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TOMATO LEAF DISEASE DETECTION USING YOLOV9 AND COMPUTER VISION

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Abstract

Tomato production is very significant in agriculture and food security and it implies that the health of these plants is very vital in this production. Thus, diagnosing the diseases of tomato leaves at the initial stage and with high accuracy allows for minimizing the losses of the crop yield and improving the quality of the tomatoes. In this paper, research demonstrate the YOLOv9 model for detecting several diseases in tomato leaves. The dataset for this work consists of various diseases such as bacterial spot, early blight, late blight, leaf mold, target spot, and black spot. For the performance of the YOLOv9 model, mAP, precision, recall values were used. From the results obtained it is clear that YOLOv9 obtains a mAP50 of 0.466 and mAP50-95 of 0.305. Most striking is the model's performance in classifying healthy leaves, with a precision of 0.659 and a recall of 1. In the accuracy assessment of the relative program, the recall achieved the highest value of 0 in early blight detection 0.854 and a mAP50 of 0.675. However, the general detection accuracy of the model was low in some of the diseases such as leaf mold and target spot and this could be due to many factors. The research also lays focus on the applicability of YOLOv9 in the automated systems for disease diagnosis and further emphasizes on the fact that the detection algorithm needs to be optimized for less common diseases. Thus, AI model as YOLOv9 in agriculture can be beneficial for crop health and decrease the level of dependence on chemical treatments for sustainable farming practices. Hence, this research avails a comprehensive diagnostic tool for early detection of diseases that address the need of the society in developing innovative precision agriculture technologies that realize high production of crops and food sufficiency.

INTRODUCTION

Global agriculture faces substantial problems because tomato leaf diseases endanger food security together with farmer sustainability(Mahlein, 2016; Mamat et al., 2022). Pathogens including fungi and bacteria alongside viruses cause different diseases that substantially reduce crop yields and degrade crop quality(Agrios, 2005; Jones et al., 2014). The late disease detection results in considerable crop losses followed by excessive chemical pesticide usage has adverse environmental effects (Nowicki et al., 2012).

The occurrence of diseases such as early blight, late blight, bacterial spot, leaf mold, target spot and black spot leads to both plant deterioration and marketability reductions which affect worldwide food distribution systems(Blancard, 2012; Wang et al., 2024).Traditionally farmers used visual inspection as their detection method but this approach proves slow and produces uncertain results(Sladojevic et al., 2016). The slow response to proper preventive measures has made these diseases worse because of delays in reaction.YOLO (You Only Look Once) along with other deep learning models under machine learning and computer vision has revolutionized agricultural disease detection in recent times. The YOLO system implemented in 2016 enables real-time object detection because it uses regression to forecast both object boundary boxes and their respective detection probabilities. YOLOv9 represents the current version of this technology which boosts performance and precision along with superior abilities to identify intricate image patterns. Real-time detection coupled with analysis functions make YOLOv9 an excellent tool for agricultural implementations because they enable prompt decision- making. The objective of this research relies on YOLOv9 technology to build an automated system for simultaneous detection of tomato leaf diseases which will minimize human-involved manual inspection while accelerating disease management procedures. An advanced functionality of deep learning algorithms enables the system to analyze images from various environmental conditions which includes changing light conditions and leaf orientations and diverse background structures thus making it suitable for multiple agricultural settings.

This research investigates the design and evaluation process of a YOLOv9 system for identifying various tomato leaf diseases efficiently and precisely. The research centers on evaluating the model performance across different conditions by comparing its results to YOLO series versions and additional detection algorithms. The investigation explores how both the model's performance and data set dimension and content diversity affect one another. The dataset comprises various images of healthy and diseased tomato leaves which are utilized to test and train the model. This investigation enhances YOLOv9 detection to support farmers by enabling them to detect diseases early so they can apply preventative actions which minimize crop reduction and increase yield production. Early detection helps produce eco-friendly farming since it enables farmers to reduce their use of chemical pesticides and fertilizers while implementing sustainable agricultural methods.Implementation of YOLOv9-based disease detection systems brings extensive advantages toward economic savings. The system delivers farmers an instant diagnostic platform which helps them take prompt decisions thus reducing their pesticide expenses and minimizing crop destruction. This detection system enables farmers to reach greater harvest quantities while lowering their farming expenses and boosting their agricultural sustainability. The study adds value to precision farming science through practical evidence about the implementation of artificial intelligence technology in crop disease observation systems. Agribusinesses should embrace AI alongside machine learning tools because their advancement enables more efficient productivity and establishes better food security that also diminishes environmental farming effects. The study demonstrates that YOLOv9 shows great promise to upgrade agricultural operations through its ability for early detection of tomato leaf diseases(Zhao et al., 2023). YOLOv9 offers farmers revolutionary healthcare management capabilities for their crops through its ability to overcome current diagnosis challenges while delivering immediate verified results. .Some major tomato diseases are shown below that will be detected by using this.

Figure 2.1: Bacterial Spot

Figure 2.2: Early Blight

Figure 2.3: Late Blight

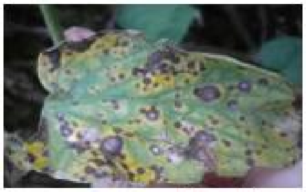


Figure 2.4: Leaf Mold

Figure 2.5: Target Spot

Figure 2.6: Black Spot

1. Litrature Review

Since Tomato leaf diseases negatively affect the global tomato production industry proper early diagnosis serves as a crucial requirement for preserving sustainable agriculture (Mahlein, 2016; Jones et al., 2014). Traditional classical image processing struggled to manage the diverse disease symptom variations and complexities (Mamat et al., 2022). The advancement in plant disease detection occurred through deep learning implementations and especially through Convolutional Neural Networks (CNNs). Research by Sladojevic et al. (2016) and Mohanty et al. (2016) confirmed that CNNs achieve remarkable accuracy when used for leaf image disease classifiers. Fuentes et al. (2017) developed a real-time deep learning-based platform that identified tomato diseases together with pests in field conditions thereby proving the operational viability of such models. Accepted research developments combined CNN and GCN approaches as proposed by Jiang et al. (2020) while Joseph et al. (2023) researched mobile diagnosis equipment. Pre- trained models in agriculture became effective through transfer learning which allowed researchers to enhance the models for precise crop-disease classification (Chen et al., 2020; Gai et al., 2024). The YOLO family achieved popularity among real-time detection frameworks because of its high performance and speed according to Saleem et al. (2019). The researchers Roy and Bhaduri (2022) integrated DenseNet with YOLOv4 to address complex agricultural environments according to their study. Additionally Wang et al. (2024) and Qi et al. (2022) further developed YOLOv5 through attention mechanism implementation to enhance detection accuracy of small and obscured disease areas. The team of Liu and Wang (2020) developed a MobileNetv2-YOLOv3 algorithm system to detect tomato gray leaf spot during its early development phase. Gai et al. (2024) also applied transfer learning to YOLOv8 for fruit detection. The combination of YOLOv9 with transformer networks in Liu and Wang (2024) led to the most recent breakthrough in fast and precise detection of tomato diseases. The sector of precision agriculture benefits extensively from these technological improvements that transition CNN-based systems to faster YOLO architecture solutions Boudaa et al. (2024).below presented the complete literature review of current work and issues that are remain not solved for this area of research based on this we designed our model that overcome this issues and provide advanced tomato disease detection in early stages.

Year	Authors	Model/Method	Key Findings
2016	Sladojevic et al.	CNNs for plant disease recognition	Showed the high accuracy of CNNs in diagnosis of the plant diseases from the images of the leaves.
2016	Mohanty et al.	Deep learning for plant disease detection	Succeeded in proving that CNNs could present higher accuracy as compared to conventional machine learning approaches in the identification of plant diseases.
2017	Fuentes et al.	Deep learning-based real-time detector	Demonstrated the possibility of applying real-time deep learning models for
			diagnose of tomato diseases and pests.
2018	Ferentinos	Comparison of deep learning models	Reasoned that CNNs are most suitable to be used in plant disease detection.
2019	Jiang et al.	CNN features with GCN for disease identification	Better at detecting the accuracy of spatial relations of an object than any other views.
2019	Ramcharan et al.	Mobile phone-based system for real-time diagnosis	Emphasized on the implication of making technology available to the farmers, and a concept of deeply learning mobile applications.
2019	Picon et al.	Transfer learning for plant disease detection	Illustrated that, due to the process of transfer learning, it is possible to obtain outstanding accuracy in some particular agricultural tasks.
2020	Chen et al.	Deep learning model for tomato leaf disease detection	Showed marked enhancements of accuracy as well as the algorithm's ability to handle noise.
2020	Saleem et al.	Review of YOLO models for plant disease detection	Stressed that higher efficiency and speed of YOLO models is beneficial when working with large data for plant diseases detection.
2021	Li et al.	YOLOv4-based method for dense environments	Emphasized on the ability of YOLO models to deal with multiple diseases at complexity of the corresponding situation.
2021	Wang et al.	YOLOv3 with attention mechanisms	Generally, better identification of small and hidden objects in the images of the tomato leaves.
2021	Chouhan et al.	Hybrid YOLOv3 and DenseNet model	Obtained significant enhancements in accuracy and reliability of tomato diseases' preliminary identification.
2022	Roy & Bhaduri	YOLOv4 for high-density environments	Showed that the YOLO models are reliable in complex scenes with several diseases.
2022	Qi et al.	YOLOv5 with attention mechanism	Improved detection efficiency in actual operating environments and particularly where the goals are small objects or even hidden.
2023	Joseph et al.	Mobile phone-based real-time deep learning system	Called for technology that can be adopted by farmers and the future applicability of deep learning for fast diagnosis.

2023	John et al.	Enhanced YOLOv7 model for real-time detection	Designed with the major goal to improve precision and rate, opening the path for YOLOv7.
2023	Wang et al.	Optimized YOLOv6 model for tomato leaf disease detection	Attained better detection and class accuracy as well as faster detection rates than the prior YOLO models.
2024	Chen et al.	YOLOv8 with transfer learning	Noted major increases in the identification accuracy of tomato leaf diseases through the fine-tuning of pretrained models.
2024	Liu & Wang	YOLOv9 with transformer networks	Enhancement in the analysis and recognition of diseases affecting tomato leaves using YOLO integrated with transformer networks.
2024	Gai et al.	Transfer learning with YOLOv8	Emphasized on the eternal of fine-tuning as a means for improving the efficiency as it relates to implementation of agricultural applications.
2024	Lee et al.	YOLOv9 for precision agriculture	Established that there is a possibility of boosting crop health management by using YOLOv9 due to its ability to detect diseases at an early stage.
2024	Zhang et al.	Ensemble approach combining YOLOv9 with other models	Demonstrated that integrating a number of models could give an all-in-one solution for tomato leaf disease identification.

2. Methodology

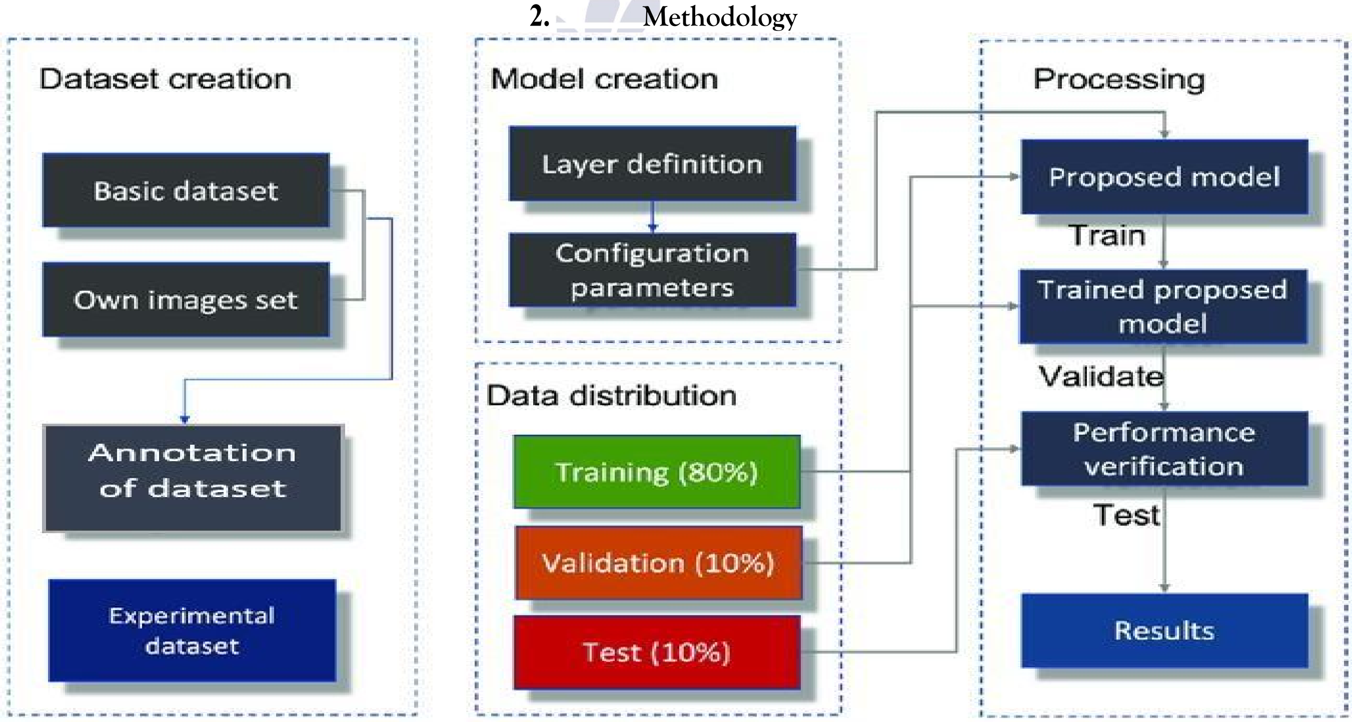


Fig.#4.1 Methodology

The research presents an automated framework which employs YOLOv9 object detection model for identifying tomato leaf diseases through deep learning. The system development follows four essential stages which begin with dataset acquisition then move through data pre-processing before training the model and finishing with evaluation. Figure 4.1 demonstrates the comprehensive methodology workflow which shows an overview of the total end-to-end pipeline operations.

This research utilized the "Tomato Leaf Diseases Detection Computer Vision" dataset that obtained from Kaggle. The dataset contains pictures of both diseased and healthy tomato leaves. The model required three separate units to achieve stability because the dataset contained real-world field images in addition to lab-controlled images and augmented synthetic pictures. The addition of these three data types created varied conditions which improved model learning capacity across different conditions below categories the dataset

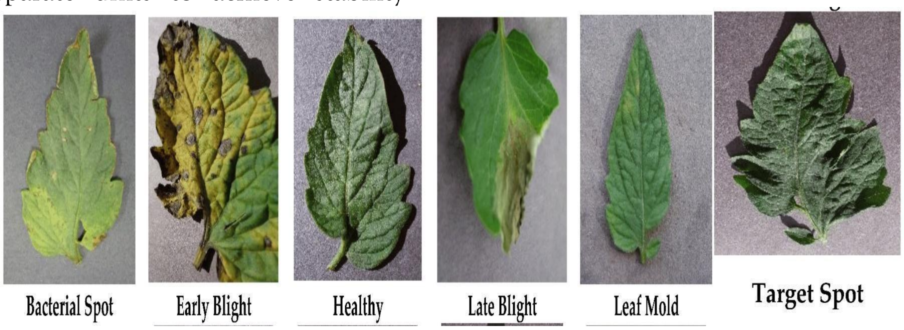


Fig.#4.2 Sample Dataset

The available images were distributed for three separate purposes including training (645 images), validation (61 images) and testing (31 images). The YOLO-formatted annotation files provided each image with standard bounding boxes alongside class labels along with normalized coordinates. As a requirement for YOLOv9 all images received resizing treatment to meet its 640×640 pixels input standard. The dataset grew in size through data augmentation techniques including horizontal flips as well as rotational and scaling transformations and boundary cropping procedures to boost generalization accuracy.This research utilized YOLOv9 as its model training framework because it demonstrated superior performance in object detection operations specifically regarding accuracy and real-time processing capabilities. Training of the custom YOLOv9 model started by accessing the official repository through cloning then setting up necessary parameters for user-specific training needs. The training continued for 75 epochs at an optimal learning rate along with a batch size of 16 to achieve stability in the learning process. The loss function included three components of classification and localization and confidence that functioned as an effective learning process guide. The whole study took place within the Google Colab environment by providing GPU acceleration capabilities together with a flexible programming space that supported code execution and dataset management and visualization features

3. The examination of model accuracy occurred using the validation dataset that was withheld for this purpose. The detection capability was evaluated through standard performance metrics that calculated precision, recall and F1-Score. The YOLOv9 model achieved successful results in identifying tomato leaf diseases and their distinction from healthy leaves during its practical tests for agricultural disease monitoring purposes.The evaluated YOLOv9 performance for tomato leaf disease detection through Precision, Recall, F1 Score and mean Average Precision (mAP) measurements. The metrics were generated through a comparison process in which model predictions from the test dataset received analysis against manual annotations for complete performance evaluation. The model showcased its disease detection abilities through Precision and Recall measurements that measured accuracy and false-positive/false-negative rates in a single value using the F1 Score. Computing mAP delivered an efficient evaluation over multiple disease classes and Intersection over Union thresholds through its averaging precision process thus demonstrating promising performance for real-world agricultural useResults

The YOLOv9 model implementation for tomato leaf disease detection comes with a complete guide that illustrates strategies for training and validation and testing methods and evaluation of model performance. Train_dual.py which was developed in

Python served as the input feeding program to provide the model with a 640×640 pixel tomato leaf dataset through 75 training cycles using an input batch quantity of
16. All parameters associated with the model architecture lived in separate .yaml files to enable exact program execution (see Figure 5.1). Model validation was conducted by applying optimized weights to images evaluated with a low confidence threshold (0.01) and an IoU value of 0.7 which allowed for detection of faint visualizations as well as testing prediction reliability . Performance verification took place by storing JSON output to validate results .

```
# train yolov9 models
!python train_dual.py --workers 8 --device 0 --batch 16 --data "/content/drive/MyDrive/tomato_disease_detection/yolov9/tomato_data.yaml" --img 640 --

# train gelan models
# python train.py --workers 8 --device 0 --batch 32 --data data/coco.yaml --img 640 --cfg models/detect/gelan-c.yaml --weights '' --name gelan-c --hy

2024-08-05 07:00:37.220094: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:485] Unable to register cuFFT factory: Attempting to register
2024-08-05 07:00:37.244136: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:8454] Unable to register cuDNN factory: Attempting to register
2024-08-05 07:00:37.251313: E external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1452] Unable to register cuBLAS factory: Attempting to regist
2024-08-05 07:00:37.268849: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructio
To enable the following instructions: AVX2 AVX512F FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
2024-08-05 07:00:38.727586: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT
train_dual: weights=, cfg=/content/drive/MyDrive/tomato_disease_detection/yolov9/yolov9_cfg.yaml, data=/content/drive/MyDrive/tomato_disease_detecti
YOLO 🚀 v0.1-104-g5b1ea9a Python-3.10.12 torch-2.3.1+cu121 CUDA:0 (Tesla T4, 15102MiB)

hyperparameters: lr0=0.01, lrf=0.01, momentum=0.937, weight_decay=0.0005, warmup_epochs=3.0, warmup_momentum=0.8, warmup_bias_lr=0.1, box=7.5, cls=0
ClearML: run 'pip install clearml' to automatically track, visualize and remotely train YOLO 🚀 in ClearML
Comet: run 'pip install comet ml' to automatically track and visualize YOLO 🚀 runs in Comet
```

Fig.#5.1 Training og YOLOV9 model

With detect_dual.py the testing phase took place to navigate through real-world situations involving new tomato leaf images which existed inside specified directories. During testing the most successful weights obtained from training were used to guarantee consistency while sustaining accuracy levels (Figure#5.2).

```
!python val_dual.py --data '/content/drive/MyDrive/tomato_disease_detection/yolov9/tomato_data.yaml' --img 640 --batch 16 --conf 0.01 --iou 0.7 --dev

val_dual: data=/content/drive/MyDrive/tomato_disease_detection/yolov9/tomato_data.yaml, weights=['/content/drive/MyDrive/tomato_disease_detection/yolo
WARNING ⚠ confidence threshold 0.01 > 0.001 produces invalid results
YOLO 🚀 v0.1-104-g5b1ea9a Python-3.10.12 torch-2.3.1+cu121 CUDA:0 (Tesla T4, 15102MiB)

Fusing layers...
yolov9_cfg summary: 580 layers, 60509770 parameters, 0 gradients, 264.0 GFLOPs
val: Scanning /content/drive/MyDrive/tomato_disease_detection/yolov9/valid/labels.cache... 61 images, 2 backgrounds, 0 corrupt: 100% 61/61 [00:00<?, ?
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 4/4 [00:07<00:00,  1.93s/it]
                   all         61        196      0.592      0.432      0.466      0.305
         Bacterial Spot         61          4      0.561       0.25      0.307      0.179
          Early_Blight         61         96      0.496      0.854      0.675      0.364
               Healthy         61         19      0.659          1      0.995      0.816
           Late_blight         61         29      0.532      0.621      0.623      0.449
             Leaf Mold         61          7          1          0      0.178      0.107
           Target_Spot         61          6      0.288      0.209      0.199     0.0985
            black spot         61         35      0.609     0.0895      0.283      0.121
Speed: 0.3ms pre-process, 80.0ms inference, 25.1ms NMS per image at shape (16, 3, 640, 640)
```

Fig.#5.2 Validation Results

The detection results demonstrated how well the model detected diseased areas among other plant components (Figure 5.3). The model performance evaluation included the calculation of precision, recall and F1 score through standard mathematical formulas.

Precision = TP/(TP + FP) Recall = TP/(TP + FN)

F1 SCORE = 2 ∗ (precision ∗ recall) / (precision + recall)

Fig.#5.4 Detection Results.

Figure 5.4 shows the results that of the YOLOV9 Model on Tomato Dataset that comes after the three phases like training, validating and testing of the dataset.

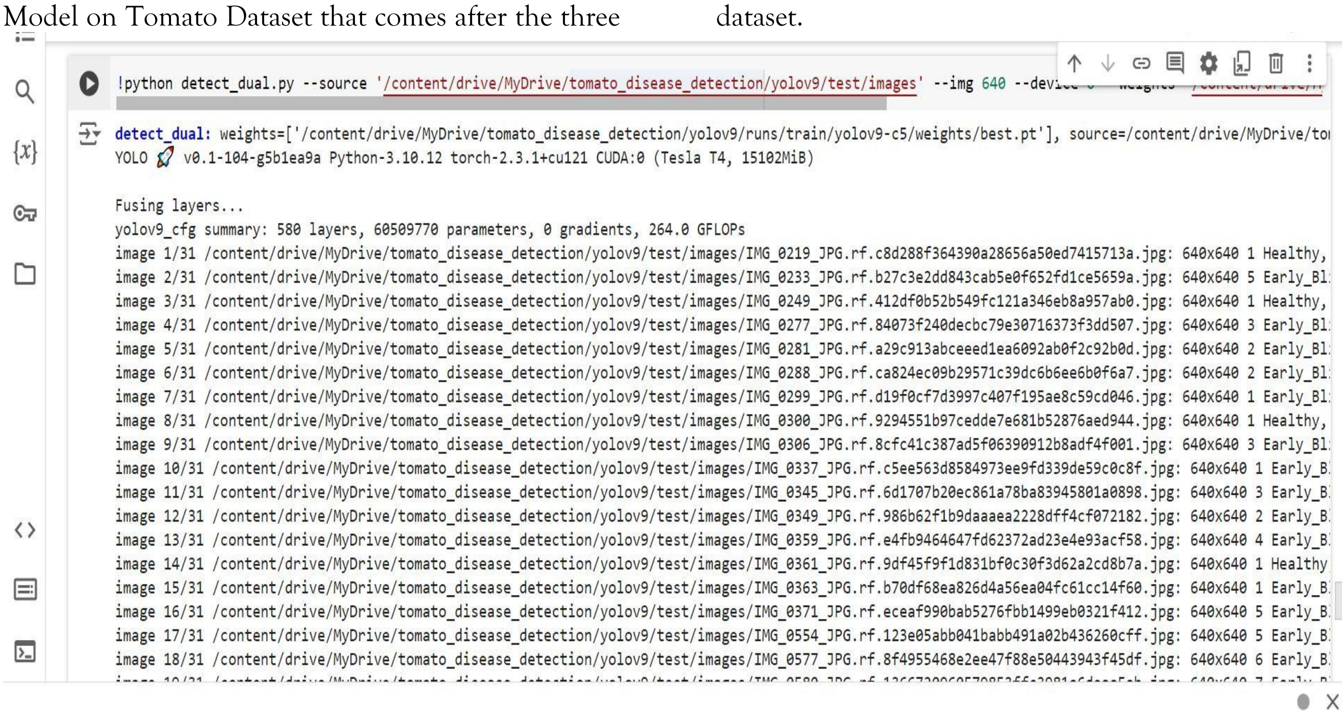


Fig.#5.5 Testing Datset using YOLOV9 Model

The graphical comparison displays original tomato leaves alongside detections made with YOLOv9 model on affected areas. The original images present unprocessed data but the detected images display precise disease areas through bounding boxes with labels applied.

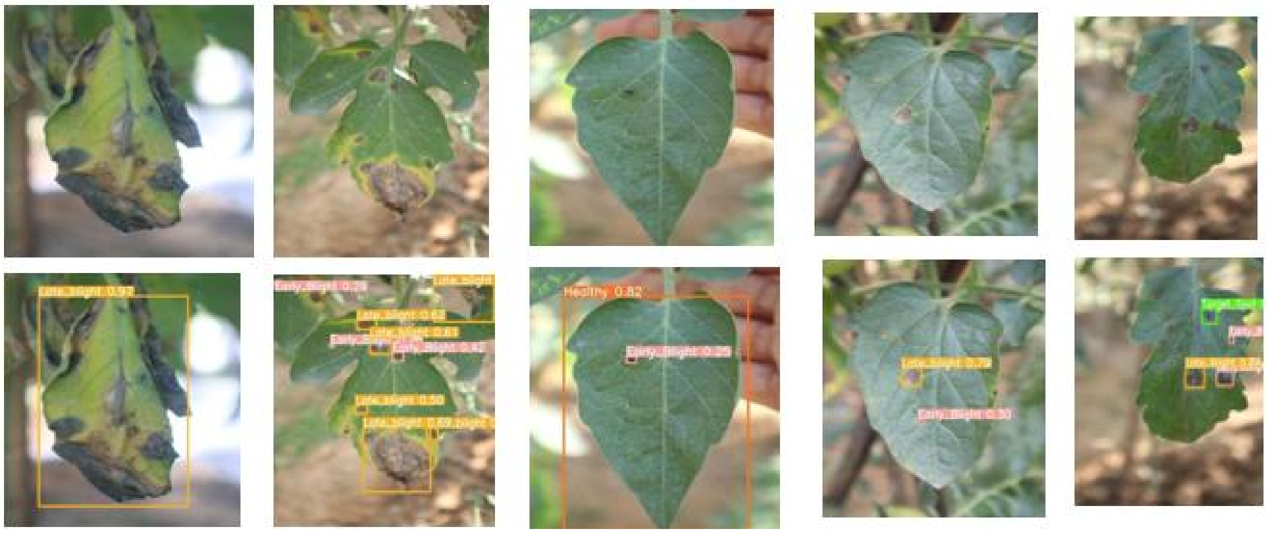
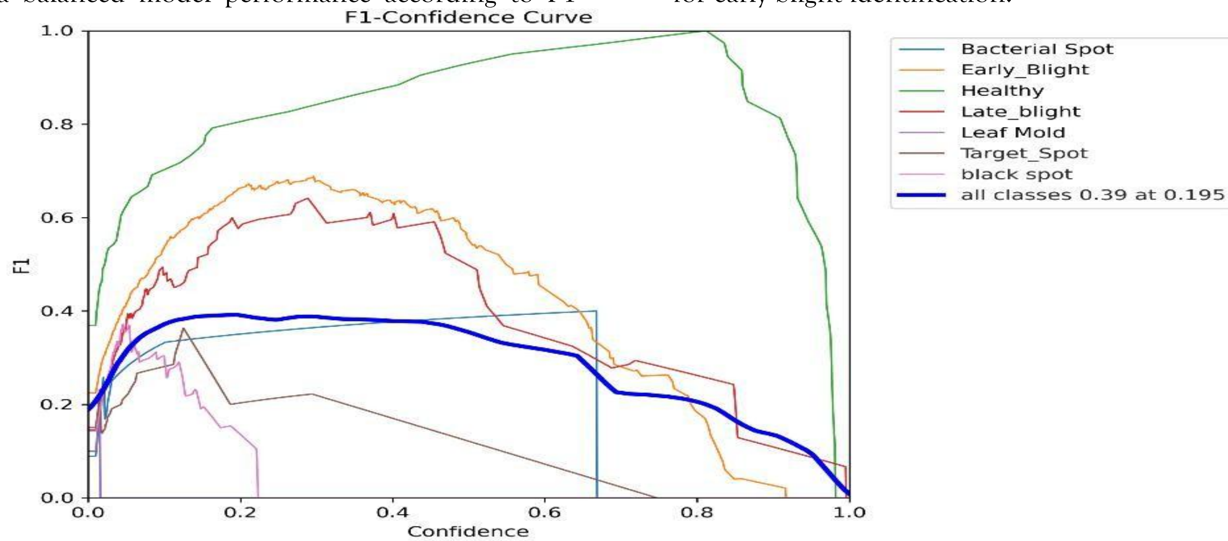
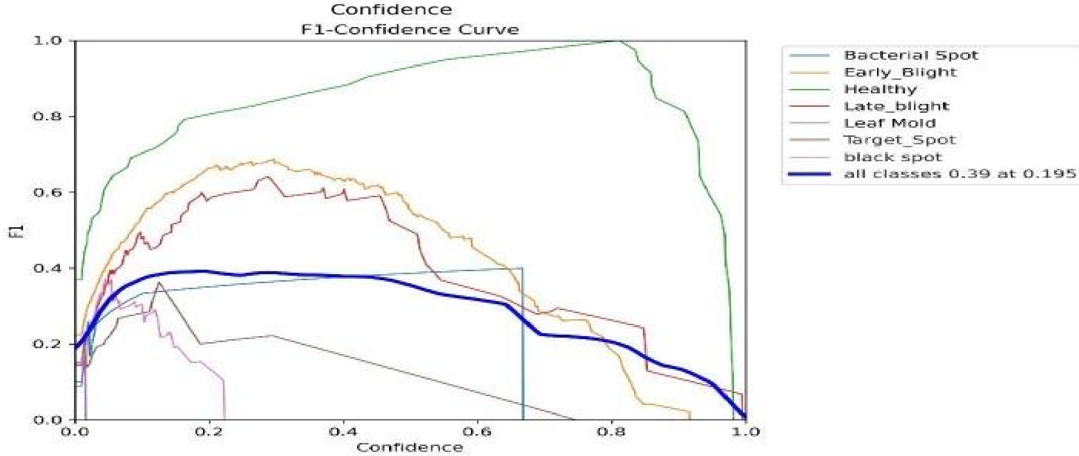


Fig. # 5.6 Original images & Detected Images

Each performance curve shown in Figures 5.7 - 5.9 demonstrated both high detection accuracy and perfect background identification abilities resulting in a balanced model performance according to F1 score metrics. The model exhibited precision values of 0.659 along with 1.0 recall in detecting healthy leaves and achieved 0.854 recall and 0.675 mAP50 for early blight identification.





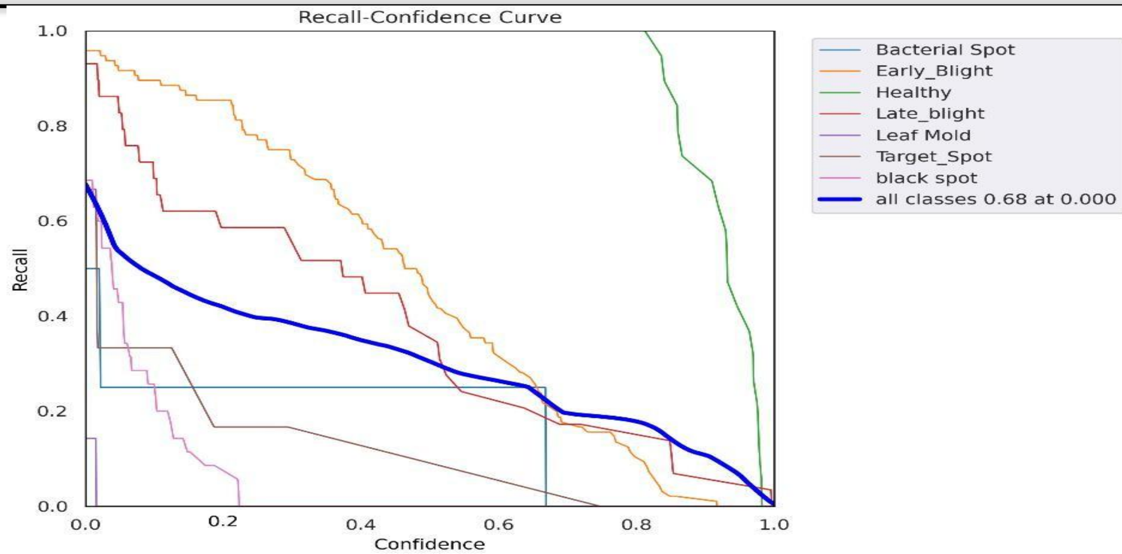


Fig.#5.7-5.9 Model Performance

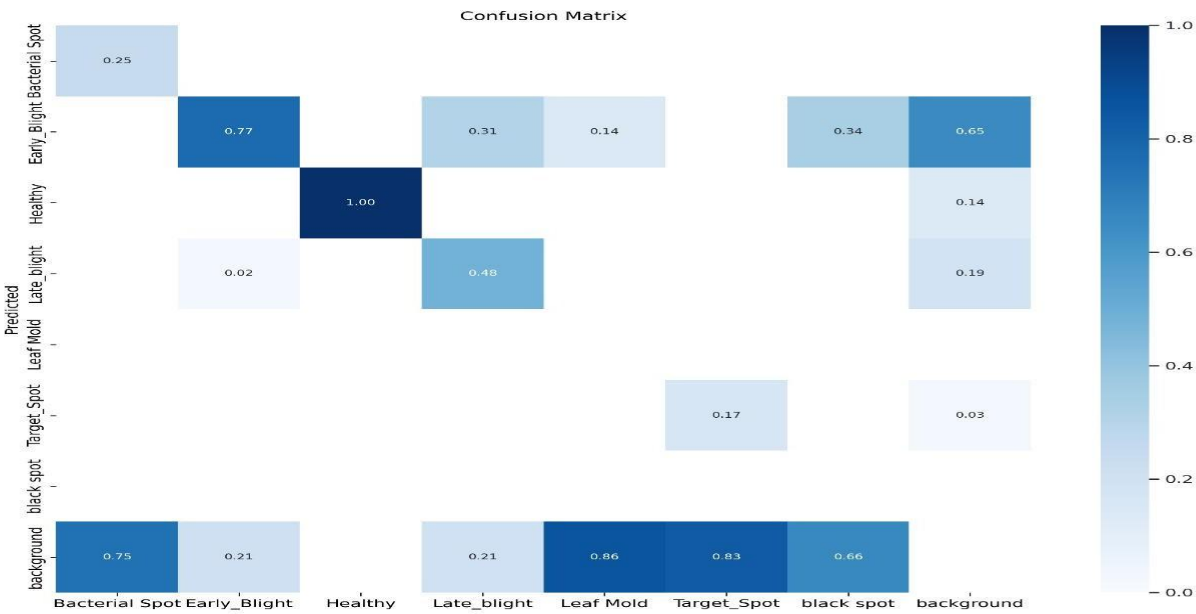


Fig.#5.10 Confusion Matrix.

The model achieves well performance on traditional disease categories based on mAP scores of 0.466 at 50% IoU and 0.305 at mAP50-95 results. The model demonstrates its classification potential for different disease categories through the confusion matrix which is shown in Figure 5.10 and supports its use in real-time smart agriculture systems. The experimental findings validate YOLOv9 as an effective model for real-time tomato leaf disease detection in precision agricultural scenarios.

4. Conclusion

As a final note while identifying that YOLOv9 model has the demonstrated the great potentiality for the early diagnosis of tomato leaf diseases this research work has manifested the pioneering direction of the application in enhancing the health of produce and therefore boosting productivity in the agricultural sector. As I can see from the result in this paper, YOLOv9 is faster and more accurate than other models and algorithms using deep learning strategies in detection and recognition of a wide range of typical diseases on the leaves of tomato plant such as bacterial spot, early and late blight, leaf mold, target spot, and black mildew. These very high levels of identification more specifically of the presence of healthy leaves are indicative of a very good model for disease identification.But the research also admits that the model is erroneous in a way that can can lead to ignoring diseases that are not so frequent for instance the leaf mold and the target spot disease. Such challenges require improvement of the model in other to boost its performance in detecting all kinds of diseases. However, the investigators acknowledge that these challenges do not negate the ability of YOLOv9 since the latter is used for the development of automated diagnosis systems for diseases. This simply could revolutionize the field of agriculture by way of providing a good solution on the part of farmers as to how best monitor the wells being of the plants to aid more in the fight against diseases.

The application of YOLOv9 in agriculture is a step up in the utilization of precision farming. This technology provides a feasible and quantifiable solution for mitigating crop losses meaning that chemical treatments that are expensive and polluting are avoided. This way, measures can be taken on time to minimize the effects of the diseases and hence increase the yields and the quality of the produce. This is a win-win situation in that farmers are economically compensated for their crops while at the same time, conserving the environment by practicing modern form of farming.However, the outcome of this study is in support of sustainable agriculture which aims at the increase of food production without compromising other aspects of the environment. The YOLOv9 model buoys how practices which are sustainable both to the environment as well as economical which can be beneficial in the advancement of farming systems for feeding the growing population in an environmentally sustainable manner.

5. Future Work

Consequently, it should refine the upcoming work in enhancing the ability of the YOLOv9 model in recognizing somewhat rare diseases. It could be as basic as tweaking of the model by training the model on a healthier population that have similar diseases but different symptoms, as complex as testing and comparing the efficiency of the model under the diverse conditions and farming settings. However, the inclusion of actual-time data from a variety of agricultural context possibly can improve the validities of this model.

7. REFERENCES

1. Boudaa, B., et al. Advancing Plant Diseases Detection with Pre-trained YOLO Models. in 2024 6th International Conference on Pattern Analysis and Intelligent Systems (PAIS). 2024. IEEE.
2. Mamat, N., et al., Advanced technology in agriculture industry by implementing image annotation technique and deep learning approach: A review. Agriculture, 2022. 12(7): p. 1033.
3. Yağ, İ. and A. Altan, Artificial intelligence-based robust hybrid algorithm design and implementation for real-time detection of plant diseases in agricultural environments. Biology, 2022. 11(12): p. 1732.
4. Mahlein, A.-K., Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. Plant disease, 2016. 100(2): p. 241-251.
5. Jones, J.B., et al., Compendium of tomato diseases and pests. 2014: APS press.
6. Agrios, G.N., Plant pathology. 2005: Elsevier.
7. Nowicki, M., et al., Potato and tomato late blight caused by Phytophthora infestans: an overview of pathology and resistance breeding. Plant disease, 2012. 96(1): p. 4-17.
8. Blancard, D., Tomato diseases. 2012: Academic Press San Diego, CA, USA:.
9. Sladojevic, S., et al., Deep neural networks based recognition of plant diseases by leaf image classification. Computational intelligence and neuroscience, 2016. 2016(1): p. 3289801.
10. Mohanty, S.P., D.P. Hughes, and M. Salathé, Using deep learning for image- based plant disease detection. Frontiers in plant science, 2016. 7: p. 1419.

11. Fuentes, A., et al., A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors, 2017. 17(9): p. 2022.
12. Ferentinos, K.P., Deep learning models for plant disease detection and diagnosis. Computers and electronics in agriculture, 2018. 145: p. 311-318.
13. Jiang, H., et al., CNN feature based graph convolutional network for weed and crop recognition in smart farming. Computers and electronics in agriculture, 2020. 174: p. 105450.
14. Joseph, D.S., P.M. Pawar, and R. Pramanik, Intelligent plant disease diagnosis using convolutional neural network: a review. Multimedia Tools and Applications, 2023. 82(14): p. 21415-21481.
15. Chen, J., et al., Using deep transfer learning for image-based plant disease identification. Computers and Electronics in Agriculture, 2020. 173: p. 105393.
16. Saleem, M.H., J. Potgieter, and K.M. Arif, Plant disease detection and classification by deep learning. Plants, 2019. 8(11): p. 468.
17. Roy, A.M. and J. Bhaduri, Real-time growth stage detection model for high degree of occultation using DenseNet-fused YOLOv4. Computers and Electronics in Agriculture, 2022. 193: p. 106694.
18. Wang, Y., P. Zhang, and S. Tian, Tomato leaf disease detection based on attention mechanism and multi-scale feature fusion. Frontiers in Plant Science, 2024. 15: p. 1382802.
19. John, S.M., et al. Enhanced YOLOv7 Model for Accurate Vehicle Detection from UAV Imagery. in 2023 International Conference on Innovations in Engineering and Technology (ICIET). 2023. IEEE.
20. Qi, J., et al., An improved YOLOv5 model based on visual attention mechanism: Application to recognition of tomato virus disease. Computers and electronics in agriculture, 2022. 194: p. 106780.
21. Liu, J. and X. Wang, Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model. Plant Methods, 2020. 16: p. 1-16.
22. Gai, R., Y. Liu, and G. Xu, TL-YOLOv8: A Blueberry Fruit Detection Algorithm Based on Improved YOLOv8 and Transfer Learning. IEEE Access, 2024.
23. Liu, J. and X. Wang, Multisource information fusion method for vegetable disease detection. BMC Plant Biology, 2024. 24(1): p. 738.
24. Bochkovskiy, A., C.-Y. Wang, and H.-Y.M. Liao, Yolov4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934, 2020.
25. Otterness, N. and J.H. Anderson. AMD GPUs as an alternative to NVIDIA for supporting real-time workloads. in 32nd Euromicro conference on real-time systems (ECRTS 2020). 2020. Schloss Dagstuhl-Leibniz-Zentrum für Informatik.
26. Russakovsky, O., et al., Imagenet large scale visual recognition challenge.
International journal of computer vision, 2015. 115: p. 211-252.
27. Jocher, G., et al., ultralytics/yolov5. Github Repository. YOLOv5, 2020.
28. Goodfellow, I., Y. Bengio, and A. Courville, Regularization for deep learning.
Deep learning, 2016: p. 216-261.
29. Bishop, C.M. and N.M. Nasrabadi, Pattern recognition and machine learning. Vol. 4. 2006: Springer.
30. Zhao, Y., et al., Precision detection of crop diseases based on improved YOLOv5 model. Frontiers in Plant Science, 2023. 13: p. 1066835.
31. Silwal, A., et al. A robust illumination-invariant camera system for agricultural applications. in 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). 2021. IEEE.
32. Rasool, A., & Ammar, A. The Dawn of AI in Agriculture: From Predictive Analysis to Autonomous Farming.

33. Kaniz, R. E., Lindon, A. R., Rahman, M. A., Hasan, M. A., & Hossain, A. (2025). The Impact of Project Management Strategies on the Effectiveness of Digital Marketing Analytics for Start-up Growth in the United States. Inverge Journal of Social Sciences, 4(1), 8–24. https://invergejournals.com/index.php/ijss/article/view/109
34. Mohsin Asad Gill, Muneera Quresh, Awais Rasool, & Muhammad Mubashir Hassan. (2023). Detection of Credit Card Fraud Through Machine Learning In Banking Industry. Journal of Computing & Biomedical Informatics, 5(01), 273–282