Comparative Analysis of YOLOv8 and YOLOv9 Models for Real-Time Plant Disease Detection in Hydroponics

Abhishek Tripathi
Dr. Vishwanath Karad MIT World Peace University, Pune, India
abhishek0akt@gmail.com

Vinaya Gohokar
Dr. Vishwanath Karad MIT World Peace University, Pune, India
vinaya.gohokar@mitwpu.edu.in

Rupali Kute
Dr. Vishwanath Karad MIT World Peace University, Pune, India
rupali.kute@mitwpu.edu.in (corresponding author)

Received: 4 July 2024 | Revised: 23 July 2024 | Accepted: 30 July 2024

 DOI: https://doi.org/10.48084/etasr.8301

ABSTRACT

Plant diseases are a significant threat to modern agricultural productivity. Hydroponic systems are also affected for various reasons. Reliable and efficient detection methods are essential for early intervention and management of diseases in hydroponics. This study investigates the use of You Only Look Once (YOLO) models, namely YOLOv8 and YOLOv9, for the detection of plant diseases in a hydroponic environment. A diverse dataset was prepared, comprising images from a hydroponics system setup and the New Plant Disease Image Dataset from Kaggle. Custom annotated images were used to train and test the models and compare their accuracy, processing speed, and robustness in hydroponic systems. The results showed that YOLOv9 is slightly better than YOLOv8 in terms of detection accuracy, as it achieved 88.38% compared to 87.22%, respectively. YOLOv8 requires less computational resources and takes relatively less time than YOLOv9 for real-time plant disease detection. Therefore, it is recommended for portable devices.

Keywords-plant disease detection; hydroponics; YOLOv8; YOLOv9; deep learning; image annotation

I. INTRODUCTION

Traditional farming methods, i.e., soil-based farming, are now hard to maintain due to changing climate patterns and decreasing cultivable land. Due to its dependence on natural phenomena, the outcome of traditional farming cannot be changed without using harmful chemicals to improve crop health. With the global population increasing and the availability of arable land decreasing due to urbanization, society is increasingly exploring innovative agricultural technologies such as aquaponics, aeroponics, and hydroponics. These approaches do not depend on soil. Hydroponics involves cultivating plants using nutrient-enriched solutions instead of traditional soil, effectively addressing challenges faced in conventional irrigation and agriculture, such as high water consumption, weed proliferation, and pest management. This technique has gained significant traction in commercial cultivation, including diverse greenhouse crops. Within a controlled hydroponic environment, crop production rates can be significantly increased, accelerating plant growth. This approach offers the advantage of reduced dependence on chemical nutrient supplements, as all essential nutrients are provided directly to plants through water. The hydroponics industry, which is rapidly expanding, has the potential to completely transform sustainable food production from small- to large-scale. [1-3]. Unlike traditional soil-based agriculture, hydroponic systems are less immune to diseases and pest attacks. However, they face unique challenges when it comes to protecting crops. In the absence of soil, hydroponic systems are not immune to pesky invaders. Aphids, spider mites, and whiteflies are among the usual suspects that can wreak havoc on hydroponic crops. Identifying these tiny foes early on is crucial, as their populations can multiply rapidly in the controlled environment of a hydroponic setup. Regular scouting and monitoring are the first lines of defense [4-5].

Although the judicious use of chemicals is an option, it comes with a cautionary note. Hydroponic farmers must tread lightly when employing chemical control methods to avoid unintended consequences. Understanding the specific needs of crops and choosing chemicals wisely can mitigate risks and protect the overall health of a hydroponic garden. Vigilance is the cornerstone of effective pest and disease management. Regular monitoring of the hydroponic system for signs of trouble is crucial. Early detection makes it possible to act quickly and stop small problems from growing into big ones. Employing advanced tools and technologies for surveillance ensures that farmers are one step ahead of potential problems [6-9].

Traditional pest and disease detection methods are time-consuming and labor-intensive. Recent advances in pest and disease detection have emerged from image processing, Computer Vision (CV), and Machine Learning (ML). However, these methods offer challenges in terms of large datasets, speed, and accuracy. Deep Learning (DL) has opened new avenues for automating plant disease detection through object detection [4, 10, 11], identifying different types of pests and diseases in the crop. There are various types of object detection models, such as RCNN, Fast RCNN, Faster RCNN, Mobile Net, and YOLO [12-14]. The YOLO models, recognized for their real-time object detection abilities, offer promising solutions in this domain. These models can quickly and accurately identify diseases in plants, allowing for prompt intervention and management. The benefits of using YOLO models in hydroponic systems include increased efficiency in disease detection, reduced labor costs, and improved overall crop health and yield. YOLO offers various versions, from YOLOv1 to YOLOv9, comprising tiny, small, medium, large, and extra-large subversions [15-19]. By incorporating advanced technologies such as YOLO models for disease detection, the hydroponics industry can further enhance crop production and ensure food security in the future. This study compared YOLOv8 and YOLOv9 for pest and disease detection in hydroponics systems.

Many studies have focused on disease detection in the CV and ML domains. Many approaches, including DL-based and traditional CV algorithms, have been employed to tackle this challenge. Conventional methods for analyzing and diagnosing diseases often involve image segmentation, thresholding, and morphological procedures [19-20]. Leaf images exhibit complex textures, shapes, and structures, necessitating multilevel and multiscale feature extraction and representation methods. YOLO-based networks have recently been used in disease detection [12-14, 21]. YOLO uses a single deep neural network to simultaneously detect the bounding boxes and class probability of an image [22]. Unlike traditional methods that use region proposal algorithms, YOLO segments the image into a grid and then predicts the bounding boxes. This results in increased efficiency and faster inference times. The YOLO algorithm has proven to be an extremely effective technique for object detection, which encompasses plant recognition and counting. Real-time detection capabilities open many opportunities for agricultural research. Plant disease diagnosis, plant phenotyping, and precision agriculture automation have all shown promising results with YOLO-based techniques [23-24]. YOLO-based approaches make detection faster and more efficient compared to other object detection models. Table I presents a review of state-of-the-art studies based on YOLO models for disease detection in soil- and hydroponic-based systems. As can be observed, YOLO versions from v5 to v9 are used to detect diseases in various plants, achieving accuracies in the range of 66 to 97%.

TABLE I. REVIEW OF PLANT DISEASE DETECTION USING YOLO

Ref.	Diseases detected	Models used	Dataset used	Hydroponic/Soil	Accuracy
[16]	Not specified	YOLOv5 and YOLOv6	Plant leaf dataset	Soil	Not Specified
[17]	Blossom end rotation, splitting, sun-scaled rotation	YOLOv8	"balanceddata dataset" in Roboflow	Soil	66.67%
[18]	Blossom end rotation, Splitting, sun-scaled rotation	YOLOv5 and YOLOv8	"balanceddata dataset" from Roboflow	Soil	86.6 - 94.3%
[25]	Tomato splitting, sun scaled, and blossom end rot.	YOLOv8, YOLOv9	Tomato disease dataset from Roboflow	Soil	93.6%
[26]	Tomato late blight, gray mold, leaf mold, leaf spot, cucumber powdery mildew, downy mildew anthracnose, eggplant brown spot.	YOLOv8n, YOLOv8n-FastNet, YOLOv8n-MobileNet	Vegetable disease dataset	Soil	92.97%
[27]	Leafy green vegetables	ResNet-50 and YOLOv5s	leafy green image dataset	Aquaponics	94.13%
[28]	Apple scab, grape leaf blight, grape black rot, potato healthy, soybean healthy, peanut brown spot, peanut rust	Optimized lightweight YOLOv5	PlantDoc dataset, peanut rust dataset	Hydroponic	90.26 - 92.57%
[29]	Rust, corn leaf blight, eyespot, and gray leaf spot	YOLOv5	High-resolution corn leaf images taken from a GoPro camera	Soil	Not Specified
[30]	Wheat mosaic virus	Not specified	Classified wheat streak mosaic disease	Soil	97.56%

From Table I, the following research gaps can be observed:

- Plant disease detection studies primarily focus on soil-based systems.
- The accuracy of the YOLOv5 model is moderate compared to v8 and v9.
- The YOLOv8 and v9 plant disease detection models achieved better accuracy for soil-based systems.
- There is a need for a customized pest and disease dataset for hydroponic systems.

- There is a need for a high-performance hydroponic plant disease detection system using YOLOv8 and v9 models.

The novelty of the proposed framework is as follows:

- A Deep Water Culture (DWT) hydroponic setup is used with basil cultivation as a case study. TDS, pH, temperature, and oxygen levels in the water are controlled according to the requirements of basil.
- The smart framework, based on computer vision, is proposed particularly for pest and disease detection for controlled environment-based hydroponics systems.
- The pest and disease dataset is customized for hydroponics systems.
- Comparison of YOLOv8 and YOLOv9 object detection models.

II. DATASET

Hydroponics cultivation is affected by various reasons, including fungal infection, and bacterial, viral, and nutrient-related issues. Figure 1 presents an overview of each category and some common diseases within it. The dataset used was based on the New Plant Disease Image Dataset [31]. To enhance the dataset's diversity and relevance, it was supplemented with additional images captured from a hydroponics setup [32]. This combined dataset consists of 3676 images for training (70 from the hydroponic setup) and 920 images for validation (20 from the hydroponic setup). There is a total of 17 classes, including 16 different diseases and one healthy. The images were annotated using LabelImg, a graphical open-source image annotation tool that enables labeling object bounding boxes in images. Figure 3 shows a sample of annotated images. The annotation process involved identifying various diseases, such as leaf blight, rust, and powdery mildew, ensuring a comprehensive coverage of potential plant health issues.

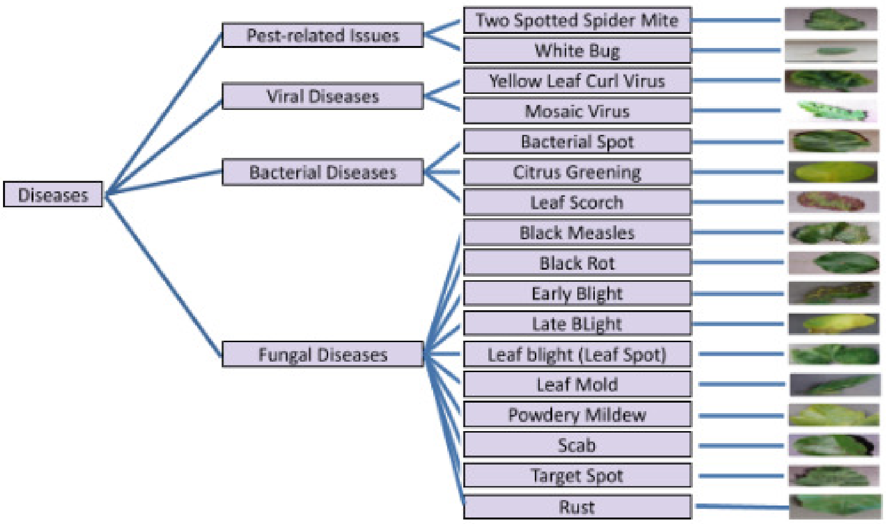

Fig. 1. Taxonomy of diseases in hydroponics.

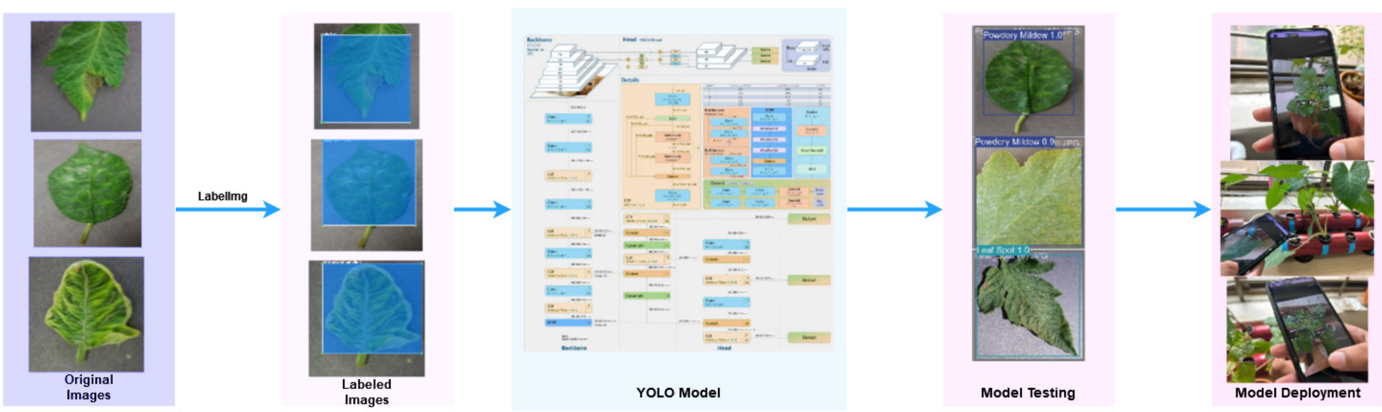

Fig. 2. Framework for DWC hydroponic-based plant disease detection system.

III. METHOD

Figure 2 shows the proposed framework for the DWC hydroponic-based plant disease detection system using YOLO. The dataset was divided into 80:20 for training and testing. The system was developed on an Ubuntu server with an Intel Xeon@2.20GHz CPU, 29 GB of RAM, and a Tesla T4 GPU with 24 GB of video memory. Python version 3.10, PyTorch version 2.1.0, and CUDA 11.7 were the programming environments. The initial learning rate for network training was set to 0.0001, and the Adam optimizer was used to update hyperparameters with a batch size of 16, a weight decay coefficient of 0.0005, a momentum of 0.937, and an Epoch count of 150. The YOLO v8 model was converted to a TensorFlow Lite format to deploy it on a mobile device. Then, a mobile application was developed using Android Studio to incorporate the converted model. The application was optimized for real-time processing to ensure efficient detection on the mobile device's hardware. Finally, the application was installed on mobile devices, allowing real-time detection and diagnosis of plant diseases directly in the field.

Fig. 3. LabelImg annotated images.

A. *YOLO Model Details*

YOLOv8 and YOLOv9 were chosen due to their efficiency in detection accuracy and speed. YOLOv8 introduced substantial architectural improvements that raised the bar for object identification. To extract features more efficiently, it modified the convolutional layers in the early stages of image processing and added a new building block. The anchor-free head represents the largest change. With the predefined anchor boxes removed, YOLOv8 can identify objects that are different in size and shape with greater accuracy. With these architectural modifications and speed-related advancements, YOLOv8 has become an effective tool for real-time object detection applications [29]. YOLOv9 is the latest version, incorporating improved feature extraction and processing capabilities. YOLOv9 provides a significant advancement in real-time object detection because of the adoption of cutting-edge techniques such as the Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI). This model achieved remarkable gains in accuracy, flexibility, and efficiency in the MS COCO dataset, setting new standards. The YOLOv9 project, which is being worked on by a different open-source team, demonstrates the collaborative nature of the AI research community, as it builds on the stable codebase provided by Ultralatics YOLOv5 [30].

B. *Model Training*

The training involved fine-tuning the models on 3676 images, while 920 images were reserved for validation. Hyperparameters were: lr/pg_0 = .0001, lr/pg_1 = 0.0001, and lr/pg_2 = 0.0001 learning rates, batch size = 16, and epochs = 150. lr/pg_0 refers to the learning rate for the backbone weights, lr/pg_1 refers to the learning rate for the YOLO layer's weights, and lr/pg_2 refers to the learning rate for additional parameters, such as biases.

C. *Evaluation Metrics*

The performance of the YOLOv8 and YOLOv9 models was evaluated using several key metrics:

- Precision: Precision evaluates the goodness of the results, calculated based on the ratio of True Positive (TP) to all positive detections, including True and False Positives (FP). A low FP rate indicates its high precision.

  $$Precision = \frac{TP}{(TP + FP)}$$

- Recall: The model's recall indicates its capacity to locate all relevant occurrences, in this case, diseased leaves. Its definition is the ratio of TP to all actual positive instances. A high recall rate suggests a low false negative rate for the model.

  $$Recall = \frac{TP}{TP+FN}$$

- mAP50 (Mean Average Precision at 50% IoU): When an Intersection over Union (IoU) threshold of 50% is reached, mAP50 assesses the precision and recall. This metric is frequently used in object detection tasks, as it shows how well the model can locate and identify items in images. The better the model performs in identifying and localizing items with at least 50% overlap with the ground truth, the higher the mAP50.

  $$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_K$$

  where AP_K is the Average Precision (AP) of class k and n is the number of classes.

- mAP50-95 (Mean Average Precision at IoU thresholds from 50% to 95%): In steps of 5%, the mAP50-95 assesses precision and recall across a range of IoU thresholds, from 50% to 95%. This offers a more thorough evaluation of the model's performance, considering its capacity to identify items that differ in how much they resemble the ground truth. Greater overall detection performance across various IoU thresholds is shown by higher mAP50-95 scores.

- Confusion Matrix: Additionally, a confusion matrix was employed to offer a thorough examination of the models' functionality.

IV. RESULTS AND DISCUSSION

A. Precision and Recall

Table II shows a precision and recall comparison for the YOLOv8 and YOLOv9 models. As can be observed, there is a marginal difference between them, as YOLOv8 achieves a precision score of 95.78% with a recall score of 96.43%, while YOLOv9 achieves a precision score of 95.93% and a recall score of 96.64%. Both the epoch-wise precision and recall were marginally greater for YOLOv9.

TABLE II. PRECISION AND RECALL COMPARISON

Model	Precision	Recall
YOLOv8	95.78	96.43
YOLOv9	95.93	96.64

B. F1 Score

Table III shows a comparison of F1 scores for YOLOv8 and YOLOv9 models, indicating a marginal difference between them. YOLOv8 achieved an F1-Score of 0.96 at a 0.544 threshold, whereas YOLOv9 achieved an F1-Score of 0.96 at a 0.536 threshold. Here, the threshold is a value applied to the confidence score. Predictions with a confidence score exceeding the threshold are considered detections.

TABLE III. F1-CONFIDENCE SCORE OF MODELS

Model	F1 score
YOLOv8	0.96 at threshold 0.544
YOLOv9	0.96 at threshold 0.536

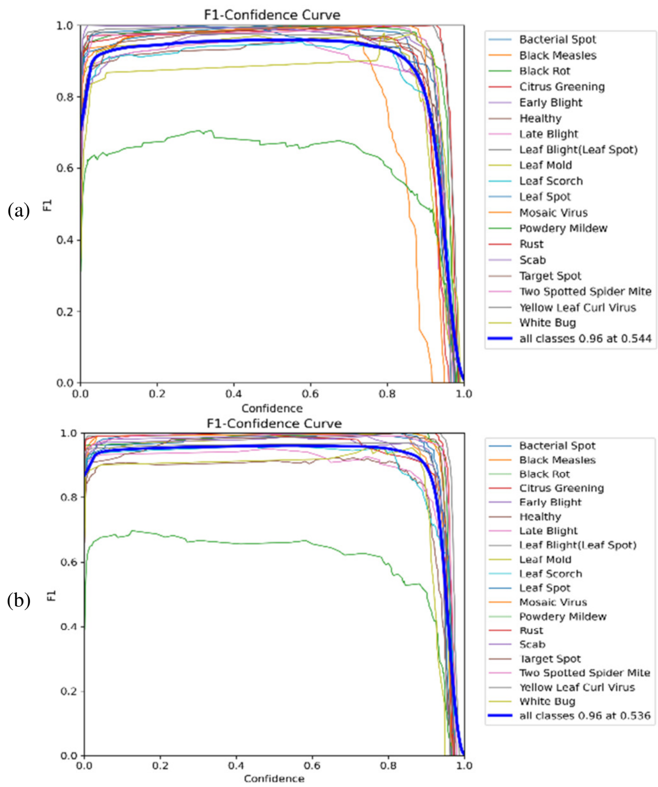

Fig. 4. F1-confidence scores of YOLOv8 (a) and YOLOv9 (b) models.

Figure 4 shows an F1 score comparison for each disease in the dataset for both YOLOv8 and YOLOv9. It can be clearly observed that both models achieve low F1 scores for Black Rot disease, indicating that the data for this disease are not perfect for training.

C. Mean Average Precision (mAP)

Table IV shows a comparison of mAP50-95 and mAP50 scores for YOLOv8 and YOLOv9 models. The scores for YOLOv8 were 87.22 and 97.39 and for YOLOv9 were 88.38 and 97.22, respectively.

TABLE IV. MAP50 AND MAP50-95 SCORES OF YOLOV8 AND YOLOV9 MODELS

Model	mAP50-95	mAP50
YOLOv8	87.22	97.39
YOLOv9	88.38	97.22

D. Confusion Matrices

The confusion matrices provide insight into the model classification performance. Figures 5 and 6 show the confusion matrices for the YOLOv8 and v9 models, respectively. The accuracy for powdery mildew was lower compared to other pest diseases in both models.

E. Number of Trainable Parameters

The number of training parameters affects the training speed. There is a significant difference between the number of parameters in YOLOv8 and YOLOv9. The number of parameters in YOLOv8 is 30, 14, 553 and in YOLOv9 is 255, 43, 881, which gives a difference of 225, 29, 328. The number of parameters significantly affects the processing speed and resources, increasing the computational complexity.

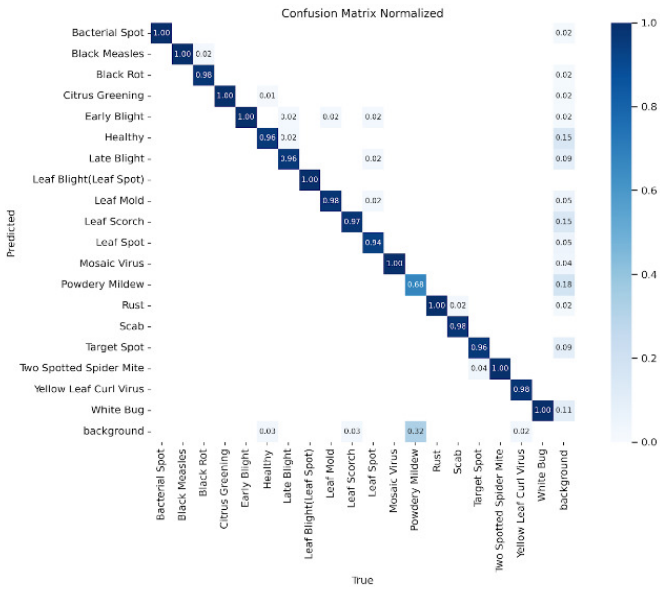

Fig. 5. Confusion Matrix for YOLOv8 model

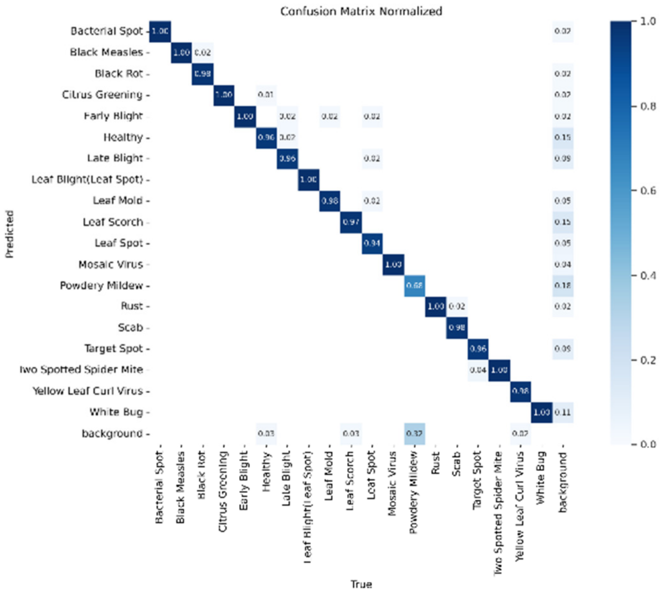

Fig. 6. Confusion matrix for YOLOv9 model.

F. Resource Requirements

Resource requirements play a vital role in real-time object detection tasks. It is necessary to use optimal computational resources for the required accuracy, as the model should be faster with good accuracy. Figures 7, 8, and 9 show clearly that YOLOv8 is faster than YOLOv9, requiring less GPU processing and power to train.

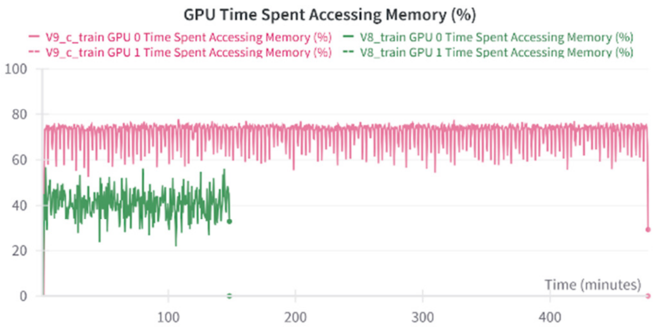

Fig. 7. Graph comparing GPU time spent accessing memory (%).

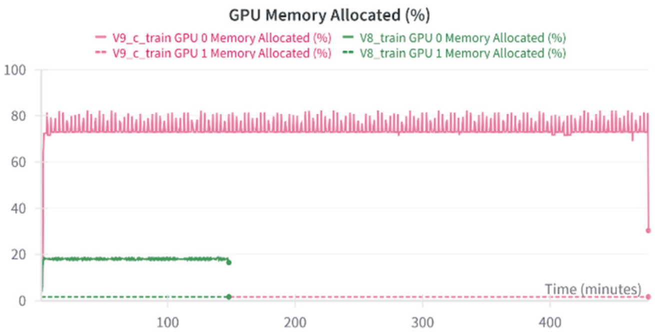

Fig. 8. Graph comparing GPU memory allocated (%).

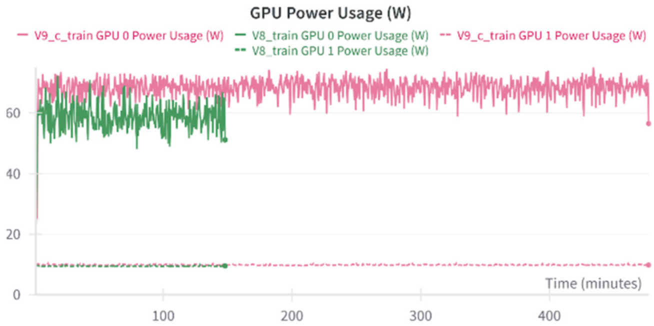

Fig. 9. Graph comparing GPU power usage (W).

V. CONCLUSION

This study provides a detailed comparison between the YOLOv8 and YOLOv9 models for plant disease detection in a hydroponics setting. The results indicate that both models offer high accuracy and efficiency, with YOLOv8 showing superior performance in terms of computational resources and speed. Thus, it can be concluded that YOLOv8 can be used to solve these problems in cases where computational resources play a vital role in the application. Further research can explore the integration of these models into real-world agricultural applications, enhancing disease management and crop yield. Future research on comparative analysis of the YOLOv8 and YOLOv9 models for real-time plant disease detection in hydroponics could explore optimizing model parameters to balance accuracy and speed, enhancing real-time detection capabilities. Investigating hybrid approaches that integrate the strengths of both models could improve overall performance. Additionally, extending the study to diverse plant species and disease types, along with integrating IoT sensors for comprehensive monitoring, could further increase the precision and efficiency of plant health management in hydroponic systems.

REFERENCES

[1] B. A. Dhananjani and K. Pakeerathan, "Organic Nutrient Solutions for Hydrophonic Spinach (Basella alba) Production in Urban Agriculture," *Journal of Agricultural Sciences – Sri Lanka*, vol. 18, no. 1, pp. 01–13, Jan. 2023, https://doi.org/10.4038/jas.v18i1.10095.

[2] R. Neppalli, Ch. G. Supriya, A. Hema, K. K. Kumar, N. V. K. Ramesh, and B. N. K. Reddy, "Estimation of Soil Salination for Crop - Yielding and How to Prevent," in *2022 International Conference on Electronic Systems and Intelligent Computing (ICESIC)*, Chennai, India, Apr. 2022, pp. 101–104, https://doi.org/10.1109/ICESIC53714.2022.9783534.

[3] J. Li, P. Yang, H. Sohail, H. Du, and J. Li, "The impact of short-term nitrogen starvation and replenishment on the nitrate metabolism of hydroponically grown spinach," *Scientia Horticulturae*, vol. 309, Feb. 2023, Art. no. 111632, https://doi.org/10.1016/j.scienta.2022.111632.

[4] A. Kundal and T. P. Sharma, "Detection of Plant Diseases in Hydroponics Farming Using Deep Learning Techniques," in *2024 International Conference on Smart Systems for applications in Electrical Sciences (ICSSES)*, Tumakuru, India, May 2024, pp. 1–6, https://doi.org/10.1109/ICSSES62373.2024.10561290.

[5] V. Rawat, N. Singh, B. Kaur, and S. Bora, "Tomato Leaf Disease Classification Using Supervised Learning Techniques: Contrasting Analysis," in *2022 International Conference on Advances in Computing, Communication and Materials (ICACCM)*, Dehradun, India, Nov. 2022, pp. 1–7, https://doi.org/10.1109/ICACCM56405.2022.10009617.

[6] J. Li, P. Yang, H. Sohail, H. Du, and J. Li, "The impact of short-term nitrogen starvation and replenishment on the nitrate metabolism of

hydroponically grown spinach," *Scientia Horticulturae*, vol. 309, Feb. 2023, Art. no. 111632, https://doi.org/10.1016/j.scienta.2022.111632.

[7] B. B. De Los Santos *et al.*, "Lettuce Root Development and Monitoring System Using Machine Learning in Hydroponics," in *TENCON 2022 - 2022 IEEE Region 10 Conference (TENCON)*, Hong Kong, China, Nov. 2022, pp. 1–6, https://doi.org/10.1109/TENCON55691.2022.9977465.

[8] J. Sharma, D. Kumar, S. Chattopadhay, V. Kukreja, and A. Verma, "A YOLO-Based Framework for Accurate Identification of Wheat Mosaic Virus Disease," in *2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Noida, India, Mar. 2024, pp. 1–4, https://doi.org/10.1109/ICRITO61523.2024.10522403.

[9] S. Jain and M. Kaur, "Design and Implementation of an IoT-based automated EC and pH Control System in an NFT-based Hydroponic Farm," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 13078–13081, Feb. 2024, https://doi.org/10.48084/etasr.6393.

[10] C. Deepa, S. M. Sanjay, V. Mosses, M. Yugeshwaran, and A. Sam Jebaraj, "Camellia Sinensis (Tea) Plant Disease Classification Using RESNET," in *2024 International Conference on Science Technology Engineering and Management (ICSTEM)*, Coimbatore, India, Apr. 2024, pp. 1–4, https://doi.org/10.1109/ICSTEM61137.2024.10560945.

[11] M. Al-Shalout, M. Elleuch, and A. Douik, "Deep Learning-Based Plant Disease Detection from Leaf Images," in *2023 24th International Arab Conference on Information Technology (ACIT)*, Ajman, United Arab Emirates, Sep. 2023, pp. 1–6, https://doi.org/10.1109/ACIT58888.2023.10453692.

[12] A. Kaur, V. Kukreja, M. Kumar, A. Choudhary, and R. Sharma, "Multiclass Classification of Tomato Leaf Diseases using a Hybrid of LSTM and CNN Model," in *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)*, Pune, India, Apr. 2024, pp. 1–5, https://doi.org/10.1109/I2CT61223.2024.10544287.

[13] S. Saxena and S. Rathor, "An Ensemble-Based Model of Detecting Plant Disease using CNN and Random Forest," in *2023 6th International Conference on Information Systems and Computer Networks (ISCON)*, Mathura, India, Mar. 2023, pp. 1–6, https://doi.org/10.1109/ISCON57294.2023.10112023.

[14] D. Tandekar and S. Dongre, "Identification of Various Diseases in Plant Leaves Using Image Processing and CNN Approach," in *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, Jul. 2023, pp. 1–6, https://doi.org/10.1109/ICCCNT56998.2023.10306979.

[15] N. Bobby, M. Indira, K. A. Peele, T. C. Venkateswarulu, and S. Krupanidhi, "Sustainable Nutritional Supplementation for Green Economy through Hydroponics System," *Indian Journal of Ecology*, vol. 48, no. 1, pp. 85–90, 2021.

[16] E. Iren, "Comparison of YOLOv5 and YOLOv6 Models for Plant Leaf Disease Detection," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13714–13719, Apr. 2024, https://doi.org/10.48084/etasr.7033.

[17] R. Ahmed and E. H. Abd-Elkawy, "Improved Tomato Disease Detection with YOLOv5 and YOLOv8," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 13922–13928, Jun. 2024, https://doi.org/10.48084/etasr.7262.

[18] H. M. Zayani *et al.*, "Deep Learning for Tomato Disease Detection with YOLOv8," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13584–13591, Apr. 2024, https://doi.org/10.48084/etasr.7064.

[19] D. Kholiya, A. K. Mishra, N. K. Pandey, and N. Tripathi, "Plant Detection and Counting using Yolo based Technique," in *2023 3rd Asian Conference on Innovation in Technology (ASIANCON)*, Ravet, India, Aug. 2023, pp. 1–5, https://doi.org/10.1109/ASIANCON58793.2023.10270530.

[20] D. F. Rose Anandhi and S. Sathiamoorthy, "Maximum Entropy Thresholding with Deep Learning Model for Rice Plant Disease Segmentation and Classification," in *2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)*, Chennai, India, Nov. 2023, pp. 1–6, https://doi.org/10.1109/RMKMATE59243.2023.10368778.

[21] L. P. Osco *et al.*, "A CNN approach to simultaneously count plants and detect plantation-rows from UAV imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 174, pp. 1–17, Apr. 2021, https://doi.org/10.1016/j.isprsjprs.2021.01.024.

[22] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, Jun. 2016, pp. 779–788, https://doi.org/10.1109/CVPR.2016.91.

[23] H. Zhang *et al.*, "Utilizing YOLO for Plant Counting in Agricultural Fields," in *IEEE International Conference on Computer Vision (ICCV) Workshops*, 2018, pp. 903–911.

[24] Y. Zhang *et al.*, "Annotation Methods for Plant Instance Segmentation and Bounding Box Generation in Training Datasets," *Journal of Imaging*, vol. 7, no. 2, 2021.

[25] H. M. Zayani *et al.*, "Unveiling the Potential of YOLOv9 through Comparison with YOLOv8," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 3, pp. 2845–2854, Mar. 2024.

[26] X. Wang and J. Liu, "Vegetable disease detection using an improved YOLOv8 algorithm in the greenhouse plant environment," *Scientific Reports*, vol. 14, no. 1, Feb. 2024, Art. no. 4261, https://doi.org/10.1038/s41598-024-54540-9.

[27] R. Abbasi, P. Martinez, and R. Ahmad, "Crop diagnostic system: A robust disease detection and management system for leafy green crops grown in an aquaponics facility," *Artificial Intelligence in Agriculture*, vol. 10, pp. 1–12, Dec. 2023, https://doi.org/10.1016/j.aiia.2023.09.001.

[28] Y. Wang, M. Wu, and Y. Shen, "Identifying the Growth Status of Hydroponic Lettuce Based on YOLO-EfficientNet," *Plants*, vol. 13, no. 3, Jan. 2024, Art. no. https://doi.org/10.3390/plants13030372.

[29] H. Wang, S. Shang, D. Wang, X. He, K. Feng, and H. Zhu, "Plant Disease Detection and Classification Method Based on the Optimized Lightweight YOLOv5 Model," *Agriculture*, vol. 12, no. 7, Jul. 2022, Art. no. 931, https://doi.org/10.3390/agriculture12070931.

[30] N. Chitraningrum *et al.*, "Comparison Study of Corn Leaf Disease Detection based on Deep Learning YOLO-v5 and YOLO-v8," *Journal of Engineering and Technological Sciences*, vol. 56, no. 1, pp. 61–70, Feb. 2024, https://doi.org/10.5614/j.eng.technol.sci.2024.56.1.5.

[31] S. Bhattarai, "New Plant Diseases Dataset." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset.

[32] A. Tripathi, "Labeled Plant Disease Dataset for Object Detection." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/e4c61cb31c19d4e663d7198a3b17182ad4a8598f716243ad7e1358dec3b3f185.