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YOLOv10-Enabled IoT Robot Car for Accurate Disease Detection in Strawberry Cultivation

Abdelaaziz BELLOUT[1,⋆], *Mohamed* Zarboubi[2,⋆⋆], *Azzedine* DLIOU[1,3,⋆⋆⋆], *Rachid* LATIF[1,⋆⋆⋆⋆], and *Amine* SADDIK[1,3,†]

[1] *LISTI, ENSA, IBN ZOHR UNIVERSITY, AGADIR, MOROCCO*
[2] *LISAD, ENSA, IBN ZOHR UNIVERSITY, AGADIR, MOROCCO*
[3] *IMIS Laboratory, Faculty of Applied Sciences, Ibn Zohr University, Agadir, Morocco*

Abstract. This study addresses the growing need for effective disease management in strawberry cultivation, a crop vital for global nutrition. We present an innovative approach that combines the YOLOv10 model with a Remote-Controlled Robot Car to revolutionize strawberry disease detection. Our system merges deep learning, IoT, and precision agriculture techniques to enable real-time monitoring of strawberry fields. This technology-driven solution offers a proactive and data-based method for identifying diseases early. Our findings show the potential of this advanced system to significantly improve agricultural practices and support sustainable food production. The YOLOv10n model achieved a 96.78% mAP-50 ratio for accurately locating diseased leaves. By integrating IoT capabilities, the system allows for remote control and continuous monitoring, eliminating the need for daily on-site expert inspections. This approach not only enhances disease management efficiency but also has the potential to increase crop yields and reduce pesticide use, contributing to more sustainable farming practices.

1 Introduction

The agricultural industry is continuously striving to meet the rising global food demand, presenting significant challenges in crop management and disease control. Strawberry cultivation, in particular, is susceptible to various leaf diseases that can drastically reduce yield and quality, posing a threat to both farmers' livelihoods and food supply chains [1, 2]. Traditional methods for diagnosing these diseases rely heavily on manual inspection, which is not only time-consuming but also prone to human error, leading to delayed interventions and potential crop losses [3]. In regions like Morocco, where strawberry farming is vital to the economy and the production has been rising steadily, reaching a total annual output of over 166,000 tonnes in 2024[4], the dependence on manual diagnostics exacerbates these challenges, highlighting the need for more efficient and accurate detection methods.

Recent advancements in technology, particularly in Artificial Intelligence (AI) and Computer Vision (CV), offer promising solutions to enhance plant disease identification processes [5, 6]. Convolutional Neural Networks (CNNs), a subset of deep learning algorithms, have demonstrated high precision in image recognition tasks, making them ideal for diagnosing plant diseases based on leaf imagery. The evolution of these technologies has led to significant improvements in disease detection accuracy and efficiency. Fuentes et al. (2017) pioneered the use of deep learning for real-time detection of diseases and pests in tomato plants, achieving mean average precision (mAP) of 83.06% [7]. This early work laid the foundation for applying similar techniques to other crops, including strawberries. Building on this, Arsenovic et al. (2019) developed a plant disease detection model using a two-stage architecture , achieving an impressive accuracy of 93.67% across various crops, including strawberries [8].

The YOLO (You Only Look Once) models have shown particular promise in real-time object detection for agricultural applications. Pertiwi et al. used YOLOv7 and YOLOv7-X to identify strawberry diseases, achieving accuracy rates of 92.5% and 92.3% respectively on a 7,337-image dataset [9]. Lee et al. developed an ensemble YOLOv5 model for early disease detection, trained on 13,393 images, achieving an average AUPRC of 81% [1]. An et al. created SDNet, an improved YOLO model for monitoring strawberry growth stages, achieving precision, accuracy and recall of 94.26%, 93.15% and 90.72% respectively [10]. Deploying these advanced AI models onto Internet of Things (IoT) devices further revolutionizes disease monitoring by facilitating real-time data collection and analysis in the field [11–13]. IoT-enabled systems can continuously monitor crop health, transmitting data to centralized platforms where deep learning models process the information to detect and classify diseases accurately. This

⋆Corresponding author : abdelaaziz.bellout@edu.uiz.ac.ma
⋆⋆e-mail: mohamed.zarboubi@edu.uiz.ac.ma
⋆⋆⋆e-mail: a.dliou@uiz.ac.ma
⋆⋆⋆⋆e-mail: r.latif@uiz.ac.ma
†e-mail: a.saddik@uiz.ac.ma

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integration not only enhances the scalability of disease detection systems ,but also empowers farmers with actionable insights, promoting sustainable agricultural practices and reducing reliance on manual inspections.

Building upon these advancements, our study aims to develop and deploy a robust deep learning system utilizing YOLOv10 for the automatic detection and classification of strawberry leaf diseases. By integrating this system with IoT devices, specifically a remote-controlled robot car equipped with a Raspberry Pi 4B, we enable real-time monitoring and prompt intervention strategies in strawberry fields. Our approach addresses the limitations of previous studies by combining the latest advancements in object detection models with practical IoT applications, potentially offering improved accuracy and real-time performance compared to earlier models. The YOLOv10n model, chosen for its optimal balance between accuracy and computational efficiency, which demonstrates the potential of our system to significantly improve disease management in strawberry cultivation, particularly in Moroccan context. The integration with a remote-controlled robot car allows for continuous monitoring without the need for constant human presence, offering a scalable solution for large-scale agricultural operations.

In the following sections, we will detail the methodology employed in developing this system, including dataset preparation, model training, and IoT integration. We will present the results of our experimental evaluations and discuss the implications of these findings for the future of precision agriculture, particularly in the context of strawberry disease management.

2 Methodology

Effective detection and management of strawberry leaf diseases require a systematic approach that leverages advanced technologies. Our proposed methodology consists of seven sequential stages, as depicted in Figure 1. The process starts with the first stage, which involves gathering images of strawberry diseases for both training and evaluating the deep learning (DL) model's performance. In the second stage, the dataset undergoes processing, where images are resized to 640x640 and augmented to increase sample diversity, expanding the images based on set parameters. The third phase is dedicated to image annotation, which is used to generate the bounding boxes based dataset. In the fourth phase, this dataset is utilized to train the YOLOv10 object detection model. The fifth phase involves validating the model's detection performance with a subset of the dataset and assessing the results. In Phase 6, the most appropriate model for the disease detection device is chosen. Finally, in Phase 7, the inference results are transmitted to the monitoring systems.

2.1 Dataset preparation

This research focuses on three primary strawberry leaf diseases: Angular Leaf Spot, Leaf Spot, and Powdery Mildew Leaf, as illustrated in Figure 2. To collect images of these diseases, we leveraged online resources,

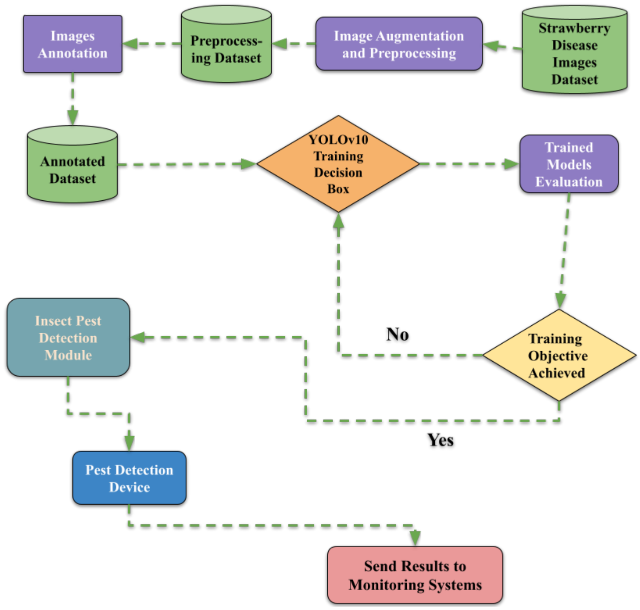


Fig. 1. Flow diagram of the research methodology

Fig. 2. Strawberry leaf disease examples

exploring public databases such as PlantDoc[14] and PlantVillage[15], as well as search engines like Google, IPM Images, and Adobe Stock Images. All images were uniformly resized to 640x640 pixels to ensure consistent proportions in width and height.

The study underscores the difficulty of acquiring a substantial dataset to ensure the optimal performance of deep learning models. Insufficient data increases the probability of overfitting and diminishes generalization capabilities. To tackle this issue, data augmentation techniques, such as zooming, flipping, rotating and blurring Figure 3, are implemented, with careful consideration given to managing potential pixel loss at the edges of augmented images. These transformations are operated randomly, resulting in additional images for each original one. This augmentation process expands the dataset to a total of 2931 images. The discussion explores the process of image preprocessing for training deep learning models, emphasizing the critical role of image annotation. This procedure entails extracting meaningful features from images and la-

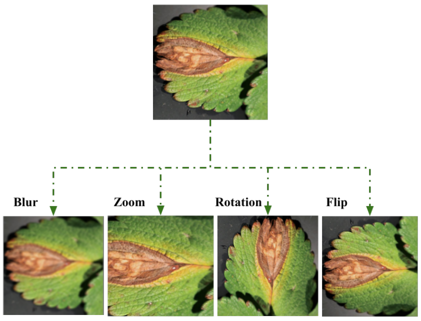
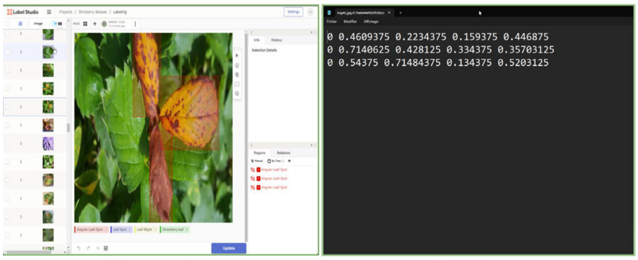


Fig. 3. Data augmentation operations



(a) Image annotation (b) Label file

Fig. 4. Image annotation: (a) Annotation task using LabelStudio, (b) Generated label Text file

beling them appropriately according to the inputs that are chosen. This provides labeled data that is essential for supervised learning models. The process is illustrated in Figure 4, In this study, LabelStudio, an open source solution [16] streamlines image annotation, enhancing accuracy and efficiency in labeling. This, in turn, improve the overall quality and effectiveness of the training dataset for the deep learning model (object detection model). The datasets are divided into training, validation, and testing sets in a 70:20:10 ratio. Specifically, the training set comprises 2,050 images, the validation set contains 587 images, and the test set includes 294 images, as the detail by class outlined in Table 1.

Table. 1. Strawberry leaf disease dataset

Class	Train	Valid	Test	Total
Angular Leaf spot	609	174	87	**870**
Leaf Spot	695	199	100	**994**
Powdery Mildew Leaf	746	214	107	**1 067**
Total	**2 050**	**587**	**294**	**2 931**

2.2 Object Detection Models

YOLOv10 introduces a revolutionary approach to object detection [17] through its consistent dual label assignments for Non-Maximum Suppression (NMS) free training. As illustrated in Figure 5, the architecture streamlines the detection process from backbone to final prediction. The backbone extracts crucial features from input images and feeds them into a Path Aggregation Network (PAN), which combines features from different layers to detect objects across various scales and complexities. The PAN's output then flows into two distinct heads: one-to-many and one-to-one, each handling both regression and classification tasks.

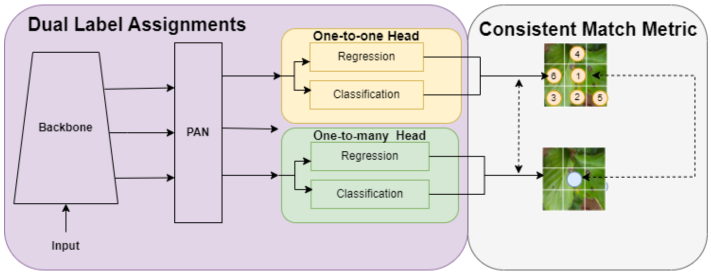


Fig. 5. YOLOv10 Architecture

The one-to-many head, shown in the upper branch of Figure 5, generates multiple potential bounding boxes for each object, while the one-to-one head in the lower branch refines these predictions for precise localization and classification. This dual approach enables YOLOv10 to handle diverse object scales and aspect ratios effectively. The model's accuracy is further enhanced by a consistent match metric, visually represented in the Figure 5. This metric optimizes the alignment between predicted and ground truth boxes by combining confidence scores and Intersection over Union (IoU) calculations, resulting in more reliable detections, particularly in challenging scenarios with overlapping objects or complex backgrounds. The launch of YOLOv10 by Ultralytics introduced five variants, from nano to extra-large, tailored to various computational needs, with our choice of YOLOv10n offering an ideal balance for our application [17]. Each variant exhibits specific network depth and feature map width, offering a variety of choices for model selection. To evaluate their performance, these variants underwent testing on the COCO dataset[18], with detailed results provided in Table 2. This table offers valuable information on the complexity of the models, measured by floating-point operations (FLOPs) and parameters (Params), and on their detection accuracy, represented by mAPval 0.5:0.95 (average accuracy calculated for different intersection-over-union thresholds between 0.5 and 0.95). Furthermore, the response speed of each model is evaluated in two distinct environments: TensorRT FP16 on T4 GPU.

2.3 Remote-Controlled Robot Car

The Remote-Controlled Robotic Vehicle represents a significant advancement in the detection of leaf diseases in strawberry crops. This system, as shown in Figure 6, integrates Internet of Things (IoT) technology for real-time monitoring of crop health. The robot's navigation is con-

Table. 2. YOLOv10 Series Models' Detection on the COCO Dataset.

Model	Params (M)	FLOPs (G)	mAPval 0.50-0.95	Latency (ms)	Latency-forward (ms)
YOLOv10-N	2.3	6.7	39.5	1.84	1.79
YOLOv10-S	7.2	21.6	46.8	2.49	2.39
YOLOv10-M	15.4	59.1	51.3	4.74	4.63
YOLOv10-L	24.4	120.3	53.4	7.28	7.21
YOLOv10-X	29.5	160.4	54.4	10.70	10.60

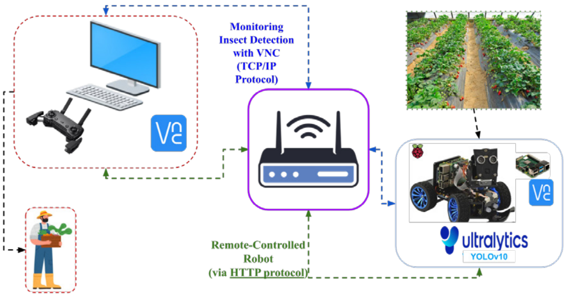


Fig. 6. Functional structure of Remote-Controlled Robot Car.

trolled remotely using the HTTP protocol, with communication facilitated by two ESP32 devices - one in the control unit and another within the robot itself.

Central to the disease detection process is a Raspberry Pi 4B, equipped with an RGB camera for image capture. These images are analyzed using the YOLOv10n model, with results transmitted to Monitoring Systems via VNC (Virtual Network Computing) over TCP/IP. Upon detection of a strawberry leaf disease, the system immediately alerts the farmer, enabling prompt intervention. Table 3 provides detailed specifications of the Raspberry Pi 4B used in this setup.

This real-time monitoring system offers farmers immediate updates on crop health, allowing for timely and effective disease management. By combining robotics, computer vision, and IoT technologies, this approach aims to enhance crop protection strategies and potentially increase agricultural productivity.

Table. 3. Raspberry Pi 4B configuration

Configuration	Parameter
Model	Raspberry Pi 4B
Operating system	Raspberry Pi OS 64 bit
Memory	4 GB
CPU	Broadcom BCM2711
Wi-Fi	2.4 GHz and 5.0 GHz IEEE 802.11b
Framework	Torch 1.13, Torchvision 0.14.0
Language	Python 3.9
Camera resolution	2592 x 1944

3 Results and Discussion

Our experiments with various YOLOv10 model sizes revealed that YOLOv10n is the most suitable for strawberry leaf disease detection on the Raspberry Pi 4B. This model strikes an optimal balance between accuracy and processing speed, crucial for real-time applications on embedded systems.

While YOLOv10s and YOLOv10m demonstrated higher accuracy, their inference times were significantly longer due to increased memory and computational requirements. These characteristics make them less practical for deployment on low-power devices like the Raspberry Pi.

YOLOv10n emerged as the most efficient solution, offering satisfactory accuracy while maintaining the computational efficiency necessary for embedded systems. This balance ensures reliable disease detection without compromising the real-time performance needed for effective crop monitoring on the Raspberry Pi platform.

3.1 Experimental setup and metrics

The YOLOv10 model training began after completing image labeling for all datasets. We used Jupyter notebook in a Windows 11 machine with an Intel Core i5-10400F CPU, 16 Go memory and NVIDIA RTX 3060 GPU (12 GB memory, driver 32.0.15.6070, CUDA 11.8). During training, images were resized to 640 pixels. The data.yaml file contained essential information like class names and numbers for training, validation, and test directories. We split the dataset into 70% training, 20% validation, and 10% testing. The YOLOv10n model underwent 300 epochs of training.

We assessed the YOLOv10n model using various metrics. Precision and recall measure correct detection accuracy and the ability to find relevant instances. We also considered detection processing time for speed evaluation. Mean average precision (mAP) at 0.5 and 0.5:0.95 thresholds provided accuracy measures across different intersection over union (IoU) levels. The model's efficiency was determined by its parameter count, size, and floating-point operations per second (FLOPs).

Precision and recall are key metrics in object detection evaluation. Precision calculates positive prediction accuracy:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

Recall measures the model's ability to identify relevant instances:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

Where: TP: Correctly identified positive instances FP: Incorrectly identified negative instances FN: Missed positive instances TN: Correctly identified negative instances

Mean Average Precision (mAP) calculations use:

$$AP = \int_0^1 P(R)dR \tag{3}$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N} \tag{4}$$

AP (Average Precision): The area under the precision-recall curve mAP (mean Average Precision): The average of APs for all classes mAPval 0.5 uses a 0.5 confidence threshold, while mAPval 0.5:0.95 averages mAP across thresholds from 0.5 to 0.95, increasing by 0.05 each time.

Figure 7 shows the training and validation results, including three types of loss: classification, box, and deformable. Classification loss measures how accurately the model predicts classes. Box loss evaluates the precision of object localization. Deformable loss quantifies errors in deformable convolution layers, which help detect objects of various scales and ratios.

The model's performance improves significantly after 85 epochs, with mAP, recall, and precision stabilizing around the 240th epoch. Table 4 presents these key results. YOLOv10's use of deformable convolution layer loss is noteworthy, as it measures errors in layers that enhance detection of objects at different scales and ratios. A lower deformable loss suggests the model handles object deformations and appearance changes more effectively.

3.2 Results of Disease Detection Device

The YOLOv10n model has shown exceptional results in detecting strawberry leaf diseases, reaching a 96% confidence level (Fig. 8). The model's accuracy in locating diseased leaves is also impressive, with a mAP-50 ratio of 96.78%. By incorporating IoT features, the system allows remote control of the Robot Car. This setup enables constant monitoring of strawberry crop health without requiring daily in-person visits from experts to the farms. The model's high performance stems from its advanced architecture and thorough training on a diverse dataset of strawberry leaf images. Its ability to quickly and accurately identify various disease types gives farmers a powerful tool for early intervention. The IoT integration not only saves time and resources but also allows for more timely responses to disease outbreaks. Farmers can now receive alerts and detailed reports on their crops' health status, enabling them to make informed decisions about treatment strategies.

Regular monitoring of strawberry greenhouses crops for signs of disease propagation is essential for early detection and intervention. Once infected plants are detected, a range of measures can be implemented to manage and control their spread. These include Integrated Disease Management (IDM) strategies[19], is a comprehensive and holistic approach to managing plant diseases in agriculture and horticulture. It combines various strategies and techniques to minimize crop losses while reducing reliance on chemical pesticides. IDM emphasizes prevention, monitoring, and intervention using a combination of cultural, biological, and chemical methods. This approach includes practices such as crop rotation, use of disease-resistant varieties, proper sanitation, optimized plant nutrition, biological control agents, and judicious use of pesticides when necessary.

Table. 4. Yolov10n Training Metrics

Precision	Recall	mAP50	mAP50-95
96.01%	91.03%	96.78%	89.76%

4 Conclusion

This study demonstrates the effectiveness of integrating YOLOv10 with IoT technology for strawberry leaf disease detection. The YOLOv10n model achieved a 96.78% mAP-50 and 89.76% mAP50-95 ratio, showcasing its high accuracy in identifying and localizing diseases. The remote-controlled robot car, equipped with a Raspberry Pi 4B and RGB camera, enables real-time monitoring and prompt disease detection in strawberry fields. The system's ability to quickly process images and transmit results via VNC over TCP/IP provides farmers with timely information, allowing for rapid response to potential disease outbreaks. This approach significantly reduces the need for manual inspections and enhances overall crop management efficiency.

The combination of deep learning, computer vision, and IoT technologies presents a promising solution for precision agriculture. By enabling early disease detection and intervention, this system has the potential to improve crop yields, reduce pesticide and herbicide use, and support sustainable farming practices. Future research could focus on expanding the model's capabilities to detect additional strawberry diseases and pests, as well as adapting the system for use with other crop types. Enhancing the robot's autonomy and integrating it with other smart farming technologies could further improve its utility in agricultural settings.

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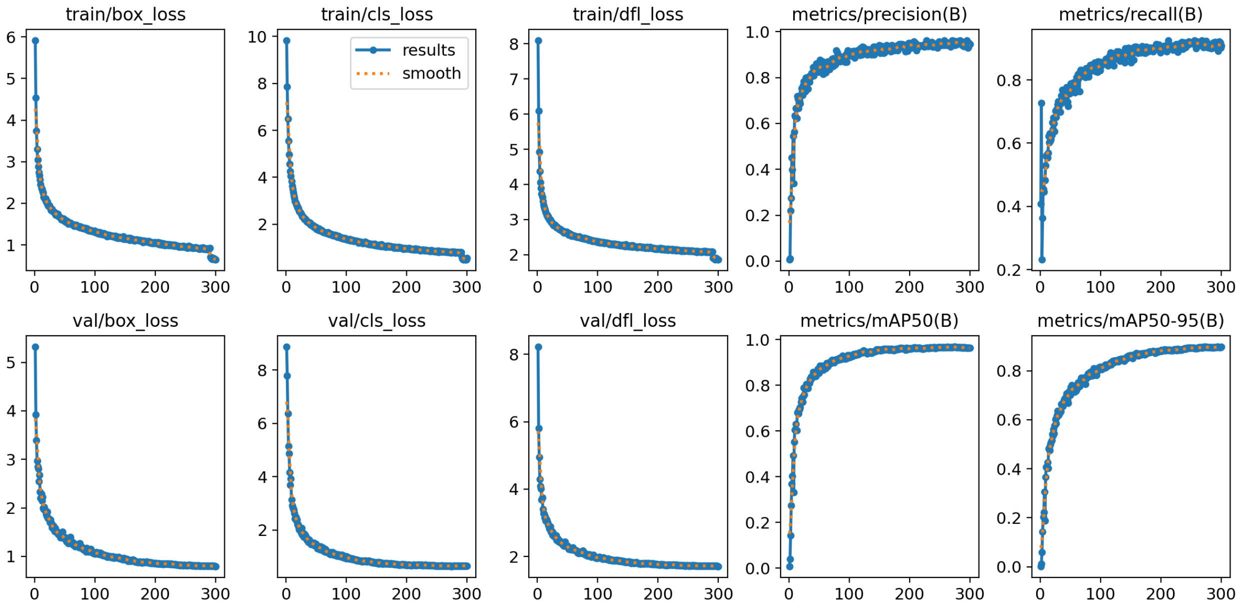

Fig. 7. Training and Validating Results of YOLOv10n on the Strawberry Leaf Disease Dataset.

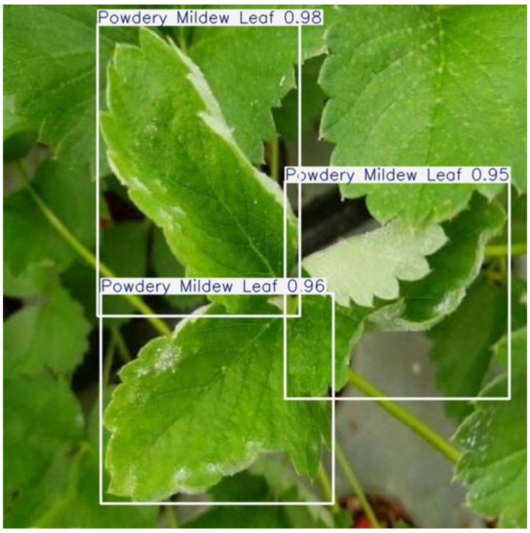

Fig. 8. Results using Remote Controlled Robot Car.

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