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Autonomous Vehicles and AI System for Cactus Disease Detection: Case of Opuntia ficus-indica and Cactoblastis Cactorum

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Abstract

The spread of the moth (*Cactoblastis cactorum*) in the southern United States, main pest that attacks the Prickly Pear (*Opuntia ficus-indica*), has raised great concern for the U.S. Department of Agriculture (USDA). The Agricultural Research Service (ARS) and the Animal and Plant Health Inspection Service (APHIS), together with the U.S. Department of the Interior, the Nature Conservancy, and the Secretariat of Agriculture and Rural Development of Mexico are developing strategies to contain the spread of the cactus moth in the region. The use of Artificial Intelligence (AI) tools based on Computer Vision has proven to be a very effective way to detect plant diseases and classify them. This paper proposes an integrated systems composed of a Transfer Learning AI model based on two models YOLOv8n (with window-detection and with segment-detection) and autonomous vehicles (drones and ground robots) to prevent and mitigate the pest attack. The models were chosen based on their efficiency and portability, since they are going to be applied in Android and Linux-based edge devices. The AI models will be evaluated based on the following metrics: precision, recall, accuracy and F1 score; and the overall system will be tested in the field by the end of the year in the US and Brazil. The objective of this work is to demonstrate the use of AI tools for plant health detection on edge devices integrated with autonomous vehicles.

Keywords
Precision Agriculture, Artificial Intelligence, Deep Learning, Smart Agriculture, Pest Monitoring.

1. Introduction
The focus of this work is to determine the health status of the cactus *Opuntia ficus-indica* (Prickly Pear) – Figure 1, and the autonomous vehicle coordination to accomplish this task.

Brazil is one of the world's leading producers of agricultural products, and disease detection through image analysis (Silva 2022; Trindade 2021) and pest control have been the focus of several studies, especially the use of biological control, which offers numerous advantages over chemical control (Softex 2024).

Gent 2024, in an analysis of the emerging market in India, and Buainain et al. 2021; Diniz 2024; Farmonaut 2024 and Oliveira 2022 in the Brazilian market, describe a series of considerations for the adoption of AI in agriculture. Based on this article and the bibliographic references, it is possible to list the following benefits, concerns and obstacles:

1.1. Benefits

• Increase in agricultural productivity due to better resource management (water, fertilizers, pesticides);
• Reduction of losses due to pests and diseases with intelligent monitoring and rapid responses;

• Acceleration of technology adoption depending on factors such as cost, rural connectivity and acceptance by farmers;
• Sustainability: Implementation of more sustainable agricultural practices, with efficient use of natural and energy resources; with consequent reduction in environmental impact.

1.2. Concerns

• Misuse of data by private companies: Many AI solutions are developed by startups or large corporations, and it is unclear how farmers' data is stored, processed and shared;
• Lack of specific regulation: India is yet to develop robust policies to protect agricultural data, leaving room for commercial exploitation without due consent from farmers;
• Inequality in access to information – Large companies can gain an advantage by monopolizing agricultural data and selling it back to farmers, creating dependence on private platforms;
• Cybersecurity – The increasing digitalization in the agricultural sector exposes farmers to cyberattacks, data theft and manipulation of critical information.

1.3. Obstacles to adoption

• Accessibility and Technological Adoption: small farmers may not have access to AI-compatible devices, such as computers, smartphones and advanced IoT sensors; as well as suffering from limited connectivity in rural areas, which makes it difficult to adopt online platforms for daily plantation operations;

• Dependence on Large Technology Companies: farmers may become dependent on private platforms, losing autonomy in decision-making; possible monopoly of agricultural data, where a few companies control access to strategic information;

• Socioeconomic Impact: possible loss of jobs in the agricultural sector with the automation of activities; exclusion of small farmers who cannot afford the costs of new technologies.

(a) (b) (c)

Figure 1. (a) - *Cactoblastis cactorum* larvae; (b) – adult phase; (c) e o *Opuntia ficus-indica* (Pricly Pear).
Source: Zimmermann et al. 2004 and the author.

In summary, the development of image-based pest detection systems integrated with autonomous vehicles presents numerous advantages, in addition to directly integrating with digital control and automation systems in agriculture.

This research project is being carried out in cooperation with the UIW (University of the Incarnate Word) of San Antonio in Texas, USA, which will provide, for this study, support from the autonomous vehicle laboratory – AVS (Autonomous Vehicle Systems) for indoor proof-of-concept validation and improvement of the AI recognition models.

1.4. Objectives

- Present the literature review;
- The implementation of two YOLOv8n models: window-detection and segment-detection for the Prickly Pear health assessment;
- Laboratory test with full integration: test of the edge computer running IA model; autonomous drone flight and communication between the edge computer, the drone and the mission controller;
- Status of the research, preliminary test results and next steps.

2. Literature Review

The Prickly Pear is a cactus quite common and of great social, cultural and economic relevance in the southern United States (Johnson and Stiling 1998). One of the pests that commonly attacks is the larva of *Cactoblastis cactorum*. This pest has been causing concern for the United States Department of Agriculture (USDA) which, since the early 2000s (Pérez-De la O et al. 2020; Durham 2006; USDA 2008; Zimmermann et al. 2004; Texas Department of Agriculture 2025; Solis et al. 2004; Hight et al. 2003) has allocated funds to research on its life cycle and to control it. Since 2024, it has encouraged the study of Artificial Intelligence (AI) techniques for the same purpose. Recent advances in the field as well as on the Internet of Things (IoT) have facilitated the creation of sophisticated pest detection systems (Peñailillo et al. 2024). AI techniques including deep learning and machine learning have proven effective in identifying and classifying insect pests based on visual and acoustic data (Ali et al. 2024; Eftekhari et al. 2024; Kim et al. 2024; Kiobia et al. 2023; Qadri et al. 2025; Shafik et al. 2025, Thomas et al. 2023; Topal et al. 2024; Vásconez et al. 2024). The development of these models was greatly facilitated using the Transfer Learning technique, which consists of reusing already trained AI models and repurposed them to perform similar tasks. Thus, available models such as Inception V3, ResNet-50 and ViT can be retrained, saving time while maintaining the same effectiveness (Maeda-Gutiérrez et al. 2024).

An AI tool that automatically detects plant health condition will allow farmers to take actions before the problem increases, optimizing pesticide application, use of resources and minimizing environmental impact (Yakkala et al. 2024). In addition, IoT sensors can provide real-time monitoring of pest dynamics, increasing agricultural response capacity (Alreshidi 2019).

Once the focus points have been determined, an efficient approach with minimal environmental impact is to launch, from drones, natural enemies of the *Cactoblastis cactorum* larva, such as *Thrichospilus* (Ribeiro et al. 2019).

Geolocation is one of the most critical aspects of autonomous vehicles control operations management. Networked Real-Time Kinematic (NTRIP) systems (Amado et al. 2024) provide accurate geolocation data essential for coordinating drone and ground vehicle movements. The existence of networks such as RBMC (Brazilian Continuous Monitoring Network) makes the use of this technology accessible (Pereira 2007). The Self-Organizing Spatial Clustering (SOSC) approach increases the efficiency of NTRIP systems by reducing computational loads and improving data handling (Shen et al. 2018). This capability is vital for managing large-scale agricultural areas, ensuring that aerial and ground vehicles operate with high precision and reliability. Drones play a key role in this integrated pest management strategy. Equipped with advanced imaging and navigation technologies (Avila and Brouwer 2021 and Vemula et al. 2021; Oliveira 2024), drones can quickly survey large areas, identifying pest infestations and assessing crop health. Their ability to operate autonomously or semi-autonomously allows for flexible deployment in any field conditions. Ground vehicles can be used for targeted pesticide application and logistical support, ensuring that interventions are efficient and effective. The development of autonomous decision-making systems is essential to optimize drone and ground vehicle operations (Padhiary et al. 2024). By leveraging AI algorithms, these systems can analyze data from multiple sources, including pest detection sensors and geolocation inputs, to make assertive decisions about resource utilization (Delgado et al. 2019; Mohammed 2024). The integration of AI with IoT technologies creates a dynamic response framework that can adapt to changing field conditions (Dias and Coelho 2019; Wakshaure et al. 2023).

2.1. Brief Overview of the YOLOv8n model:

The YOLO (You Only Look Once) family is known for its real-time object detection capabilities, balancing speed and accuracy effectively. YOLOv8n (nano) is the smallest and most efficient variant of the YOLOv8 model, optimized for deployment on resource-constrained devices, including mobile and embedded systems. It features an input size of 640 × 640 × 3 and employs CSPDarknet as its backbone with a detection head that follows the YOLO framework for bounding box regression and classification. YOLOv8n is designed with 3.2 million parameters, making it extremely lightweight while maintaining competitive detection performance. It leverages anchor-free detection, a modified loss function, and improved architectural efficiencies, leading to enhanced speed and accuracy over previous YOLO models. This model is well-suited for real-time applications where low latency and high efficiency are required, such as robotics, autonomous systems, and real-time video analytics.

3. Methods

For this research there is extensive use of powerfull workstations with graphics cards like the Nvidia RT-4060, Nvidia Jetson Nano edge computing units, Quanser (Qdrone), Skydio and Teledyne drones, Warthog 2025 and Qcar and Qbot (from Quanser 2025) robot vehicles integrated with the MATLAB/Simulink Hardware-in-the-Loop simulation system - Figure 2.

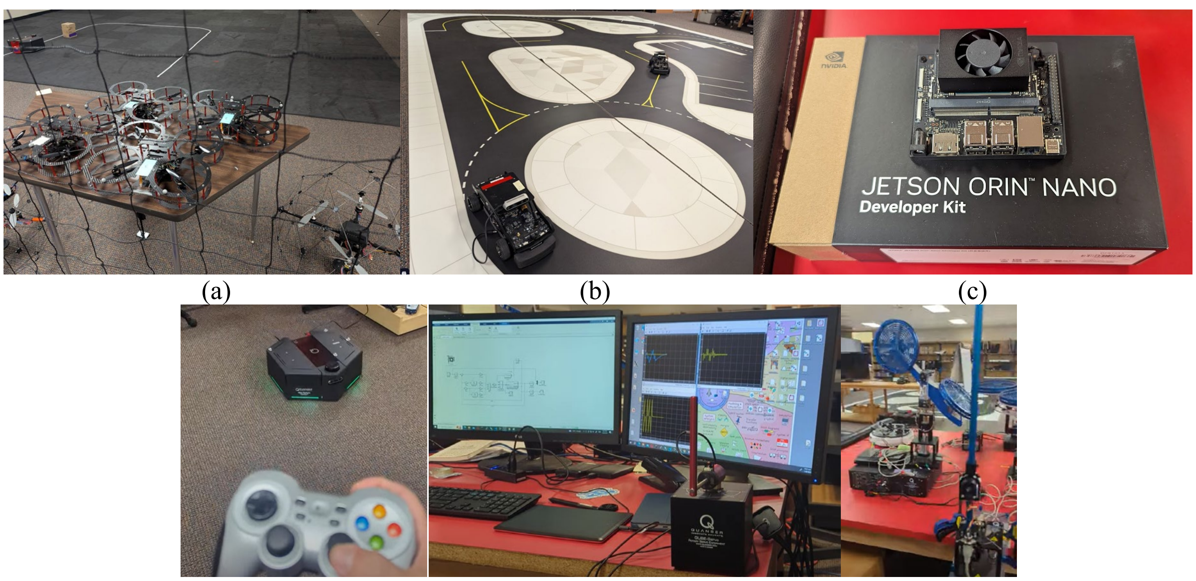
All the simulations and indoor testing were done in the AVS lab in UIW, Texas.
It is also important to note that although the flights are over private property, there are restrictions such as flying below 400 ft above ground level and avoiding restricted airspace. The legislation pertaining to the flight of unmanned vehicles is detailed in the commercial pilot license for unmanned aerial vehicles (Part 107, Remote Pilot 2022).

4. Data Collection

The data collection is divided into two sections: first, the AI model, where the preparation of the dataset and the result of the test dataset are discussed. Second, where the qualitative results of the drone with edge computing integration are shown.

4.1. AI model

The basic Convolutional Neural Network (CNN) structure is shown in Figure 3. The convolution operator which is basically a filter, is applied to a specific location in the input image, called receptive fields. The CNN then moves the receptive field over the image and, at each location calculates the sum of the products of a set of weights times the pixel value. There are two main reasons for doing this: the first is reducing data and the second, generating the feature maps used to identify specific characteristics such as edges, lines and angles. The parameters of each convolutional unit are obtained by optimizing the backpropagation.



(a) (b) (c)

(d) (e) (f)

Figure 2. (a) indoor flying test room and the Qdrone; (b) indoor testing track and the Qcar; (c) Jetson Nano edge computer board; (d) ground robot Qbot; (e) and (f) workstations with MATLAB/Simulink Hardware-in-the-Loop simulation system.

Figure 4 shows the architecture used in this work. Data preprocessing is recognized as a critical phase in the machine learning (ML) workflow, often consuming a significant portion of the total time allocated for deploying an ML model. Various studies emphasize that preprocessing accounts for a substantial percentage of the overall effort and time in model deployment. For instance, a 2016 Data Science Report, in an article by Ramel's 2016 points out that in typical deep learning tasks, online data preprocessing can comprise up to 60% of the total training time.

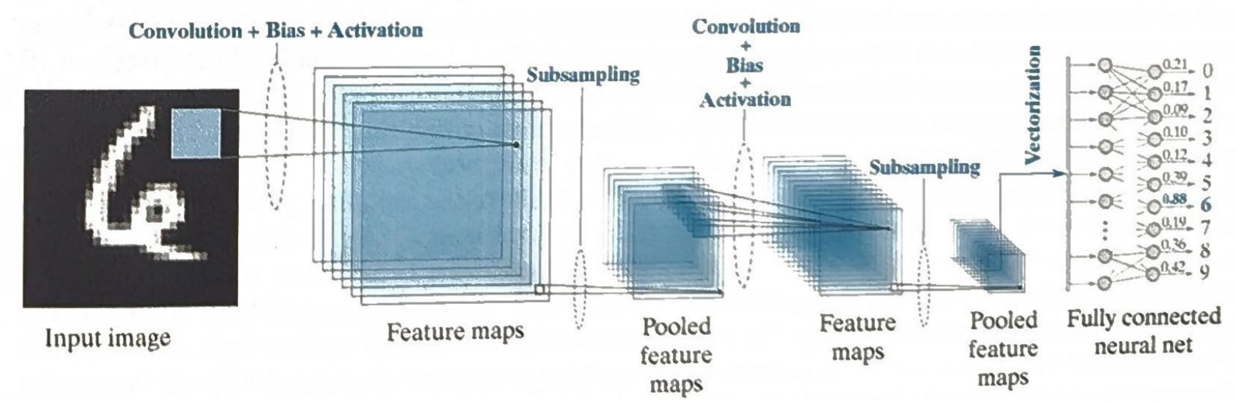


Figure 3. Basic CNN model. Source: Gonzalez and Woods 2023.

The process of the datasets preparation (training, validation and test), started with 145 images of different classes selected. Using the data augmentation techniques, such as rotation, flipping (vertical or horizontal) and adding noise, the final dataset was divided into 233 samples for training, 32 for validation, and 32 for testing. The next step was doing the annotation and segmentation, highlighting each class – Figure 12a and 13a respectively.
The results shown on Table 2 were made according to the hyperparameters in Table 1.

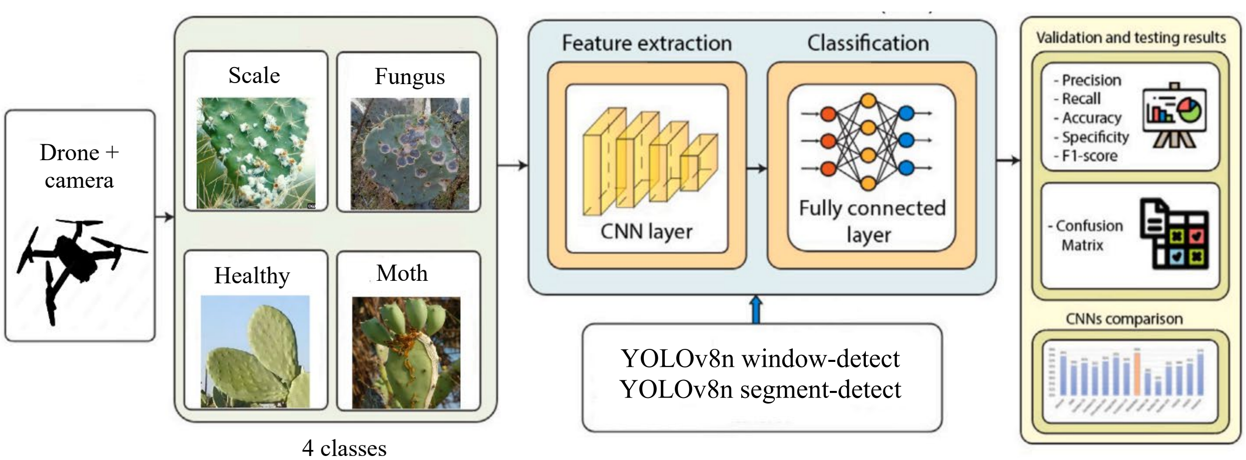


Figure 4. CNN used in the Transfer Learning model training. Source: adapted from Váscoñez et al. 2024.

Table 1. hyperparameters used to train the YOLOv8n window-detect and YOLOv8n segmentation-detect models.

Hyperparameter	**YOLOv8n window**	**YOLOv8n segmentation**
Input	640 × 640 (window)	640 × 640 (segmentation)
Activation functions	SiLU (Swish)	SiLU (Swish)
Epochs	50	50
Batch size	16	16
Optimizer	SGD	SGD
Learning rate	0.01	0.01
Loss function	BCE + CIoU	BCE + CIoU
Number classes	4	4

4.2. Integration with autonomous vehicles

The object classification model was integrated into a Jetson Nano board, Figure 2c, that was mounted on a Qdrone – Figure 5.

Jetson nano-
top side

Webcam
facing down

(a) (b)

Figure 5. The Qdrone1 with the Jetson Nano mounted on the top side (a) and a webcam on the bottom side (b)

A critical part of the implementation was the integration of the Jetson Nano board with the Qdrone controller board, the Intel Aero Computer Board (Intel 2025). The solution was making them communicate via serial port: Uart1 of the Jetson Nano on J41 and Uart 4 on the Qdrone Expantion board as shown in Figure 6. The webcam was hooked up in the Jetson Nano USB port.

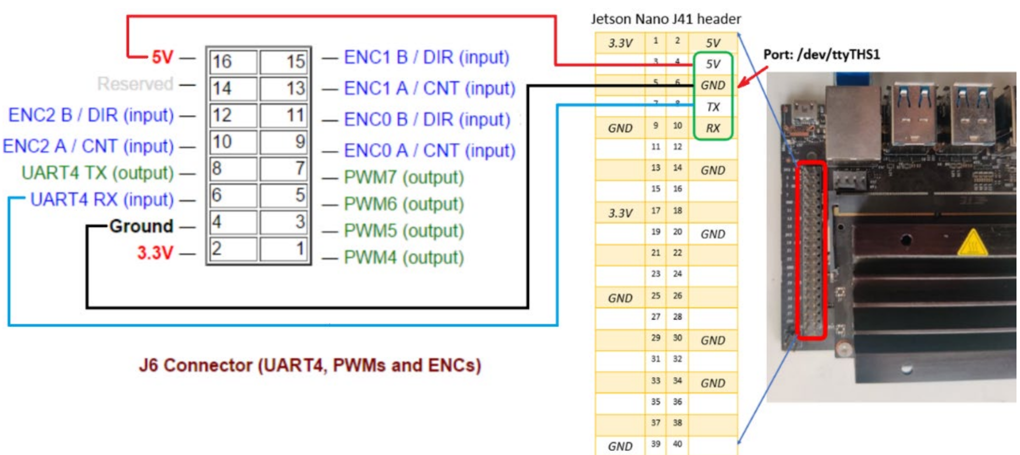


Figure 6. Serial communication connection between the Jetson Nano and the expansion board on the Qdrone1.

Joystick Interface

Command Generation

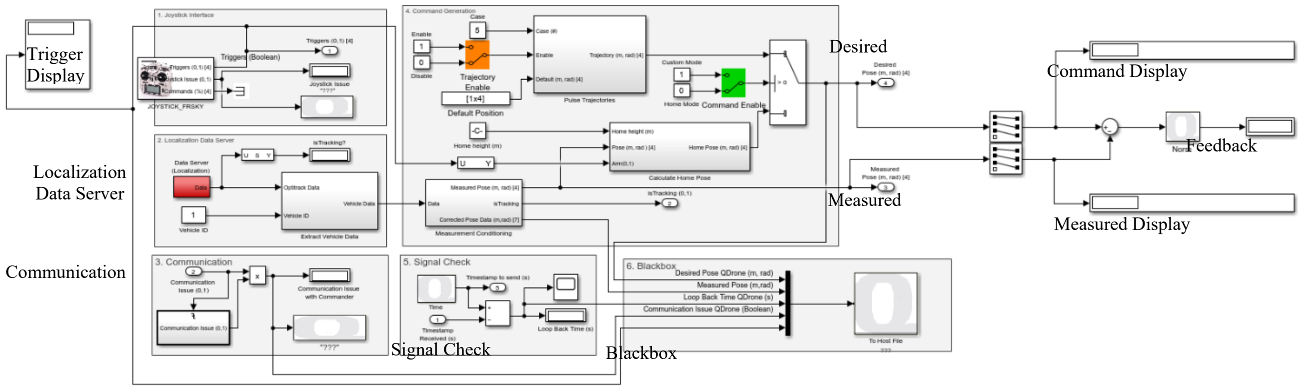


Figure 7. Simulink block of the Mission Control that runs on the Workstation.

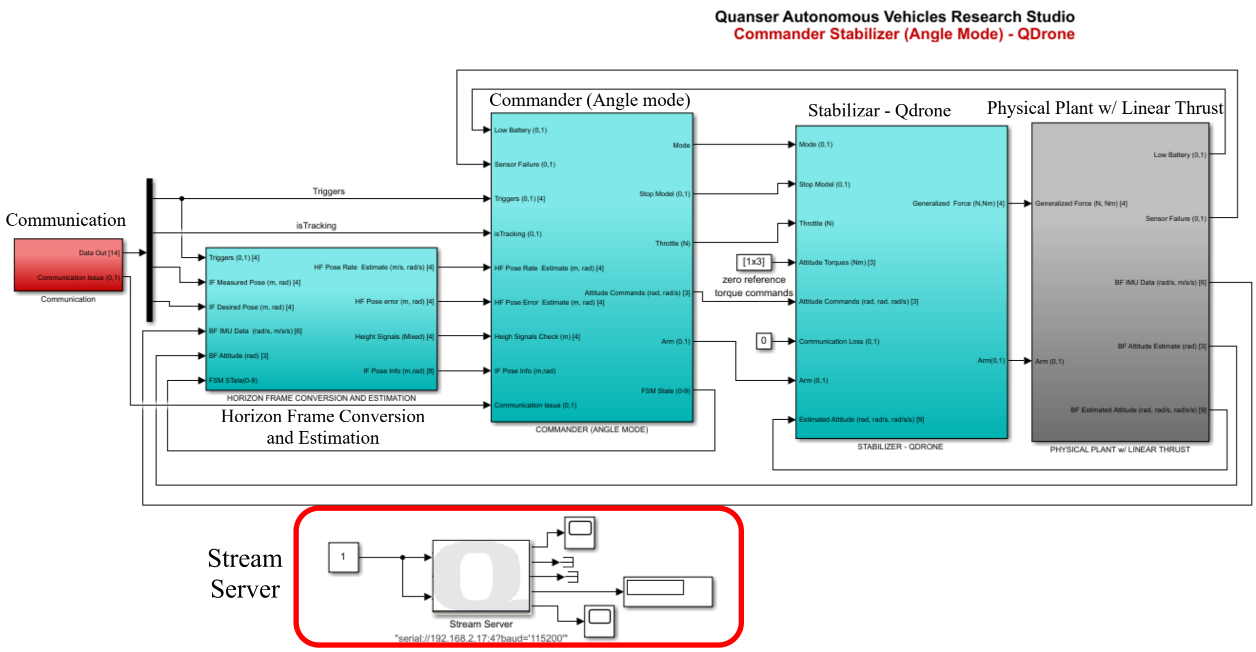


Figure 8. Simulink block of the Commander Stabilizer running on the Qdrone1. The Stream Server block is responsible for the interface between the Qdrone and the Jeton Nano.

The two Simulink models, depicted in Figures 7 and 8 were used to control the Qdrone1 flight and get the data transmitted by the Jetson Nano.

5. Results and Discussion

Here are presented the quantitative results of the AI models and qualitative results of the system integration with the AI model running on edge computer (Jetson Nano), sending data to the drone (Qdrone1) which sends the data via WiFi to the mission controller (workstation running MATLAB/Simulink). Figures 9 and 10 show schematic diagrams of the complete system that will be used in this research. The combination of drones and ground vehicles creates a synergistic effect, where aerial reconnaissance informs ground operations, leading to a more coordinated response to pest threats.

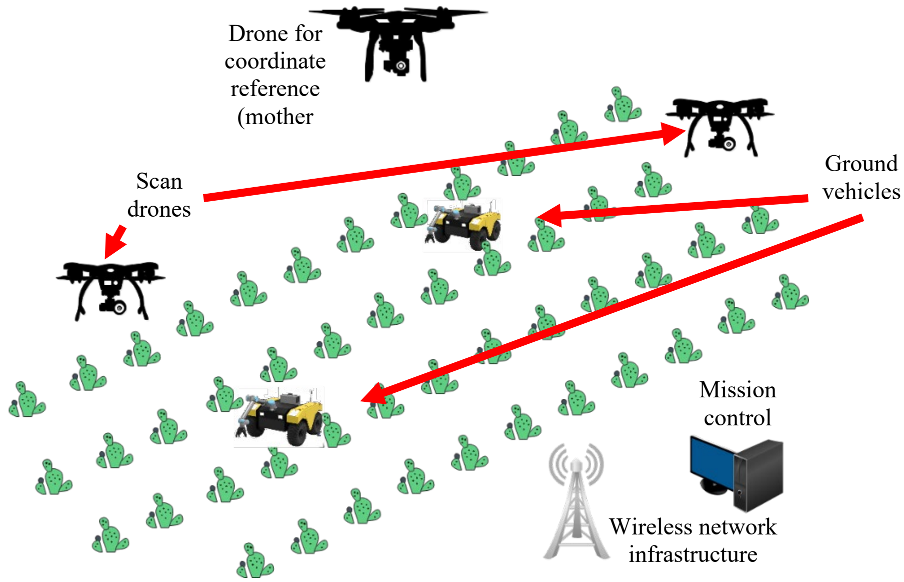


Figure 9. Overall view of the system and its elements. Source: the author

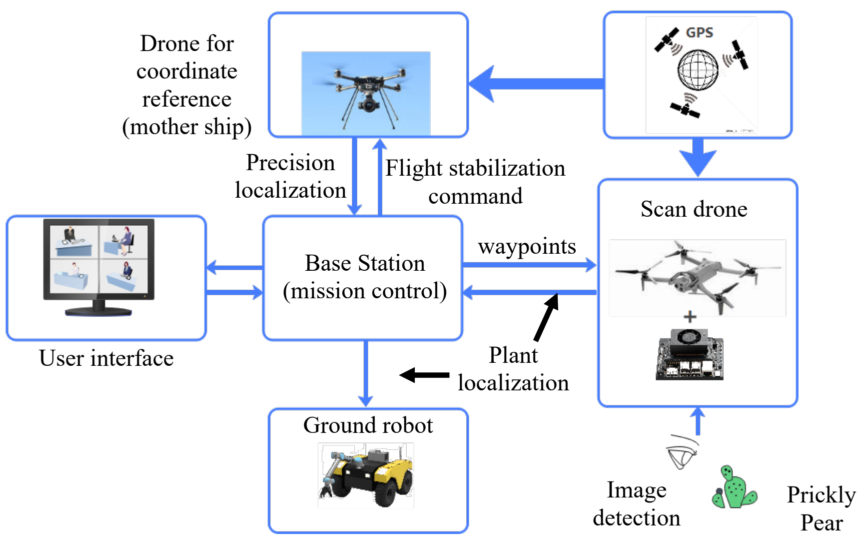


Figure 10. system information flow of Prickly Pear health detection system. Source: the author

5.1 Numerical Results of the AI Classifier

The models were tested on a dataset of 32 images for each disease type. Table 2 shows the summary of the health detection model results.

Table 2. Test classification results

Metrics	YOLOv8n window-detect	YOLOv8n segment-detect
Precision	100%	94%
Recall	42,2%	35,4%
Accuracy (<50% confidence)	38,69%	32,62%
F1-score	36%	39%

From the results on Table 2, although the Precision was high in both cases, all other metrics were low. High Precision means that there are very few false positives. However, a low Recall means that it missed a lot of detections. It can be confirmed by the low Accuracy, where both true positives and true negatives were, in most cases, not detected. F1-Score is the overall score of the model, showing that it needs more training data.

During the tests, it became clear that some classes were not easily detected, confirming the numeric results.

5.2 Graphical Results

Figure 11 shows the confusion matrix. The diagonal elements are the correctly predict samples. This shows that the models are not well fitted and fine tunning is needed. Although the confusion matrix for the window-detection shows 100% correct detection for prickly pear, more samples are needed to train for other classes. This can be easily noticed when analyzing the labeled vs predict images, where it is clear when the model failed in detecting some classes or wrongly detecting others.

Figures 12 and 13 show a set of four images on the left and the same four images on the right. The left side are the labeled images used for training and the right side, the output from the Object Detection Model. From those images the model had difficulty in classifying correctly and, for example, on the upper right of Figure 13, it missed a lot of detections (many locations of scale damage).

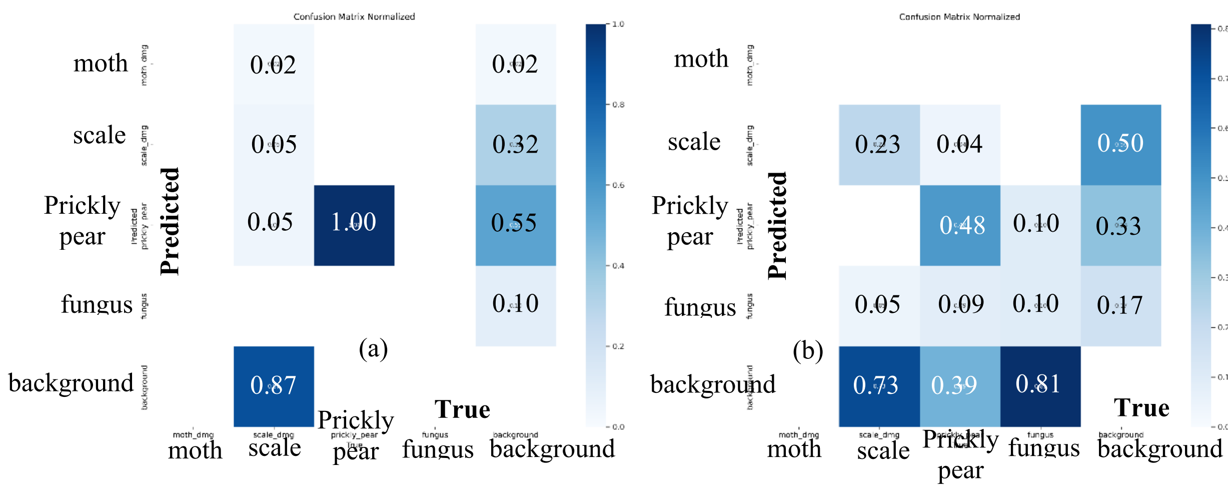


Figure 11. Confusion matrix. (a) – window-detection, (b) – segment-detection

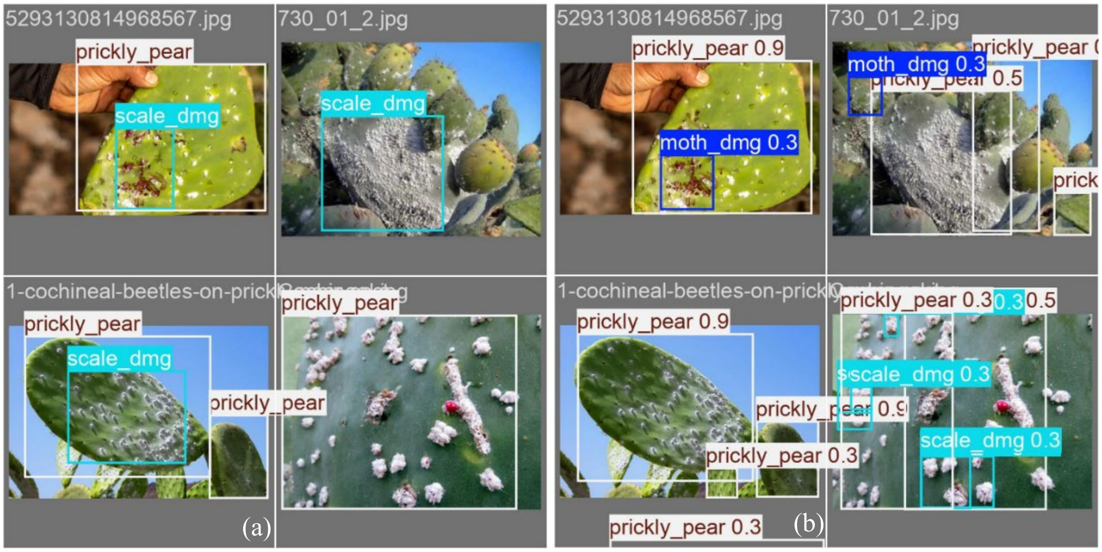


Figure 12. Labeled (a) vs Predict (b) images for window-detection

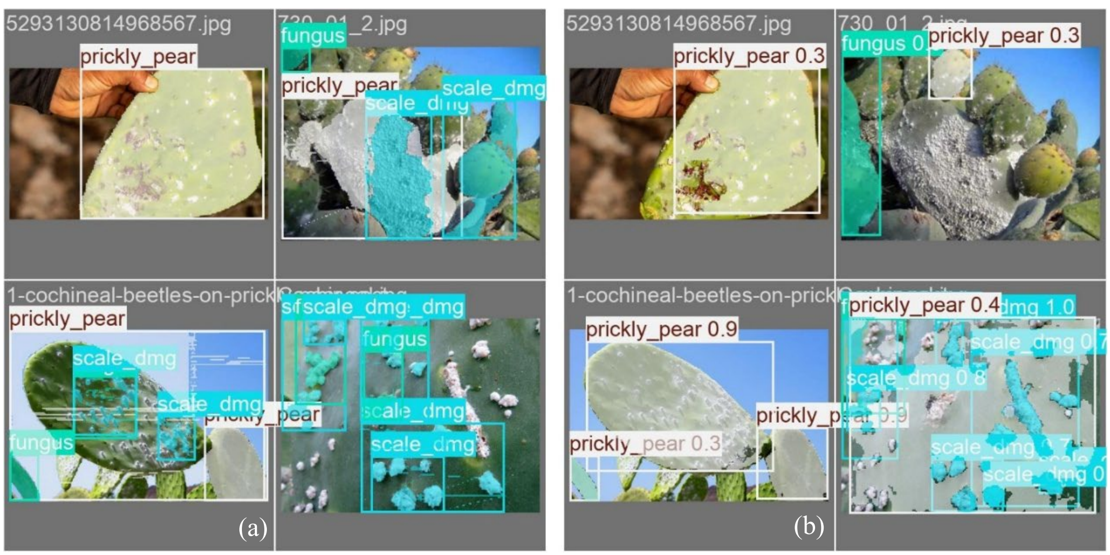


Figure 13. Labeled (a) vs Predict (b) images for segment-detection

5.3 Proposed Improvements to the AI Model

To improve the model performance, the number of samples in the dataset should be increased. Another important consideration is to balance the number of samples for each class.

5.4 Results of the laboratory integration tests

The test setup is shown in Figure 14 at the moment when the drone, flying at 1 m high, detects the target object on the ground. The detection is confirmed by the control station monitor, as shown in the picture.

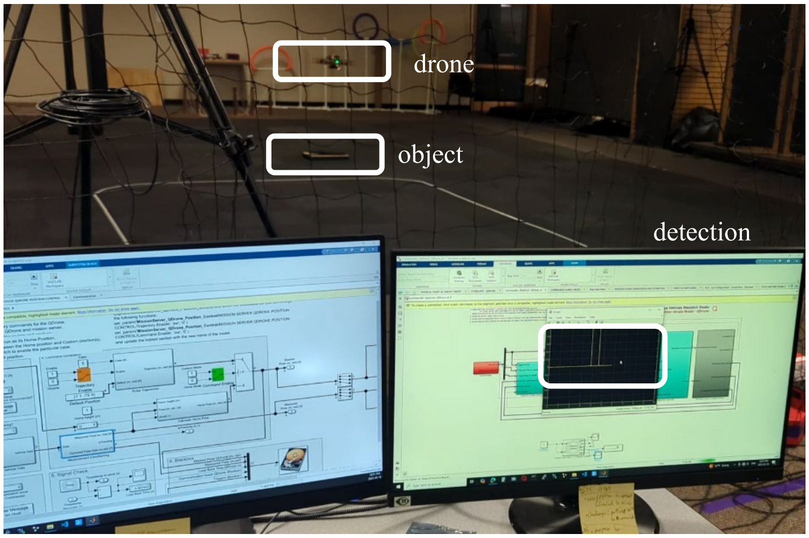


Figure 14. system integration with edge computer, drone and control station

6. Conclusion

This work shows the applicability of the AI models, although they still need adjustments to improve the detection performance metrics. However, for this application, the preliminary results show that window-detection is a better choice in terms of detection, memory usage and speed to assess the Prickly Pear health condition.

The overall system was validated in laboratory, demonstrating its capabilities. However, the models (window-detection and segment-detection) still show low recall and accuracy results. The proposed strategies to improve model performance are: increasing the dataset size; balancing class representation; and adjusting hyperparameters. For instance, a high number of epochs can led to overfitting, making the model lose its generalizing capability.

The next step for this project is to improve the models and validate the system in the relevant environment (outdoors).

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