

Integrating YOLO model with Transfer Learning for High-Accuracy Detection and Localization of Quince Leaf Diseases

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Received: 28 August 2024

Revised: 30 November 2024

Accepted: 08 January 2025

Available Online: 27 July 2025

How to cite this article:Naderi Beni, A., Bagherpour, H., & Amiri Parian, J. (2026). Integrating YOLO model with Transfer Learning for High-Accuracy Detection and Localization of Quince Leaf Diseases. *Journal of Agricultural Machinery*, 16(1), 25-37. <https://doi.org/10.22067/jam.2025.89407.1277>

Abstract

Correct and timely diagnosis of plant diseases is crucial for improving crop performance. Therefore, developing a precise and reliable intelligent system for managing leaf diseases in trees is very important for farmers. This study aims to develop an artificial intelligence-based solution for detecting leaf diseases in quince trees using a state-of-the-art single-stage object detection model, YOLO (You Only Look Once). Images of diverse leaf diseases affecting this tree were collected from multiple sources, including agricultural research centers in Isfahan Province, Iran, relevant websites, and researchers. In this study, a transfer learning approach was employed to evaluate three well-known YOLO models (YOLOv5m, YOLOv7, and YOLOv8m) based on their detection and identification performance. Statistical metrics, including precision, recall, F1-score, and accuracy, were used to evaluate and compare the performance of the investigated models. The results indicate that the accuracy of the YOLOv5m, YOLOv7, and YOLOv8m models were 78%, 83%, and 87%, respectively. Experimental results revealed that YOLOv8m, trained from scratch on the dataset, demonstrates substantial capability in identifying leaf diseases in quince trees. In addition, a comparison showed that this model outperformed other investigated models with scores of 0.87, 0.66, 0.69, and 0.67 for accuracy, precision, recall, and F1-score, respectively. Based on the overall results of this research, the YOLOv8m model trained in this study can be introduced as a specialized tool for this particular crop. Therefore, the developed model in this study, specifically tailored to quince leaf diseases, can be integrated into diagnostic software for tree leaf diseases. Such software can assist farmers in accurately diagnosing diseases, ultimately reducing economic losses.

Keywords: Detection, Fire blight, Leaf blight, Leaf diseases, Machine learning

Introduction

Various agricultural and horticultural diseases are among the most significant factors affecting crop yield and quality. Controlling these factors has consistently been one of the major challenges in agriculture. The quince tree is not exempt from these risks, as numerous diseases affecting this crop have

been identified worldwide. These diseases can damage the leaves, branches, and trunk of the tree. Given the limited knowledge of farmers and the lack of access to expert horticulturists, farmers rely on personal experience to manage tree diseases and distinguish between different types. Consequently, the results are often more subjective. Such predictions are generally less accurate, and the identification of diseased leaves may be accompanied by a higher degree of error. Therefore, establishing a suitable framework for accurate and reliable disease detection is both necessary and essential (Oerke, 2006; Savary *et al.*, 2019).



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<https://doi.org/10.22067/jam.2025.89407.1277>

Recent advancements in hardware technology and enhanced computational speeds have propelled the development of image processing-based machine learning algorithms, significantly advancing the automation of plant disease detection. [Ramesh *et al.* \(2018\)](#) proposed a machine learning-based classification technique for detecting diseases in certain crops. In a similar study, deep learning techniques, particularly convolutional neural network (CNN) models, were applied for the identification and diagnosis of plant diseases using images of both healthy and infected plant leaves ([Ferentinos, 2018](#)). [Castelao Tetila, Brandoli Machado, Belete, Guimaraes, and Pistori \(2017\)](#) investigated six different machine learning approaches for identifying infected soybean leaves, with images captured from various heights by an unmanned aerial vehicle. Their research findings indicated that color and texture features significantly impact detection accuracy. Multiple CNN models were trained on a dataset of 500 natural images, encompassing both healthy and diseased rice leaves and stems, to classify 10 prevalent rice diseases effectively. Experimental results showed that the proposed model was able to distinguish diseases with an average accuracy of 95.48% ([Lu, Yi, Zeng, Liu, & Zhang, 2017](#)). The application of deep learning architectures for detecting diseases and pests in tomato plants using images of different resolutions was explored ([Fuentes, Yoon, Kim, & Park, 2017](#)). [Sladojevic, Arsenovic, Anderla, Culibrk, and Stefanovic \(2016\)](#) proposed an innovative method for plant disease detection using deep convolutional networks. By isolating plant leaves from their surrounding environment, the proposed CNN-based model successfully identified 13 common plant diseases. The experimental results indicated that the proposed CNN-based model exhibited strong detection performance, with an average accuracy of 96.3%. [Tiwari, Joshi and Dutta \(2021\)](#) introduced a dense CNN model for the detection and classification of diseased plant leaves obtained from images of different

resolutions. [Hu, Wei, Zhang, Bao, and Liang \(2021\)](#) developed a model to evaluate the severity of tea leaf blight using photographs of natural scenes. The initial disease severity (IDS) index was determined by segmenting disease spot locations on tea leaf blight images using an SVM classifier.

YOLO is a widely utilized algorithm in computer vision for object detection. Unlike traditional object detection methods, which often involve multiple sequential processing stages, YOLO performs object recognition and bounding box regression in a single forward pass through a neural network, streamlining the detection process. ([Xue, Xu, Bai, & Lin, 2023](#)). The earlier version of the YOLO family, YOLOv5m, has been effectively employed across various fields, such as fruit recognition for harvest robots ([Kuznetsova, Maleva, & Soloviev, 2020](#)), vehicle detection ([Kasper *et al.*, 2021](#)), and face recognition ([Yang *et al.*, 2020](#)). Due to the high capability of the YOLOv7 algorithm, this model has attracted considerable attention from machine learning and data modeling researchers. Several researchers have applied it to various recognition tasks, such as duck detection and counting ([Jiang *et al.*, 2022](#)), defect detection in different materials ([Wang, Wang, & Xin, 2022](#)), and vehicle tracking ([Tran, Pham, Nguyen & Jeon, 2022](#)). [Gallo *et al.* \(2023\)](#) utilized the YOLOv7 model to identify weeds within a dataset of Chicory plants. Similarly, the YOLOv7 architecture was employed for fruit detection in orchards, which facilitated the task of harvesting robots in locating and gathering fruits ([Chen *et al.*, 2022](#); [Zhou *et al.*, 2022](#)). Given the high capabilities of the YOLO algorithm family in identifying leaf diseases and pests in agricultural products, this study aimed to use YOLOv7 as a baseline model.

To the best of our knowledge, there has been no research conducted to evaluate quince leaf diseases using deep convolutional neural network algorithms. The lack of research on this topic can be attributed to several limitations. A primary challenge is the limited availability of leaf images for training and

evaluating the YOLO model. At present, there is no dedicated database specifically designed for leaf diseases of this crop. Another factor may be that this crop is cultivated only in a limited number of countries, which could lead to a lack of interest among researchers in developed countries in using artificial intelligence algorithms for identifying diseases of this crop. The present study is designed to identify and diagnose the main and common leaf diseases of quince trees using images taken from orchards in Iran. According to research history, this is the first time that YOLO models are being used as the base architecture for detecting quince leaf diseases. Therefore, this study pursues the following two primary objectives to achieve an optimal model. 1. Conduct a comparative analysis of state-of-the-art YOLO models for the automatic detection of quince leaf diseases. 2. Establish a database of quince leaf images to enable researchers who intend to test their developed deep learning models on quince leaf images.

Materials and Methods

Image acquisition

The images of quince tree leaves were sourced from various origins, including the Agricultural Research Center of Isfahan Province, relevant scientific websites, and

prior researchers who conducted studies on this crop. The images were captured using a Samsung A720 smartphone with an initial resolution of 2592×4608 pixels. Since the images are captured at high resolutions, preprocessing is required to match the input size expected by YOLO. Therefore, the training images were resized to the target input dimensions of 640×640 . In this study, three common leaf diseases of quince trees, including leaf spot (early leaf blight), fire blight, and leaf blight, were prepared. Their differences are illustrated in Fig. 1. For training YOLO models, an effort was made to obtain 400 images of each leaf disease, ensuring an equal number of images for each disease category. Given that training deep learning networks requires a substantial number of images, new images were generated using standard augmentation techniques, including rotation, horizontal flipping, vertical flipping, and brightness adjustment at two levels. These augmentations were applied solely to the training and evaluation datasets. For training the YOLO network, the images and labels were partitioned into training, validation, and test sets in a ratio of 70:15:15. As a result, 4200 images were designated for the training set, 900 images for the validation set, and 180 images for the test set.

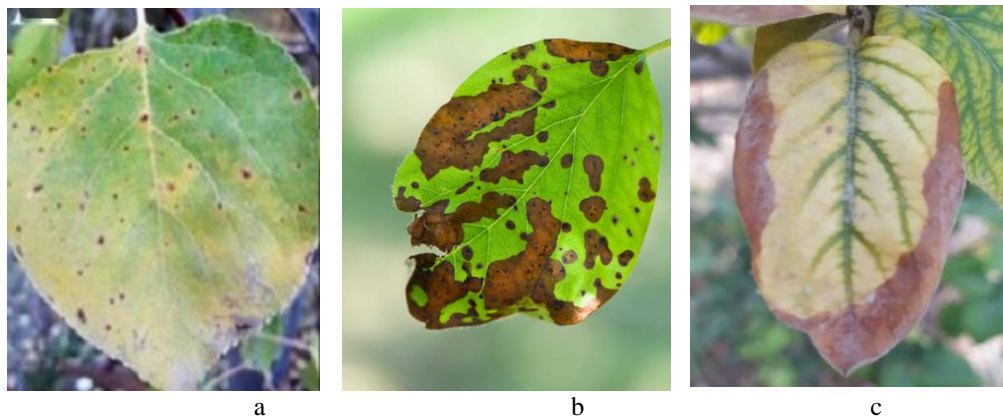


Fig. 1. Common quince leaf diseases: a) leaf spot, b) leaf blight, and c) fire blight

Image labeling

For the preparation of images for training the YOLOv7 network and delineating the bounding boxes around the diseased areas on

the leaf surface, it is essential to label only the diseased spots as features and identify their corresponding class. To perform the labeling, the LabelImg software was utilized to annotate

the diseases on the leaf surfaces. An example of a labeled leaf and its corresponding

coordinates is illustrated in Fig. 2.

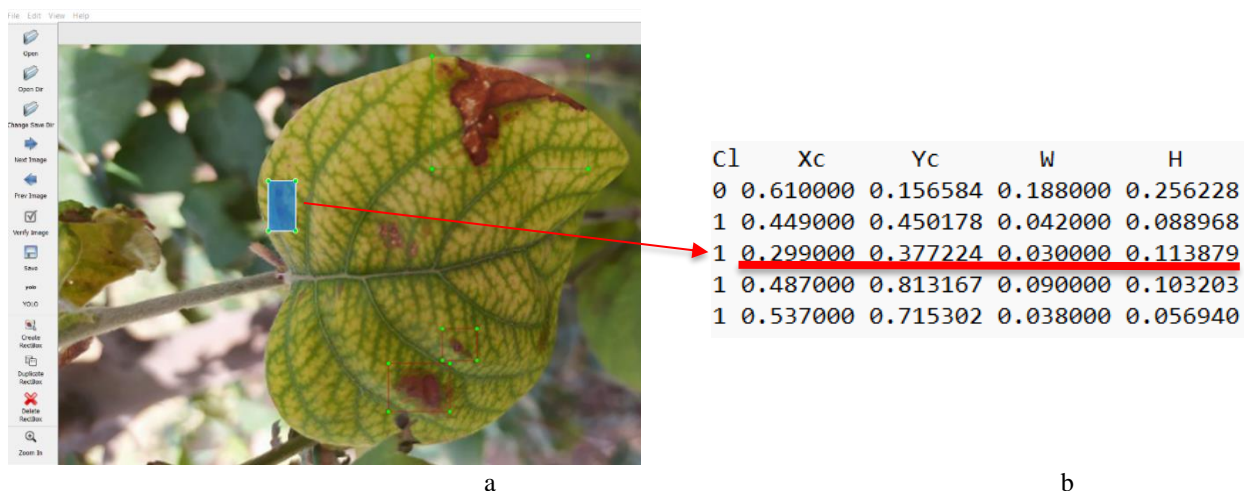


Fig. 2. Labellmg interface as a graphical image annotation tool for generating bounding boxes around defects; a) software interface, and b) coordinates of the created boxes

YOLO architectures

YOLOv5

YOLOv5, released in 2020 by Ultralytics, introduced an evolution in object detection with its focus on practicality and deployment. Unlike its predecessors, YOLOv5 is not an official iteration from Joseph Redmon, the original creator of YOLO, but it has gained significant adoption due to its ease of use, lightweight nature, and fast inference speeds. The architecture follows a CSPNet (Cross Stage Partial Network) backbone to enhance feature extraction and reduce computation. It incorporates a PANet (Path Aggregation Network) neck for better spatial and semantic feature fusion and uses the YOLO head for bounding box regression and classification (Paul *et al.*, 2022).

YOLOv7

YOLOv7, introduced in 2022, is considered one of the most efficient YOLO models in terms of speed and accuracy trade-offs. The model builds on the concepts of YOLOv4 and YOLOv5m while introducing several new techniques to optimize performance. It incorporates preprocessing strategies from YOLOv5m and employs mosaic data augmentation, which is effective for detecting small objects. In terms of architecture, it

introduces expanded ELAN (E-ELAN) as an enhancement of ELAN, forming the computational backbone of YOLOv7. E-ELAN employs techniques like shuffle, expand, and merge cardinality to continuously boost the network's learning capacity without affecting the gradient path. Group convolution is employed to increase the channel and cardinality within the computational block, allowing different sets of blocks to learn various features. Moreover, YOLOv7 integrates compound model scaling for concatenation-based models, maintaining the model's original attributes while optimizing its structure. The model also emphasizes various trainable optimization modules and techniques, collectively referred to as "bag-of-freebies" (BoF), which enhance performance without increasing training costs. Its ability to outperform other YOLO models in both FPS (frames per second) and mAP (mean Average Precision) has solidified its reputation in object detection benchmarks (Wang, Bochkovskiy, & Liao, 2023).

YOLOv8

YOLOv8, the latest release from Ultralytics, aims to unify the simplicity of YOLOv5m with architectural advancements inspired by YOLOv7 and other state-of-the-art

techniques. It integrates a custom backbone with features like convolutional block attention modules (CBAM) and a decoupled head design for separate regression and classification tasks, enhancing precision. YOLOv8 further improves training efficiency through adaptive training hyperparameters and supports advanced post-processing techniques such as non-maximum suppression with soft thresholds. This model is designed with an emphasis on real-time applications and ease of deployment, supporting ONNX and TensorRT exports. Its scalable design enables it to cater to a variety of edge and cloud-based tasks, making it a comprehensive tool for modern object detection needs (Francesco, 2023).

Training process of YOLOv7

The YOLO package is set up by

downloading and cloning the 'YOLOv5m', 'YOLOv7', and 'YOLOv8m' code from GitHub. The latest version of 'YOLOv7' is compatible with Torch and can be easily executed using 'Google Colab'. This process generates a new directory on the system named 'YOLOv5m (7,8)', which includes the model's pre-trained weights and the corresponding YOLO directory structure. After training is completed, a new subfolder is created within the 'YOLOv5m (7,8)' directory. The path to this subfolder is specified as 'YOLOv7/run/training/experiment/weights/last.pt'. The size of the weight file will vary according to the 'yaml' configuration used. Fig. 3 illustrates the block diagram of the training and testing framework for the investigated model.

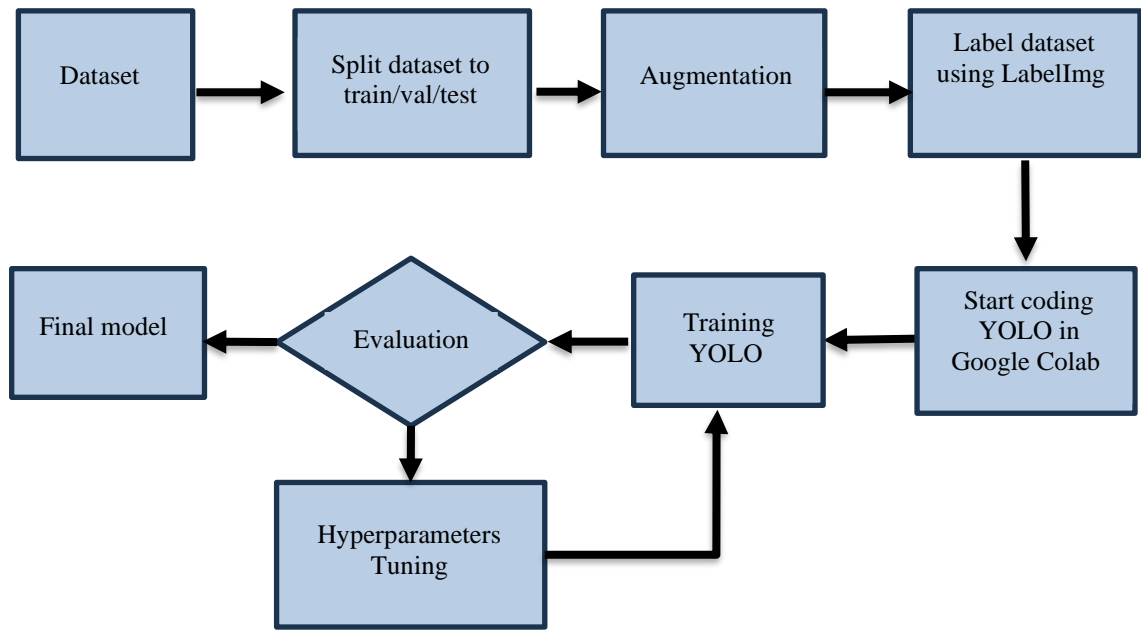


Fig. 3. Block diagram of the training and evaluation process for the proposed 'YOLOv5m (7,8)' model

One of the crucial steps after implementing a machine learning-based system is its evaluation using test datasets. To assess the performance of the YOLO network in identifying leaf diseases in quince trees, various metrics are utilized, including accuracy (Eq. 1), precision (Eq. 2), recall (Eq. 3), F1-score (Eq. 4), and mean average precision (Eq. 5).

$$Precision = \frac{TP+TN}{TP+FP+FP+FN} \times 100 \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (3)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \quad (4)$$

$$mAP = \frac{1}{N} \sum_{i=1}^N AP \times 100 \quad (5)$$

where True Positives (TP) denote instances where the model correctly identifies the positive class, and True Negatives (TN) represent instances where the model accurately identifies as the negative class. False Positives (FP) and False Negatives (FN) are the instances where the model incorrectly predicts as positive and negative classes, respectively. In Equation 6, AP refers to the area under the precision-recall curve, typically calculated using numerical integration, and N represents the number of classes.

Results and Discussion

The Confusion Matrix obtained from YOLOv5m, YOLOv7, and YOLOv8m are illustrated in Fig. 4. The number of TP combinations for every class is displayed on the diagonal, from top left to bottom right. The result of YOLOv5m (Fig. 4(a)) shows that 78% of all objects in the class of leaf spot, 73% of all objects in the class of leaf blight, and 83% of all objects in the class of fire blight were properly classified. Furthermore, the model identified that 22% of the leaf spot class remained unrecognized. 22% of all objects of leaf blight was found grouped as unknown, and 17% of all objects of fire blight class were categorized as unknown and were not categorized by the classifier into any class. The results presented in Fig. 5(b) indicate that 85%, 77%, and 88% of all objects in the leaf spot, leaf blight, and fire blight classes, respectively, were correctly classified. Moreover, as illustrated by the confusion matrix in Fig. 5(c), YOLOv8m outperformed the other models in detecting all three classes. Specifically, the YOLOv8m model achieved proper classification rates of 88%, 83%, and 91% for the leaf spot, leaf blight, and fire blight classes, respectively. As the results of the confusion matrices show, the performance of all models in detecting fire blight is higher than that for leaf blight and leaf spot. The misclassification of leaf spot and leaf blight diseases by the networks is primarily attributed to their similar patterns, which are characterized by dark spots of varying shapes on the leaf surface. In contrast, fire blight

presents a distinct visual pattern with burned or uniform areas along the leaf margins, markedly different from the patterns observed in leaf spot and leaf blight. Consequently, the results obtained from the confusion matrix align logically with these distinctive visual features.

Fig. 5 illustrates the trends of precision, recall, mean Average Precision (mAP), and error (class) rates. The convergence of the loss metric, coupled with the other performance metrics, demonstrates the effectiveness and adequacy of the training process for all YOLO models. In Fig. 5, the trend of evaluation parameters, particularly the loss diagram, indicates that all models improved rapidly from the starting point to 40 epochs, after which the improvement plateaued. A comparison of the loss across the three models reveals that YOLOv8m converges at 60 epochs, whereas YOLOv7 and YOLOv5m achieve convergence at 120 epochs. The faster convergence of YOLOv8m highlights its superior learning capability compared to the YOLOv7 and YOLOv5m models.

Table 1 presents the evaluation parameters for the three investigated models. The results indicate that fire blight disease, owing to its distinct features and differentiation from other diseases, achieved the highest F1-score. This score highlights the superior performance of all models in classifying fire blight compared to leaf spot and leaf blight diseases. Leaf spot disease, which has visual similarities with both fire blight and leaf blight, demonstrates the highest error rate among the diseases studied. The mean F1-scores of YOLOv5m, YOLOv7, and YOLOv8m were 61%, 64%, and 67%, respectively. These results indicate the superior discriminative capability of YOLOv8m in detecting leaf diseases.

Comparing the results of this study with those of other research, the findings demonstrate that the YOLOv8m model exhibits a high capability in detecting diseases in quince trees. In the identification of bacterial leaf diseases in flax using an artificial neural network, the model achieved an accuracy of 85% in classifying three types of

diseases (Rothe & Kshirsagar, 2015). The detection of five different diseases in tea plants was examined and evaluated using the YOLOv7 algorithm. This evaluation utilized 4,000 images of diseased tea leaves, resulting in the following performance metrics:

accuracy of 97.3%, precision of 96.7%, recall of 96.4%, mAP of 98.2%, and F1-score of 98.5%. These results highlight the superior capability of the YOLOv7 network compared to other deep learning networks such as CNN (Soeb et al., 2023).

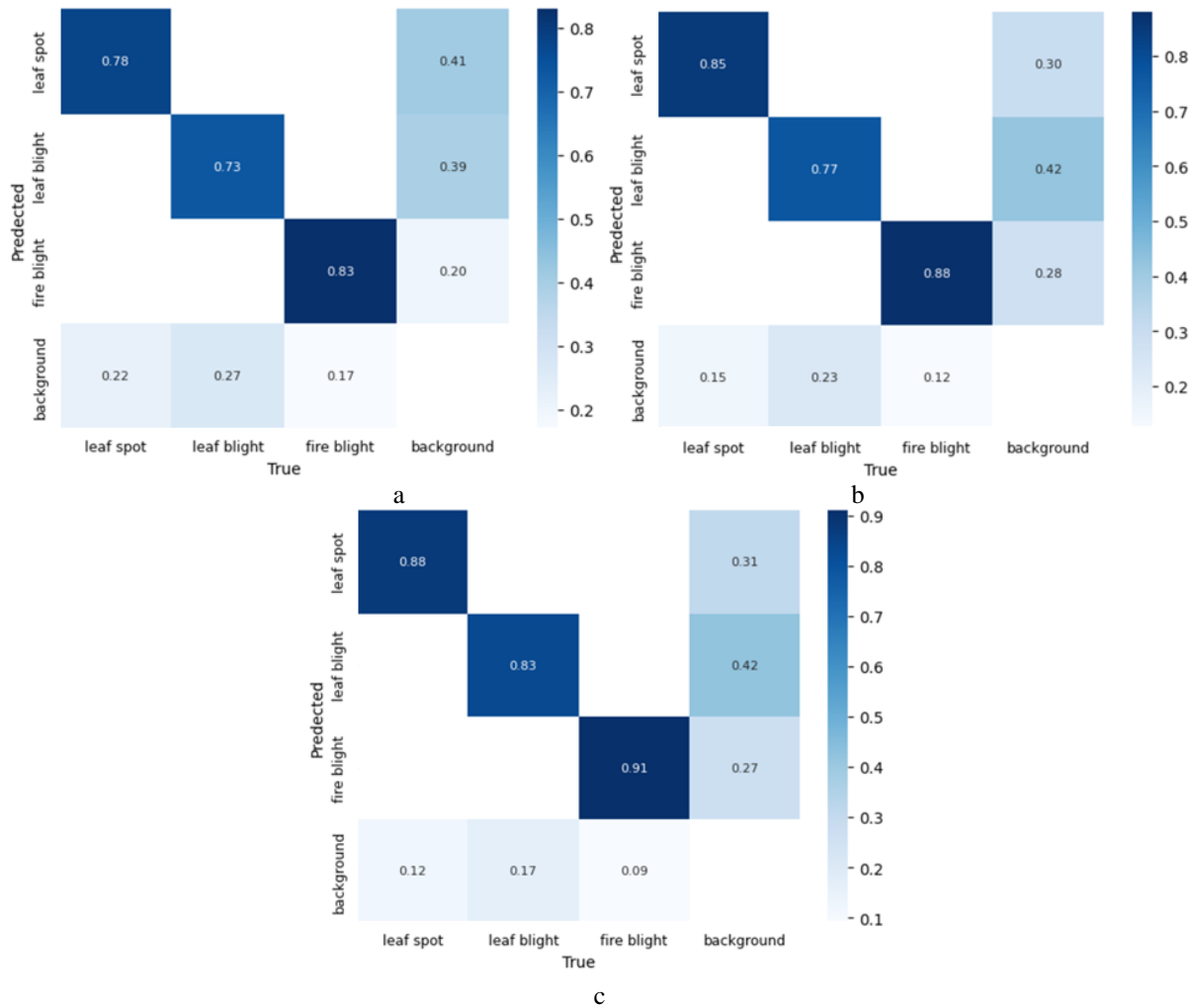


Fig. 4. The confusion matrix of: (a)YOLOv5m, (b)YOLOv7, and (c)YOLOv8m

Table 1- Details of evaluation metrics of the validation dataset for YOLO v5m, v7, and v8m models

| Model | Leaf disease | Precision | Recall | F1-Score | Accuracy |
|---------|--------------|-----------|--------|----------|----------|
| YOLOv5m | Leaf Spot | 0.62 | 0.53 | 0.57 | 0.78 |
| | Leaf Blight | 0.53 | 0.63 | 0.58 | |
| | Fire Blight | 0.68 | 0.70 | 0.69 | |
| YOLOv7 | Leaf Spot | 0.58 | 0.61 | 0.59 | 0.83 |
| | Leaf Blight | 0.59 | 0.64 | 0.61 | |
| | Fire Blight | 0.74 | 0.69 | 0.71 | |
| YOLOv8m | Leaf Spot | 0.62 | 0.60 | 0.61 | 0.87 |
| | Leaf Blight | 0.61 | 0.69 | 0.65 | |
| | Fire Blight | 0.75 | 0.78 | 0.76 | |

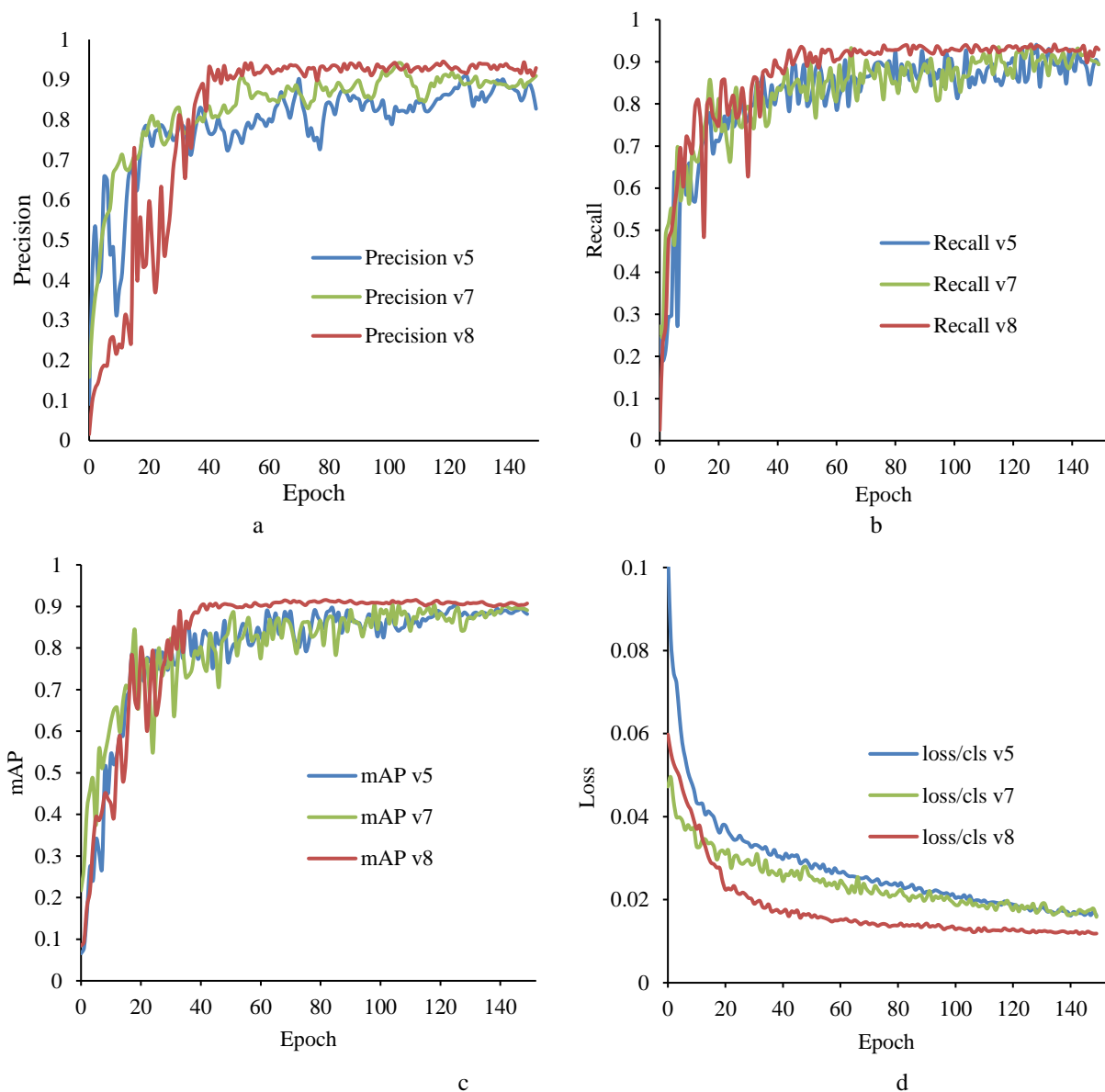


Fig. 5. Visual evaluation metrics of YOLOv5m, YOLOv7, and YOLOv8m for the training dataset: (a) Precision, (b) Recall, (c) mAP, and (d) Loss of class

The lower evaluation metrics in the current study can be attributed to the significant disparity in the number of training images. We utilized 400 images per class, whereas the tea plant study employed too many images per class. In a comparative study of the YOLOv4 and YOLOv7 models, a dataset of 54,305 images was utilized to identify 26 different diseases across 14 plant species. The mAP-50 values achieved by these models were 68.2 for YOLOv4 and 69.7 for YOLOv7, indicating suboptimal performance for a diagnostic

application (Xinming & Hong, 2023). A comparison of research findings indicates that in the development of YOLO models for detecting multiple diseases, increasing the number of classes adversely affects model accuracy. Based on the results from YOLO networks trained on COCO (Common Objects in Context) data, which includes 80 classes and over 330,000 images, the reported precision was less than 85%. Given the relatively low overall performance of the YOLO model trained on COCO data, it is

recommended to enhance its detection capabilities by retaining the initial YOLO structure with frozen parameters in the feature extraction block. The neural network portion can then be retrained using specialized images to achieve improved performance. In similar studies aimed at detecting various agricultural crop diseases, the technique of transfer learning has been employed. YOLO networks have been employed for detecting the type and location of diseases in various crops, including cucumber (Lou *et al.*, 2021), grape (Guo, Feng, Li, Yang, & Yang, 2022), tomato (Chowdhury *et al.*, 2021), and tea (Soeb *et al.*, 2023). The differences between our results and those of these studies can be attributed to various factors, such as the type of features used, the number of training images, and, most

notably, the ambient conditions. In most of these studies, the leaf samples exhibited distinct color differences from the background, which facilitated easier identification and segmentation. In the present study, the image backgrounds were complex, and the leaves often had colors similar to the background, making it challenging for the models to distinguish them effectively. The overall results of these studies indicate the good capability of all transfer learning methods or the pre-trained networks in the classification of new images. The results from several test images are illustrated in Fig. 6. As shown in this figure, all diseases were identified with high confidence scores, highlighting the robust capability of the YOLO network in detecting the diseases studied in quince trees.



Fig. 6. The results of the developed YOLO model for identifying quince leaf diseases in the test dataset

Conclusion

Accurate and timely diagnosis of diseases

in trees and plants can significantly enhance crop yield. The quince tree, extensively

cultivated in certain regions of Iran, is a significant export product that can play a valuable role in the country's economy. Consequently, maintaining the health of this crop and effectively controlling its diseases is of paramount importance to farmers. This research focused on providing a rapid solution for detecting major diseases in quince trees, including leaf blight, fire blight, and leaf spot. A key reason for selecting these specific diseases is their nearly identical shapes and characteristics. The close resemblance in features among these diseases can present challenges for accurate detection. Three well-known state-of-the-art algorithms, including YOLOv5m, YOLOv7, and YOLOv8m, were employed for the classification and identification of these diseases. These models not only offer high accuracy but also operate at high speed, making them an ideal choice for disease detection. Upon examining the evaluation parameters, the evaluation metric of F1-score for fire blight was higher than for leaf blight and leaf spot. The variation in evaluation metrics across the classes can be attributed to differences in the underlying characteristics of the diseases. Fire blight exhibits distinct characteristics compared to the other two diseases, resulting in enhanced separability and higher detection accuracy. This study demonstrates that YOLOv8m

achieves superior performance on our dataset and paves the way for the development of a comprehensive software solution for disease detection in quince trees. However, accurate diagnosis and effective treatment of plant diseases require consideration of non-pathogenic factors. Variables such as over-fertilization, irregular watering, unfavorable environmental conditions (e.g., light, temperature, and humidity), and pest activity can produce symptoms resembling those of diseases. Thus, a comprehensive investigation of all potential factors, including soil and plant analyses, is essential for precise diagnosis and selection of appropriate treatment methods.

Conflict of Interest: The authors declare no competing interests.

Author Contributions

A. Naderi Beni: Methodology, Data acquisition, Data pre and post processing, Numerical/computer simulation.

H. Bagherpour: Supervision, Conceptualization, Methodology, Statistical analysis, Validation, Review and editing services, Numerical/computer simulation.

J. Amiri Parian: Methodology, Technical advice, Review and editing services.

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مقاله پژوهشی

جلد ۱۶، شماره ۱، بهار ۱۴۰۵، ص ۳۷-۲۵

بهره‌گیری از مدل یادگیری عمیق مبتنی بر شبکه YOLO برای تشخیص و مکان‌یابی بیماری‌های برگ درخت به

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تاریخ دریافت: ۱۴۰۳/۰۶/۰۷

تاریخ پذیرش: ۱۴۰۳/۱۰/۱۹

چکیده

توسعه یک سیستم هوشمند دقیق و قابل اعتماد برای مدیریت بیماری‌های برگ درختان برای کشاورزان بسیار ضروری است. این مطالعه با هدف توسعه یک راهکار مبتنی بر هوش مصنوعی برای شناسایی بیماری‌های برگ درختان به، با استفاده از یک مدل پیشرفته و تک‌مرحله‌ای تشخیص اشیاء به نام YOLO انجام شده است. تصاویر بیماری‌های مختلف برگ این درخت از منابع متعدد، شامل مراکز تحقیقاتی کشاورزی استان اصفهان، وبسایت‌های مرتبط و پژوهشگران گردآوری شده است. در این پژوهش، از رویکرد یادگیری انتقالی برای ارزیابی عملکرد سه مدل شناخته‌شده شامل YOLOv7، YOLOv5m و YOLOv8m استفاده شد. ارزیابی و مقایسه مدل‌های مورد بررسی بر اساس شاخص‌های آماری مانند دقت (Precision)، بازخوانی (Recall)، امتیاز F1 انجام گرفت. نتایج نشان داد که دقت مدل‌های YOLOv7، YOLOv5m و YOLOv8m به ترتیب ۷۸٪، ۸۳٪ و ۸۷٪ بوده است. نتایج تجربی نشان داد که مدل YOLOv8m توانایی قابل توجهی در شناسایی بیماری‌های برگ درختان به دارد. علاوه بر این، مقایسه مدل‌ها نشان داد که مدل YOLOv8m با امتیازات ۰/۸۷ برای دقت، ۰/۶۶ برای بازخوانی، ۰/۶۹ برای امتیاز F1 و ۰/۶۷ برای میانگین دقت، عملکرد بهتری نسبت به سایر مدل‌های بررسی شده دارد. بر اساس نتایج کلی این پژوهش، مدل YOLOv8m آموزش‌دیده در این مطالعه می‌تواند به عنوان ابزاری تخصصی برای این محصول خاص معرفی شود. بنابراین، مدل توسعه‌یافته در این مطالعه که به‌طور ویژه برای بیماری‌های برگ درخت به طراحی شده است، می‌تواند در نرم‌افزارهای تشخیصی بیماری برگ درختان ادغام شود. چنین نرم‌افزارهایی می‌توانند به کشاورزان در تشخیص دقیق بیماری‌ها کمک کرده و در نهایت زیان‌های اقتصادی را کاهش دهند.

واژه‌های کلیدی: آتشک، بیماری برگ، تشخیص، زخم برگ، یادگیری ماشین

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