Machine Learning for Agriculture: YOLOv7 for Multiple Tomato Fruit Diseases Detection

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Tomato fruit diseases are a significant problem for agriculture, causing substantial crop losses globally and impacting productivity. This research explores how YOLOv7 can be utilized to identify and categorize tomato fruit diseases, using a dataset of 2044 labeled images. Advanced image processing techniques such as contrast enhancement and noise reduction were used to train the model and improve detection accuracy. The findings showed an mAP of 89.5%, alongside an 86.2% precision rate and an 82.2% recall rate, indicating the model's strong capability in detecting diseased fruit accurately and reducing false positives. Significantly, the model successfully reached a 97% accuracy rate in identifying Spotted Wilt Virus, a common disease in tomatoes. These results highlight the model's great capability for practical use in farming settings, where accuracy and timely identification are essential. The research suggests that incorporating machine learning methods like YOLOv7 into disease detection systems can greatly enhance early recognition, decrease crop damage, and lessen the need for chemical treatments. Future efforts will focus on improving the model's ability to identify instances and expanding its use in real-time detection systems in the field.

Keywords: convolutional neural network, machine learning, disease detection, tomato fruit diseases, YOLOv7

1. Introduction

As the world's population rises, much more effort and creativity will be required to enhance the global supply chain, lower food loss and waste, increase agricultural production in a sustainable way, and ensure that everyone who is hungry or malnourished has access to healthful food.

The second Sustainable Development Goal of the UN is to end world hunger by 2030. A number of variables, including the pandemic, conflict, climate change, and growing inequality, have contributed to the alarming rise in the global crisis of hunger and food insecurity since 2015.

The tomato, Solanum lycopersicum, is more than just a fruit; it's a major factor in agricultural growth, economic prosperity, and human health. Its essential relevance is solidified by its high nutrient profile, global market presence, and contribution to the development of novel farming techniques.

Tomatoes ranked as the most produced vegetable with 186 million tons in 2022, according to the United Nations Food and Agriculture Organization (FAO). However, the Philippine Statistics Authority (PSA) recorded that in April to June 2023 tomato production was estimated at 70.33 thousand metric tons, indicating an annual decrease of -1.8 percent from the 71.59 thousand metric tons output in the same quarter of last year.

Tomatoes are susceptible to several plant illnesses caused by bacterial, fungal, viral, and viroid pathogens because of their genetic makeup (Panno et. Al., 2021). The impact of plant diseases on food security has an international dimension. Farmers are adversely affected by plant diseases, irrespective of their location, medium, or technological capabilities. In the present day, early illness identification can be difficult and necessitates meticulous preparation (Umar et. Al., 2023).

With their expertise, forestry and agricultural professionals, as well as farmers, can identify fruit tree diseases and pests on the spot. This method is difficult, time-consuming, and ineffectual in addition to being subjective. Inexperienced farmers may make bad choices and use drugs irresponsibly when diagnosing. Pollution would not only lower quality and production but also cause unnecessary financial losses. To solve these problems, the use of image processing techniques for plant disease identification has grown in favor (, Zhang et. al., 2021).

Image processing is an important and actively researched field in many disciplines. There are several applications for image recognition, such as face identification, video analysis, image categorization, and so forth. A branch of machine learning called deep learning (DL) has demonstrated remarkable performance in picture identification (Pak et. al., 2017). When processing image characteristics, DL makes use of the multi-layer structure, which greatly improves the efficiency of image recognition (Jiang et. al., 2018). One of the most popular machine learning techniques nowadays is deep learning, which has just lately made its way into the agriculture industry as a fresh approach to image analysis. Their success can be attributed to their high abstraction levels and their capacity to instinctively recognize intricate details in images (Torres et. al., 2020).

Fruit flaws including abnormalities, deficits, and illnesses can be found with great potential using object detection algorithms, particularly YOLO. The effectiveness of YOLO in improving item recognition and classification—including determining the freshness of fruits and vegetables—has been shown by these investigations. Nonetheless, a lot of fruit growers in places with little access to contemporary equipment still assess fruit quality by hand, which slows down production and necessitates the use of knowledgeable specialists or farmers (Oei et. al., 2023). Of them, the YOLO (You Only Look Once) series of algorithms has garnered significant interest due to its robust, real-time, and efficient features, making it a classic one-stage algorithm. YOLO converts the object detection problem into a regression problem and outputs the category and object location data (Yue et. al., 2024).

The goal of this research is to investigate YOLOv7's potential for disease and health detection in tomato fruits. We'll look into a number of image processing strategies to help YOLOv7 detect tomato fruit diseases more accurately. An approach for the effective identification and categorization of fruit diseases will be developed, integrating YOLOv7 with picture enhancement techniques. Ultimately, studies utilizing a dataset created specifically for this purpose were used to assess how well the YOLOv7 disease detection algorithm performs in identifying the health and diseases of tomato fruits.

2. Literature Review

The population of the world is expected to increase from 7 billion in 2010 to 9.8 billion by 2050. The demand for food in general will rise by more than 50% in tandem with rising salaries in developing nations. Despite this, there are still hundreds of millions of hungry people on the planet, and 25% of yearly grenhouse gas emissions worldwide are caused by changes in land use connected to agriculture. Nowadays, almost half of all vegetated land is used for agricultural purposes (Searchinger et. al., 2019).

Native tomatoes have been an essential component of Filipino cuisine for many years. They can be eaten on its own or with salted eggs and onions as a main course. The tomato is a highly sought-after crop and a significant commercial vegetable in the Philippines. In both highland and lowland regions, it is commonly grown. According to a survey on the demand for vegetables in urban and rural families, tomatoes are highly desired in both. In the Philippines, there is relatively little tomato output during the hot, humid months due to flooding, high temperatures, and the presence of pests and illnesses.

In recent years, there has been a surge in the application and testing of machine learning-based fruit disease recognition algorithms, particularly deep learning. Machine learning offers a more dependable and accurate alternative to traditional approaches, providing a better solution to issues like blockage and green tomato detection.

This is shown by the research of Siddiquee et al. They tried out a system that uses the cascaded object detector, a machine learning technique, in conjunction with more traditional image processing methods like "color trans-formation," "color segmentation," and "circular Hough transformation" to identify ripe tomatoes. Research shows that compared to conventional methods, machine learning techniques improve accuracy by 95% (Siddiquee et. al. 2020).

Xu et al. improved upon the YOLOv3-tiny strategy to find ripe tomatoes in a faster and more accurate manner. Modifications to the main network improved the model's accuracy, and the inclusion of images in more challenging situations strengthened detection. The results showed that the proposed model outperformed the YOLOv3-small approach by 12% (F1-score = 91.92%) (Xu et. al., 2020).

Although it can be challenging to find green tomatoes in greenhouses, Mu et al. developed a detection system that can. The model uses a deep convolutional neural network and a pre-trained Faster R-CNN architecture with ResNet-101 and Yolov4 to obtain an accuracy of 87.83% when recognizing tomatoes. It is based on the Common Objects in Context (COCO) dataset (Mu et. al., 2020).

In order to extract the most important features, the authors of devised a novel method based on attention-based dilated CNN and Yolov5. Both Otsu segmentation and bilateral filtering were used in the preliminary processing of the images. After the photos have been preprocessed, the CGAN model is applied to them to generate synthetic images. In order to classify previously examined attributes, a logistic regression (LR) classifier was used, which achieved an accuracy of 96.6% (Islam et. Al., 2022).

A neural network made up of VGG 16 and AlexNet was trained by Rangarajan et. al. to differentiate between a disease-free tomato cultivar and six others. Training parameters such as batch size, bias, weighted learning rate, and number of pictures used were varied in order to assess performance. It was discovered that AlexNet outperformed VGG 16 in terms of accuracy and performance velocity (Rangarajan et. al., 2018).

Liu et. al. developed the YOLO-Tomato model based on YOLOv3 detection. To do this, we replaced the more widely used R-box with the suggested C-box in a 179 dense framework for feature extraction. When comparing moderate occlusions to severe occlusions, the model 180's detection accuracy increased by 4%, resulting in an overall accuracy of 94.58% (Liu et. al., 2020).

Over the years, the YOLO series has been one of the best single-stage real-time object detector categories (Bochkovskiy et. al., 2020). YOLO transforms the object detection task into a regression problem, predicting the positions and categories of multiple objects in a single forward pass, achieving high-speed object detection. After years of development, YOLO has developed into a series of fast models with good performance (Wang et. al., 2023).

However, all YOLO variants generate many redundant bounding boxes, which NMS must filter out during the prediction stage, which significantly impacts the detector's accuracy and speed and conflicts with the design theory of real-time object detectors (Gong, 2024).

The utilization of YOLO models in agriculture, like spotting weeds, observing crops, and identifying diseases, demonstrates their capability to deliver timely and precise outcomes (Hussain, 2023). The continuous progress in YOLO models has broadened their range of uses, making them indispensable tools in various industries, including agriculture. Future research is expected to concentrate on enhancing model efficiency and investigating potential applications (Estilong, 2024).

The YOLOv7 architecture combines the strengths of the You Only Look Once (YOLO) framework with practical design choices for accurate and instant object detection (Kumar et. al., 2023). It comprises numerous components working together to recognize and classify items in a given image (Li et al., 2022).

3. Case and Methodology

A. Data Collection

The researcher conducted an interview to gather a comprehensive data regarding the status of tomato fruit diseases in Region I. According to the Senior Research Specialist from the DA-Ilocos Region Integrated Agricultural Research Center (ILIARC), the commonly produced tomato variety produced and sold in the markets is the Diamante Max F1 or Diamante Max Fantastic. This data was confirmed by the research specialist from the Department of Agriculture Regional Office 1 specifically from the office of High Value Crops Development Programs (HVCDP). The images used in the dataset are of the Diamante Max F1, a hybrid tomato, is resistant to many diseases, but it is known for being highly perishable due to its high moisture content and thin skin that is easily damaged by high temperatures (Conception et. al., 2021).

A dataset for detecting diseases in tomato fruits was established by gathering images from two main sources: online resources, picking out top-notch tomato pictures from the web specifically Google Dataset Search, and existing datasets, utilizing pertinent and openly accessible datasets from Kaggle and Roboflow Universe. From these sources, the dataset in the study were divided into five primary groups namely anthracnose, bacterial spot, blossom end rot, spotted wilt virus and healthy tomatoes, as shown in Figure 1.

anthracnose Bacterial spot Blossom end rot Spotted wilt virus Healthy

Figure 1 Tomato fruit classes

While tomato ranks as the fourth most produced vegetable based on the volume of production in the Philippines, Dimayacyac et. al. (2022) found anthracnose disease affecting tomato production in the field and during marketing and storage.

Akraym et. al. (2024) state that the presence of tomato bacterial spots, caused by different bacteria from the Xanthomonas family, can lead to significant decreases in tomato production, with potential yield reductions of around 40%.

The findings of Coulibaly et. al. (2023), share the same with effect blossom end rot (BER) that may cause severe economic losses.

In line with these findings, the tomato spotted wilt virus (TSWV) has led to notable reductions in crop yield being ranked within the top 10 plant viruses. This underscores the need for a faster and more precise detection technique according to Zhang et. al. (2021).

According to the Chief of Regional Crop Protection Center from the DA Regional Office 1, Diamante Max F1 is very vulnerable to the diseases such as anthracnose, bacterial spot, spotted wilt virus and blossom end rot.

This dataset was uploaded and published in Roboflow website on October 10, 2024. Despite the fact that the initial dataset includes 1,136 images, the expanded dataset comprises 2044 images. The expanded dataset was split into three sets for training, validation, and testing purposes. More precisely, 1816 images (equivalent to 89%) were designated for the training set, while 114 images (6%) were assigned to both the validation and testing sets. The dataset was divided into these sets with an average split of 89:6:6, as illustrated in Figure 2.

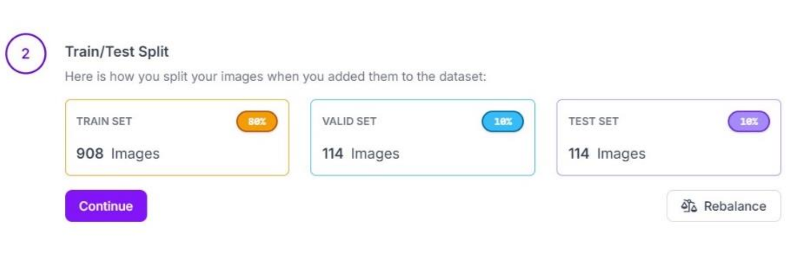

Figure 2 Dataset distribution

B. Image Annotation

Roboflow was used to resize images in the dataset, converting them to a uniform size of 640×640. The next procedure involved uploading the dataset, manual image labeling, and defining specific labels. All the images were uploaded to the Roboflow website.

Next, the images were individually annotated. Rectangular and polygon shapes were manually drawn around the tomato fruit images to accurately outline its position and dimensions in the image. This accurate labeling guarantees precise detection and classification in the succeeding steps.

Then, every tomato was given varying labels to indicate its state. The labels "Anthracnose," "Bacterial spot," "Blossom end rot," "Spotted wilt virus," and "Healthy Tomato" were used to show if a disease was present and its type. Figure 3 depicts the annotated data visually, showing details on label distribution and tomato bounding box locations.

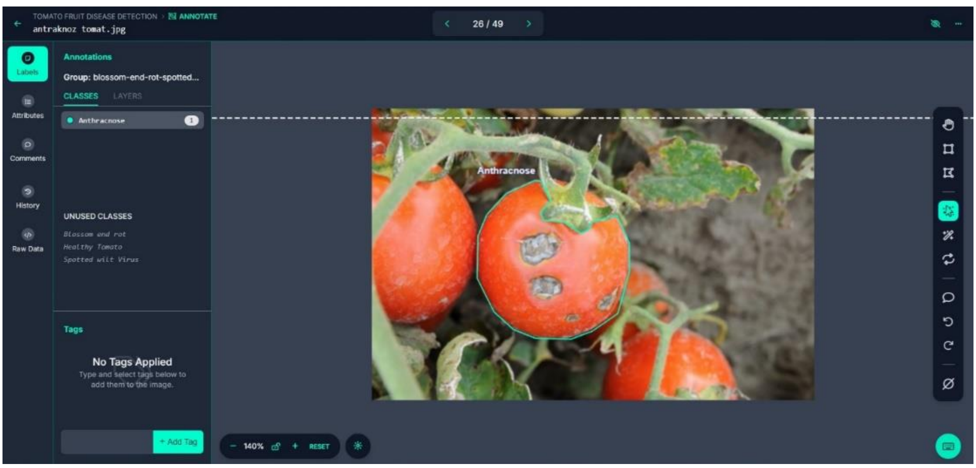

Figure 3 Annotated image

C. Data Preprocessing

During the preprocessing of the images, the dataset was divided into three distinct subsets with care to train and evaluate tomato fruit disease detection models effectively.

The training set, which accounts for 80% of the data, acts as the foundation for model training. Throughout this procedure, the model gains the ability to detect patterns and recognize important characteristics needed to differentiate between healthy and diseased fruit.

Meanwhile, the 10% validation set is essential for confirming the model's performance while it is being trained. It is utilized to adjust hyperparameters and prevent overfitting, guaranteeing the model generalizes effectively to new data.

Likewise, the test set (10%) remains unused during training and is saved for the final assessment of the model's performance on new data. This impartial assessment provides a dependable measure of the model's real-world performance.

D. Data Augmentation

After carefully labeling the images in Roboflow, data-augmentation techniques were implemented. This method seeks to enhance the dataset by expanding its size and varying its content. Data augmentation can reduce the likelihood of overfitting, which is a typical problem when training models with restricted data.

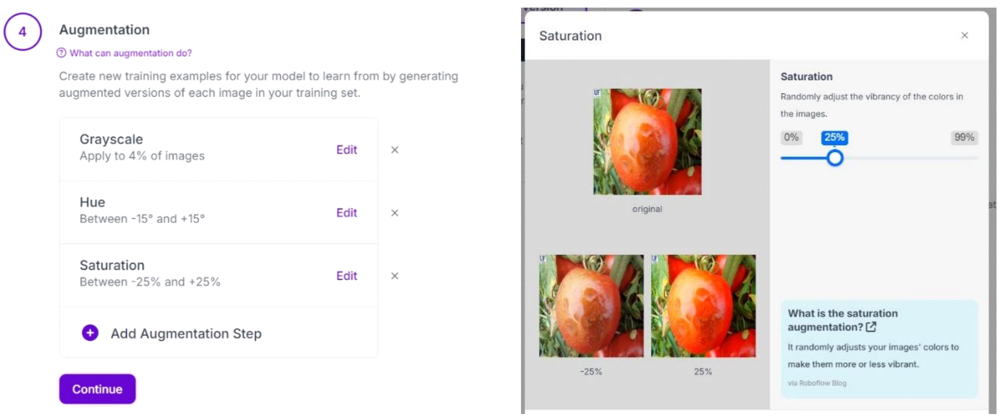

Figure 4 Example of data augmentation.

Figure 4 illustrates a range of data augmentation techniques used, including flipping, cropping, rotating, and altering color spaces like Grayscale, Hue, and Saturation. These techniques produce more pictures using the original data set, expanding its diversity and providing the model with a broader range of scenarios for training. The number of pictures rose to over 2000 images following resizing and data augmentation.

MODEL EVALUATION

Assessment of performance includes analyzing Precision, Recall, and mean Average Precision (mAP) which provide data on accuracy and adaptability per Wu et al. (2023).

Valuable insights on the accuracy and flexibility of the model were obtained through experiments conducted on validation and test datasets. Additionally, a visual evaluation was conducted to compare the models' predictions with annotations, aiming to improve understanding of its performance and identify areas for enhancement.

Recall is a measurement determining the proportion of correctly recognized instances out of all the true positive instances in the dataset. The formula shown in Equation 1 is used to determine recall.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad \text{(Equation 1)}$$

On the other hand, precision evaluates how accurate the identified cases are out of all instances labeled as positive by the model. Equation 2 shows the formula for accuracy.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad \text{(Equation 2)}$$

The Mean Average Precision (mAP) evaluates how well the model performs in various categories by calculating the average of the Average Precision (AP) scores for each category. Equation 3 describes the calculation for mean Average Precision (mAP).

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{APi} \quad \text{(Equation 3)}$$

In this case, N represents the complete quantity of classes. The mAP value was determined by utilizing the Intersection over Union (IoU) metric for calculation.

The average of precision and recall is used to assess the F1 score. When dealing with imbalanced datasets, it is beneficial to take into account both true positives and false negatives. Equation 4 demonstrates the calculation formula for the F1 score.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{(Equation 4)}$$

Evaluating the performance of the model measures its capability in detecting different types of road defects and handling damage situations. Precision and recall measure the correctness of identifying damages, whereas mAP assesses overall performance across all categories. The F1 score offers an equal evaluation of precision and recall. Assessments point out the strong and weak points of the model, enabling modifications to enhance accuracy in detecting tomato fruit diseases.

4. Results

This part discusses the outcomes of training and validating the YOLOv7 model for identifying tomato fruit diseases. The study evaluates how well the model performs using metrics like accuracy, recall, mAP, and F1 score. The evaluation emphasizes the model's ability to detect diseases. It examines differences in performance among different categories. Analyzes possible overfitting problems by thoroughly assessing the model's performance and suggesting potential enhancements.

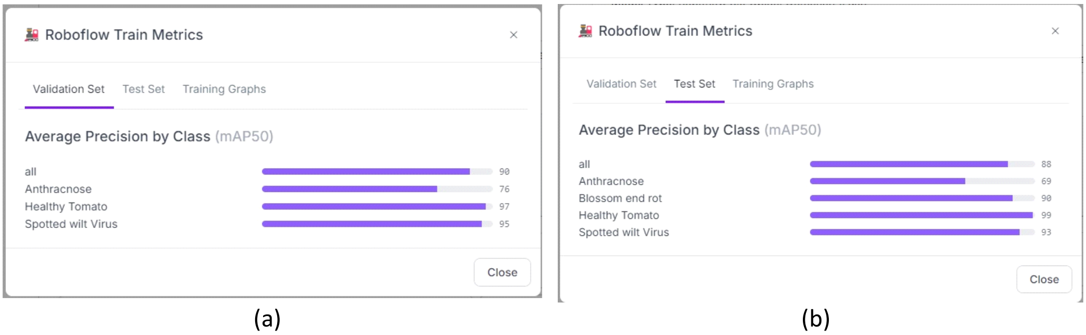

Figure 5 Training Metrics of the Model Per Class from (a) Validation set and (b) Test Set

Figure 5 displays the mAP50 (mean Average Precision at an IoU threshold of 0.5) for both the test and validation sets, highlighting the performance of the tomato disease detection model across different classes.

In the validation set, the overall mAP50 was slightly higher at 90%, with "Healthy Tomato" and "Spotted wilt virus" maintaining high precision at 97% and 95%, respectively. "Anthracnose" again showed the lowest precision at 76%, though slightly improved compared to the test set. These results indicate that the model performs well overall, particularly in detecting "Blossom end rot" and "Healthy Tomato," but faces challenges in accurately identifying "Anthracnose." The lower performance for "Anthracnose" suggests that further refinement is needed, either through additional training data, improved feature extraction, or model tuning to enhance its precision for this specific disease class.

However, the model in the test set achieved an overall mAP50 of 88%, with high precision for "Blossom end rot" (at 90%) and "Healthy Tomato" (at 99%), and "Spotted wilt virus" at 93%. However, the model's precision for detecting "Anthracnose" was significantly lower at 69%, suggesting potential difficulties in identifying this specific disease.

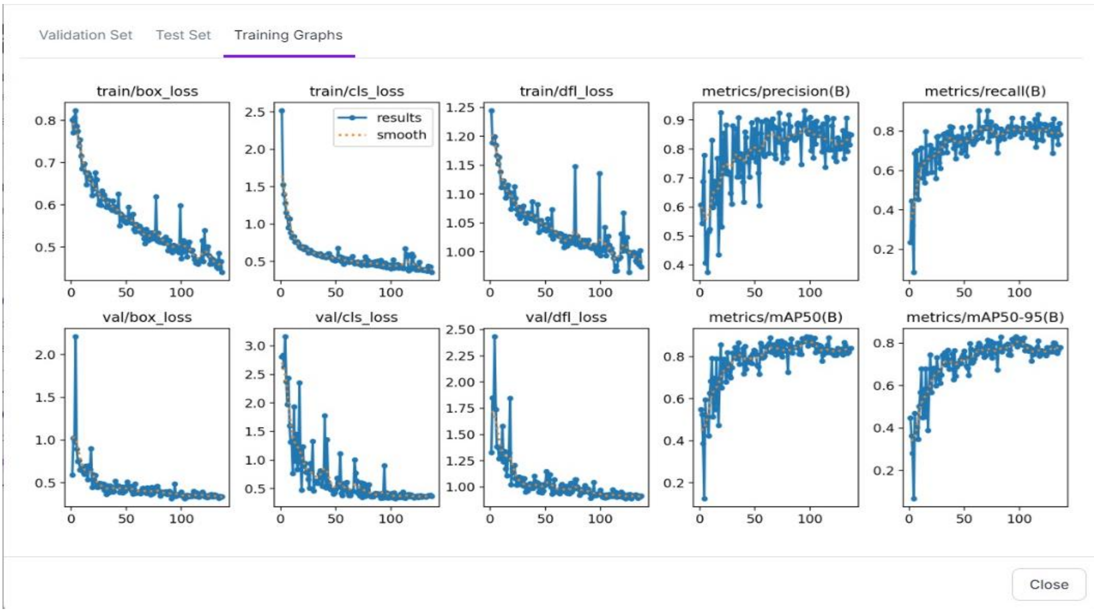

Figure 6 Training and Validation Losses, Precision, Recall, and mAP Training and Validation Losses

Meanwhile, the training graphs as shown in Figure 6 offers important insights into how the model has been learning and support the results from the test and validation sets. As shown, the box loss, classification loss, and distribution focal loss all decrease steadily throughout the training process, which indicates that the model is effectively improving its ability to predict both bounding boxes and classify diseases. The validation losses also decrease consistently, suggesting the model is generalizing well without overfitting. Precision and recall increase as the training progresses, with precision reaching stable, high levels after around 40 epochs. This is consistent with the high precision scores for "Blossom end rot" and "Healthy Tomato" observed earlier. Both mAP50 and mAP50-95 metrics show a notable rise and eventually stabilize, which matches the high detection accuracy seen in the test and validation metrics. However, the lower precision for "Anthracnose," as previously noted, is mirrored here in the training results, pointing to difficulties the model faces in accurately identifying this specific disease. The graphs confirm that the model is performing well across most classes, though some refinement may still be needed to improve the accuracy for "Anthracnose."

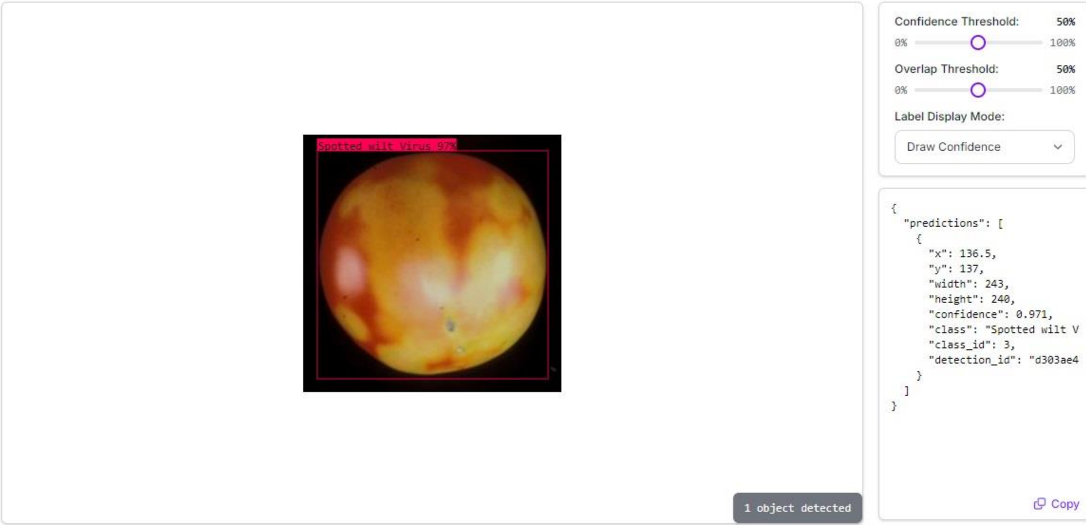

Figure 7 Visualization of the tomato fruit disease detection model's deployment

The tomato fruit disease detection model presented in Figure 7, trained with 2044 images and assessed using the YOLOv7 Object Detection framework, displays a strong ability to detect diseases, achieving a mean average precision (mAP) of 89.5%. This indicates strong alignment between predicted and actual disease states at various confidence thresholds, showing a well-calibrated model. Boasting an 86.2% accuracy rate, the model is highly effective at distinguishing diseased tomatoes, reducing the chance of false positives which is crucial in agriculture to prevent wasted resources. Nevertheless, the model's sensitivity may have some limitations as indicated by the recall rate of 82.2%, suggesting that some cases of the disease may not be accurately detected. The model's ability to detect Spotted Wilt Virus with 97% confidence highlights its strength in identifying certain diseases, but this achievement may not apply equally to all types of diseases.

Overall Performance Across All Classes

The Tomato Fruit Disease Detection model's results, with 89.5% mAP, 86.2% precision, and 82.2% recall, suggest that the model shows excellent performance in identifying and categorizing tomato diseases.

An mAP score of 89.5% indicates that the model can effectively identify diseases at various IoU thresholds, demonstrating a strong compromise between precision and recall.

An 86.2% accuracy means the model is mostly correct when predicting a disease, with only a small number of false positives. This is essential in agricultural usage, as it prevents unneeded treatments or incorrect diagnoses.

Still, the model's 82.2% recall rate shows its effectiveness but reveals potential for enhancing detection to ensure all instances of diseases are captured, with 17.8% of diseased tomatoes possibly remaining undetected. This may result in missed chances for prompt intervention, possibly enabling diseases to spread or deteriorate within a farming setting. Hence, although the model exhibits potential for practical application, especially in precision agriculture, enhancing recall is crucial to make sure that fewer sick tomatoes are missed, therefore boosting the model's dependability in practical scenarios where overlooked instances could impact crop production and food safety.

5. Conclusion

In conclusion, The Tomato Fruit Disease Detection model demonstrates high accuracy, with an exceptional 89.5% mAP and 86.2% precision, highlighting its ability to accurately detect diseased tomatoes. Despite an 82.2% recall rate, there are still some instances where diseases go unnoticed, highlighting a need for enhancement to achieve better overall disease detection. The research makes a notable contribution to the precision agriculture industry with a dependable and effective tool for detecting diseases in tomatoes at an early stage. This model can assist farmers in taking prompt and specific actions to safeguard their crops, ultimately enhancing yield and sustainability by minimizing misdiagnoses and false positives.

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