] Collected 1,524 images at various time intervals, resolution, and field conditions, to detect citrus disease through a robust system. They integrated the object detection model YOLOv4 with EfficientNet as classification model, achieving 89.0% as classification accuracy and 87.2% as F1-score, that demonstrate hybrid deep learning efficiency in monitoring citrus diseases field. Building upon this foundation, **Ali** [17] enhanced data training diversity by applying mosaic scaling with techniques of image translation, to evaluate YOLOv5, YOLOv7, and YOLOv8 subsequently, YOLOv8 showed better performance in versatility and precision, it success in terms of single and multiple disease detection through individual images.

To improve detection of subtle disease symptoms, **Wang et al.** [18] produced LSD-YOLO, which enhances YOLOv8 features to appear as convolutional block attention model. Including a small target tailored as a detection layer that can detect small lesion spots, aiming to improve sensitivity to infections in early stages. Similarly, **Wu Xie** [19] put traditional models like faster R-CNN in comparison with R-CNN that using modified YOLOv8. Although the variants of R-CNN can produce high accuracy, they demand high computational requirements making them unsuitable to be deployed in real-world under orchard conditions. The combination of YOLOv8 model with multi-feature selection capabilities, built a good balance between inference speed and accuracy.

Chen [20] developed YOLOv4 through a detection mechanism that contained four scales, with K-means clustering support for optimal anchor box sizing. The detection of diseases in multiresolution datasets enhanced through this adaption, and achieved higher performance over other contemporary systems, like YOLOv3, Detectron2, and SSD.

Wu et al. [21] introduced SAW-YOLO, to detect small area citrus pest using multiscale object detection system. The system combines a backbone novel spatial pyramid model that can preserve fine-grained attributes, with deeper network layers. Moreover, the attention attribute fusion and distribution head augments the fusion of shallow and deep attributes, presenting accurate detection across different pest sizes. SAW-YOLO manage to achieve 90.3% accuracy for the newly updated IP-CitrusPests13 dataset, that contains 13 citrus disease types, this result surpasses the baseline YO:Ov8 without a large increase in the size of the system.

Jiang, Li, and Zhao [22] employed YOLOv4 integrated with unmanned aerial vehicle (UAV) imaging to detect Huanglongbing, a devastating citrus greening disease. By capturing aerial imagery and processing it through a YOLOv4-based model, they achieved effective large-scale disease detection with high precision, demonstrating the ability of the model to manage variability in lighting, canopy coverage, and disease manifestation across citrus groves.

Ding and Taylor [23] introduced an automatic citrus leaf disease detection system that relied on traditional image processing techniques, such as color and texture analysis, rather than deep learning. Although their work predates the widespread adoption of YOLO models, it provided foundational insights into feature extraction methodologies, which modern YOLO frameworks now automate and optimize for real-time deployment in disease detection tasks.

Ghosal et al. [24] combined YOLOv3 with explainable artificial intelligence techniques, specifically Grad-CAM, to enhance transparency in citrus disease detection. Their framework not only achieved high detection accuracy but also provided visual explanations for the model's predictions, thereby improving trust and interpretability. This model marks an improvement toward combining explainability into high-performance YOLO-based agricultural disease systems.

Shoaib et al. [25] used ROI-based segmentation algorithms for plant disease detection in sophisticated agricultural settings. When it comes to small, anomalous shaped, and diseased plants the conventional models tend to falter since the background signals can cover the symptoms, so researchers used segmentation mechanism (ROI) to have better identification in areas of interest. In a similar manner, mask R-CNN uses layers of ROIAlign to extract regions contain specific lesion, aiming to effectively detect and draw the boundary of diseases in harvests like tomatoes, grapevines, and rice. Also, U-Net models, which were produced in medical imaging, used in related tasks but to detect plant pathology, providing pixel-level ROI, to improve the symptoms recognition ability in citrus greening and curl virus of tomato leaf. Although these techniques show great performance capabilities in lesion segmentation, they tend to be computationally demanding and unsuitable for real-time applications in field settings.

Gomez-Flores et al. [26] introduced a two-step ROI approach that was used in CitrusUAT, where LAB color transformation and Otsu thresholding extracted the leaf regions against the background. Subsequently, it used ROI extraction to crop the inner leaf, where the disease symptoms are most apparent. This technique effectively suppresses background noise and enhances feature extraction, enabling accurate spatial localization of lesions and leaf boundaries.

Tang et al. [27] implemented ROI to target the most informative parts of the leaf and reject background noise. Local sub-region fusion has been found effective in hyperspectral imaging to enhance early detection of citrus diseases such as anthracnose, where subtle differences between healthy tissues and asymptomatic and symptomatic tissues have to be detected. Deep learning networks have also been used to further develop ROI use by incorporating attention-based systems, including the RoI-attention network (RA-Net), which refocuses a model on lesion-related areas to improve the segmentation of small disease spots.

Bagga and Goyal [28] applied ROI extraction to segment the entire framework. Mask R-CNN and mask scoring R-CNN, among others, use ROIAlign to outline instance-level lesion boundaries, delivering highly accurate disease detection in tomato, rice, and grapevine. Pixel-based models such as U-Net and SegNet were also applied to medical imaging to isolate small symptomatic areas in crops such as citrus and tomato, and DeepLabv3+ uses multiscale ROI extraction to handle complicated and overlapping lesions.

Moon and Kim [29] produced attention-based mechanisms that performed reframing through ROI to address the challenge of detecting small disease lesions. The RA-Net introduced a multistage framework where initial segmentation outputs are used to generate ROI-attentive images, which highlight diseased pixels and their surrounding context. By progressively refining lesion predictions through sequential stages, RA-Net achieved superior segmentation performance on small lesions while remaining lighter than transformer-based approaches. Although highly effective for lesion segmentation, RA-Net, similar to other segmentation-heavy models, focuses on pixel-level refinement rather than balancing accuracy with inference speed for large-scale deployment.

Though different YOLO variant applications of YOLOv5 and YOLOv8 have been implemented to detect diseases in plants, most research did not critically examine the limitations of the architecture through the detection accuracy measured as its baseline. YOLOv5 added modular enhancements to the scalability of training and flexibility of deployment, whereas YOLOv8 made advances in detection with the addition of decoupled head structure and anchor-free predictions, which led to improved localization of the object and convergence. Both models employ non-maximum suppression (NMS) post-processing, resulting in redundancy and additional time lag on inference particularly on dense or overlapping lesions typical of crop disease imageries. Comparatively, the YOLOv10 model uses two label assigning strategies to adopt an NMS-free training mechanism, that removes the bottlenecks post-processing steps and keeps the high accuracy detection of multiple objects. Furthermore, YOLOv10 deploys classification heads in ultra-lightweight manner, down-sampling decoupled-spatial-channel, and rank-guided block optimizations, which save calculations and maximize attribute representation. The dual problem of accuracy and real-time inference speed can directly be solved by this innovated architecture and plagues previous YOLO use in the agricultural realm with more readily justifications in YOLOv10 adoption to meet the needs of citrus disease monitoring [30].

An integration of ROI with YOLOv10 is proposed to address the need for a detection system that achieves high accuracy, real-time performance, and domain-specific robustness simultaneously, contribute not only to advancing computer vision methodologies but also for supporting sustainable agricultural productivity through precise and timely plant disease detection. This design focuses on the lesion as provided by ROI-based segmentations and uses YOLOv10 as an efficient and fast detection model without the use of extensive preprocessing and multistage refinements. This effort not only improves the technical robustness of citrus disease diagnosis but also provides a practical framework for early intervention, precision agriculture, and disease spread prevention in orchards.

3. OVERVIEW OF THE YOLOV10 MODEL

YOLO has emerged as one of the most powerful and widely adopted algorithms in the object detection field, particularly noted for its fast inference and resource-efficient operation. The core strength of the YOLO architecture lies in its compact model size, end-to-end structure, and rapid inference speed, which makes it particularly effective in environments that need low latency, such as video stream analysis and embedded systems. Unlike known two-stage detectors, YOLO applies a single-stage detection framework that treats object detection as a parameter regression task, enabling end-to-end prediction of spatial positions and object classes through a single execution of the network [31].
The structural simplicity of YOLO enables it to process full images holistically, allowing the model to learn global contextual features and thereby reduce false positives caused by misidentifying background elements as objects. This global perspective, combined with its architecture's strong generalization capacity, enables YOLO to transfer learned representations effectively across different domains. Furthermore, by eliminating the need for region proposal stages, YOLO achieves significant speed advantages, thus making it feasible for real-time detection tasks. Despite these strengths, earlier versions of YOLO were known to trade off detection accuracy, particularly for small or densely packed objects, in favor of speed. However, ongoing architectural enhancements in recent YOLO variants (e.g., YOLOv5, YOLOv8, YOLOv10) continue to address these limitations through advanced feature fusion, attention mechanisms, and anchor-free detection strategies [31-32].

A significant breakthrough in reducing inference latency and streamlining the detection pipeline is achieved through YOLOv10's innovative architecture. By removing the traditional NMS step and introducing a novel NMS-free training paradigm built upon dual label assignment strategies, YOLOv10 attains harmony between computational performance and detection efficiency. This design not only maintains a lightweight model footprint but also enhances real-time object localization capabilities, making it highly suitable for deployment in resource-constrained and latency-sensitive applications [33].
Architecturally, as shown in Fig. 1, YOLOv10 incorporates several key innovations. One of these is that it utilizes compact classification heads alongside spatially and channel-wise separated down-sampling, supported by a rank-guided block structure to improve computational performance and detection precision. These elements collectively contribute to a reduction in parameter count and computational overhead, thereby enhancing the model's deplorability through a large variety of platforms, from efficient cloud infrastructures to resource-constrained edge devices. Moreover, YOLOv10 demonstrates exceptional scalability without sacrificing inference speed or accuracy [34].

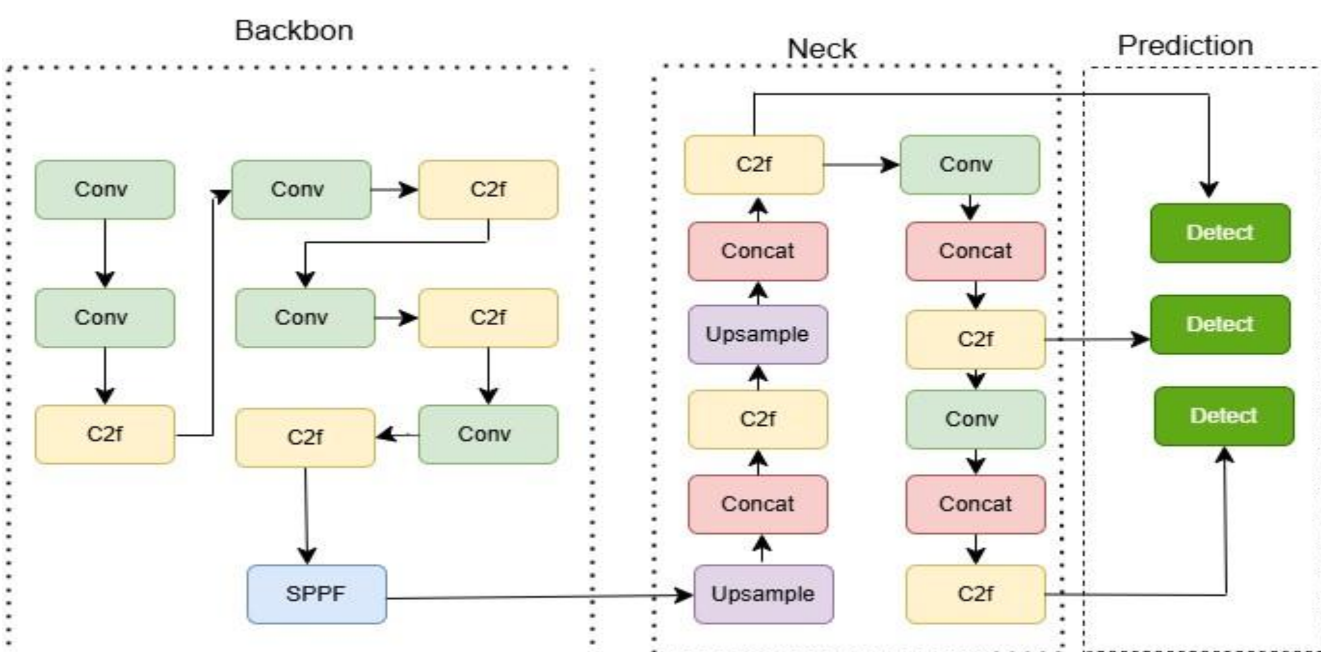

Fig. 1. YOLOv10 two-layer architecture

4. METHODOLOGY

The methodology proposed to detect citrus diseases using an integration of ROI extraction with the advanced YOLOv10 as an object detection model is illustrated in Fig. 2.

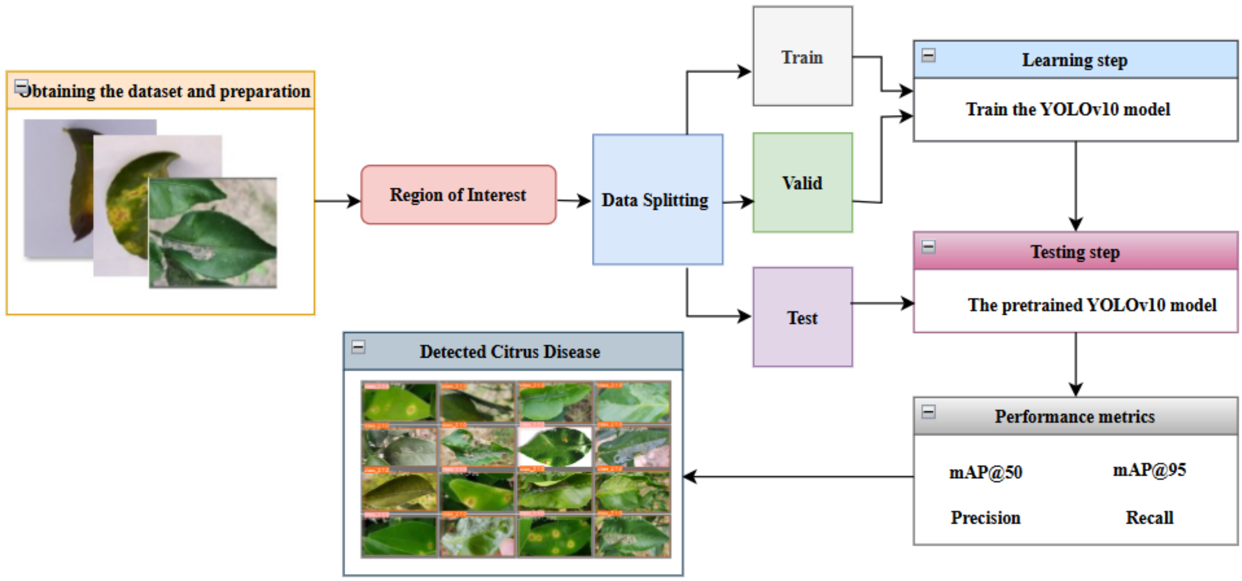

Fig. 2. Diagram of the proposed methodology (ROI-YOLOv10)

4.1 Obtaining the dataset and preparation

Initially, an annotated dataset that was published in [37] was used for our experiments. In the present study, a comprehensive and high-resolution image dataset was used, specifically curated to support the recognition and detection of citrus leaf diseases through advanced computational techniques. The dataset collects three clinically significant citrus diseases: anthracnose, citrus canker as a total of 1,944 images, each represented by carefully annotated visual samples. Every image within the dataset maintains a standardized resolution of **640 × 640 pixels**, captured under controlled lighting and consistent background conditions. The uniform conditions ensure visual clarity and compatibility with automated image analysis workflows. Machine learning and deep learning models use this dataset as an efficient resource for benchmarking and upgrading aimed at early-stage disease identification. Such efforts are central to enhancing precision agriculture, optimizing plant health monitoring, and informing epidemiological modeling related to disease transmission dynamics in citrus crops [35].

- Anthracnose, caused by the fungal pathogen *Colletotrichum gloeosporioides*, is characterized by necrotic lesions accompanied by chlorotic halos.
- Citrus canker, resulting from infection by *Xanthomonas axonopodis* pv. *Citri* presents as raised, corky lesions with prominent yellow halos.
  Leaf miner infestation, attributed to the larvae of *Phyllocnistis citrella*, is visually distinguished by serpentine mines that trace the internal leaf structure.

4.2 Preprocessing of the dataset

ROI pooling enables the efficient extraction of fixed-size feature maps from convolutional layers by selecting specific regions within the image that have a higher chance of containing objects. This step is central to improving computational performance and localization precision in traditional object detectors [36].

An ROI is mathematically modeled as a binary mask M(x, y), where only selected areas of the input image are processed further [37]. In Equation (1), the coordinates of the ROI are defined as a rectangular portion of the image, based on the upper-left corner of the ROI. This step is performed to isolate only the relevant section of the input image such as an infected leaf or a diseased spot without the rest of the irrelevant background data.

$$ROI = \{(x,y) \mid x_0 \leq x \leq x_0 + w, y_0 \leq y \leq y_0 + h\} \quad (1)$$

where

- (x_0, y_0)= top-left edge of the ROI
- w, h = width and height of the ROI
- x, y = pixel coordinates inside

In Equation 2, the features within the bounded area are extracted and aggregated into a fixed grid, and the obtained feature representation will have uniform dimensions, independent of the size of the ROI. This ensures that it can be compatible with later deep learning layers.

$$ROI_{Pooled} = \text{pooling } (F[X_{min}: X_{max}, Y_{min}: Y_{max}]) \quad (2)$$

where

- $x_{max} : x_{min} = width$
- $y_{max} : y_{min} = height$
- $width\ , height =\ bounding\ box\ coordinates$

For example, we have an image of a citrus leaf that has a disease. With the help of the ROI bounding box, the area of interest (i.e., the lesion) is surrounded by an ROI that excludes the soil and the surrounding leaves, as explained in Fig. 4. Then, Equation (2) uses ROI pooling on this region, which creates a feature map with a fixed size based on lesion-specific information. This helps eliminate background noise and significantly enhances detection accuracy.

a) b)

Fig. 3. Example image: a) original image b) original image after ROI

4.3 Data splitting

The dataset was randomly split into three sets: training, validation, and testing, which contained 1555, 194, and 195 samples, respectively. Table 1 shows the number of images in each class of the dataset.

TABLE I. NUMBER OF INSTANCES IN EACH IS USED AS THE TRAINING, VALIDATION, AND TESTING SETS

Class Label	Training	Validation	Testing
Anthracnose	170	19	20
Citrus canker	258	63	25
Leaf miner infestation	1123	112	150

4.4 Training the YOLOv10 model

A two-stage training approach was employed to develop an effective system for citrus disease diagnosis. First, an ROI segmentation model was trained to isolate the relevant parts of citrus images, typically the fruits and leaves, enhancing the quality and focus of the input data for subsequent analysis. This preprocessing step ensures that only meaningful visual content is passed to this stage. Subsequently, the YOLOv10 object detection model was trained with the Citrus dataset after determining the ROI. Adam optimizer was trained with a momentum of 0.9, a learning ratio of 0.001429, a batch size of 16, a weight decay of 0.0005, and 30 epochs. The integrated programming environment, Google Colab (Colab Pro), utilizes the Python 3.11 language and Type 4 GPU (T4) for speedier calculations.

4.5 Evaluation metrics

In study that involves citrus disease detection, especially one involving deep learning algorithms that are used for object detection such as the YOLOv10 model, the model's effectiveness can be evaluated by using three commonly used performance metrics, which are mathematically represented as shown in Equations (3)–(6) [38].

- $Precision = TP \;/\; (TP + FP)$ (3)
- $Recall = TP \;/\; (TP + FN)$ (4)
- $mAP@50 = \frac{1}{N} \sum_{i=1}^{N} AP_i \,@50$ (5)
- $F1 = \frac{2*Precision*Recall}{Precision+Recall}$ (6)

where

TP (true positive) represents the number of cases that were accurately predicted to be positive.

FP (false positive) is the number of samples that were wrongly predicted as positive.

FN (false negative) is the number of cases that were improperly predicted as negative.

AP is the mean precision for class i, with an intersection over union threshold of 0.50.

N is the number of classes

5. RESULTS AND DISCUSSION

This section presents the results of citrus disease detection using the ROI-YOLOv10 model.

A- Performance metrics

This study randomly partitioned the dataset into three independent sets, namely, training, validation, and testing, with a ratio of 80%, 15%, and 5%, respectively, to validate the proposed models' efficacy. Table 2 shows the experimental results of the proposed ROI-YOLOv10 model and indicates that the model outperforms the baseline YOLO10 through all evaluation metrics on training, validation, and test datasets. YOLO10 achieved moderate detection accuracy with training and validation mAP@50 values of 0.911 and 0.912, respectively, and mAP@95 values around 0.706–0.707. However, the test performance dropped to 0.84 (mAP@50) and 0.644 (mAP@95), along with a decline in precision (0.848) and recall (0.774), suggesting overfitting and reduced generalization capability. By contrast, ROI-YOLOv10 delivered consistently high performance, with test mAP@50 and mAP@95 both reaching 0.984, precision at 0.939, recall at 0.977, and F1 at 0.975. These results reflect significant improvements in detection accuracy and robustness, indicating that the incorporation of ROI features in ROI-YOLOv10 contributes to better object localization and fewer false positives. The superior generalization capability of ROI-YOLOv10 makes it a strong candidate for real-world deployment in critical object detection applications.

TABLE II. RESULTS OF THE PROPOSED MODEL COMPARED WITH THE YOLOV10

Model		mAP@50	mAP@95	Precision	Recall	F1-score
YOLO10	Training	0.911	0.707	0.892	0.818	0.85
	Validation	0.912	0.706	0.89	0.82	0.85
	Test	0.84	0.644	0.848	0.774	0.809
ROI-YOLOv10	Training	0.99	0.99	0.956	0.961	0.958
	Validation	0.985	0.985	0.972	0.941	0.956
	Test	0.984	0.984	0.939	0.977	0.957

Fig. 4 illustrates the qualitative detection results produced by the proposed ROI-YOLOv10 model on a diverse set of leaf disease images. Various types of leaf infections are identified and localized by the model effectively , such as leaf miner, canker, and anthracnose, as indicated by accurately placed bounding boxes and class labels. The system consistently demonstrates high detection accuracy and robustness despite variations in background complexity, lighting , leaf orientation, and disease severity. The model shows capability of handling dense scenarios in object detection and recognition by using multiple disease instances within a single image. The minimal overlap of bounding boxes and precise classification further confirms the system's strong generalization ability. These visual outcomes complement the quantitative performance metrics, reinforcing ROI-YOLOv10's effectiveness for real-time, field-level plant disease monitoring applications.

Fig. 4. Visual results for the proposed citrus disease detection model (ROI-YOLOv10)

B- Inference speed comparison

Fig. 5 presents a comparative analysis of the inference speed between the baseline YOLOv10 and the proposed ROI-YOLOv10 system during the two phases of training and testing. The results reveal that the proposed system consistently achieves lower inference times, with approximately 4.6 ms during training and 8.2 ms during testing, compared with 5.4 and 10.4 ms for YOLOv10, respectively. These results show that ROI-YOLOv10 not only enhance detection accuracy but also offer superior, efficient computations. The reduced latency is particularly advantageous for real-time systems, such as autonomous models and video surveillance, where rapid and accurate object detection is critical. The balance of high precision with lower inference time highlights the scalability and practical application of the proposed model in performance-sensitive environments.

Fig. 5. Inference time comparison

C- Comparison of the proposed model with previous work

The proposed detection model is compared with earlier works on related applications in Table 3. The proposed ROI-YOLOv10 system demonstrates notable improvements over existing methods in citrus disease detection in terms of inference speed and detection accuracy. In contrast to Xin et al. [16], who achieved 89.0% classification accuracy using a hybrid YOLOv4-EfficientNet pipeline, our model achieved superior performance with mAP@50 of 0.984, mAP@95 of 0.984, recall of 0.977, precision of 0.939, and F1 of 0.957. Unlike Ali [17] and Wang et al. [18], who focused on general YOLOv5–v8 variants and enhancements for small-target detection without reporting full evaluation metrics, the proposed method integrates ROI-based segmentation before detection, allowing for better localization and generalization. Wu Xie [19] proposed a lightweight YOLOv8 variant for balanced speed and accuracy. Still, our approach goes further by achieving both high detection accuracy and reduced inference time (8.2 ms testing), validated in a real-world application. Chen [20] improved YOLOv4 using multiscale detection, but our method's region-based segmentation, combined with YOLOv10, offers more precise detection of disease-affected areas. Additionally, Ghosal et al. [24] introduced explainable AI with YOLOv3 and Grad-CAM, whereas our approach prioritizes real-time efficiency and high accuracy of detection results in the field. Overall, the proposed ROI-YOLOv10 method outperforms previous studies by offering a robust and efficient pipeline tailored for early and accurate citrus disease detection under practical agricultural conditions.

TABLE 3. COMPARISON OF THE PROPOSED SYSTEM WITH RELATED STUDIES

References	Model	Dataset Size	Evaluation Metrics
Xin et al. [16]	YOLOv4 + EfficientNet	1,524 images	Accuracy 89.0%
Ali [17]	YOLOv5 / YOLOv7 / YOLOv8	More than 1,000 labeled images	mAP@50–95 = 96.1
Wang et al. [18]	LSD-YOLO (YOLOv8 enhanced)	4,441 healthy 718 diseased	Detection accuracy = 90.62 mAP@50–90 = 80.84
Wu Xie [19]	Modified YOLOv8	Self-built dataset of HLP symptoms	mAP@50 = 84.7 Precision = 82.7
Chen [20]	YOLOv4 (4-scale enhanced)	Multiresolution datasets	Accuracy = 96.04 Detection time = 0.06 s per frame
Ghosal et al. [24]	YOLOv3 + Grad-CAM	6,000 citrus disease images	Accuracy = 94.13%
Proposed model	**ROI+YOLOv10**	**1,944 images**	**mAP@50 = 99** **mAP@95 = 99** **precision = 95.6** **recall = 96.1** **F1= 95.8**

6. CONCLUSION

In this study, we proposed a citrus disease detection framework that integrates ROI segmentation with the YOLOv10 architecture (ROI-YOLOv10) to enhance the productivity of citrus crops and to reduce the adverse effects of leaf diseases. The ROI-YOLOv10 results significantly outperform those of the baseline YOLO10 across all performance metrics, including mAP@50, mAP@95, precision, and recall, with consistently high scores across training, validation, and test datasets. Unlike YOLO10, which exhibits signs of overfitting and diminished test performance, ROI-YOLOv10 maintains exceptional generalization, achieving test mAP@50 and mAP@95 values of 0.984, precision of 0.939, recall of 0.977, and F1 of 0.957. These findings demonstrate the effectiveness of combining ROI mechanisms into the YOLO architecture, leading to improved detection accuracy and robustness. The superior performance and stability of ROI-YOLOv10 confirm its suitability for deployment in real-world object detection scenarios and establish a practical foundation for future research and application in safety-critical domains. Future research will focus on extending the ROI-YOLOv10 framework to a wider variety of citrus diseases and pest infestations by enhancing its generalizability. Model optimization techniques such as pruning and quantization will be explored to enable real-time deployment on edge devices. Additionally, integrating multimodal data sources, including hyperspectral and UAV-based imaging, may further improve early detection performance under diverse field conditions.

Conflicts of Interest

The authors declare no conflicts of interest.

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