PVY Report: 2024-2025

PROJECT TITLE

Integrating Deep Learning and Machine Vision for Efficient Detection and Management of Potato Virus Y

PROJECT LEAD
Aitazaz A. Farooque, PhD, P.Eng.
Professor
Industry Research Chair - Precision Agriculture
School of Climate Change and Adaptation
Faculty of Science

University of Prince Edward Island
Room #: DSC 408
550 University Ave, Charlottetown
PE, Canada C1A 4P3
Email: afarooque@upei.ca; Ph: (902) 566 6084
Website: http://www.upei.ca/profile/aitazaz-farooque

PROJECT COOPERATORS

PEI Potato Board

Executive Summary – Year 2 Progress (2024–2025)

Following foundational work in Year 1, including dataset development, model prototyping, and initial robot design, Year 2 focused on refining hardware and software systems to enhance real-world functionality for Potato virus Y (PVY) detection. A multi-faceted approach addressed challenges related to data quality, field operability, and end-user utility.

Hardware Enhancements: The autonomous electric robot was significantly upgraded. Key improvements included integrating global shutter cameras to eliminate motion blur, waterproof housing for weather resistance, and a redesigned foldable camera boom to increase field coverage from 3 to 5 rows. Real-time kinematic (RTK) modules enhanced spatial accuracy for mapping infected plants, while artificial LED lighting and sun-blocking curtains ensured high image clarity under diverse lighting conditions. A secondary battery was installed to extend operational time to 6–8 hours per deployment.

Connectivity and Data Flow: A Starlink satellite dish was mounted on the robot, enabling real-time connectivity in remote rural locations where cellular networks are unreliable. This allowed instant cloud upload and processing of image data, significantly improving workflow efficiency and reducing latency in disease detection.

Dataset Expansion and Model Refinement: The upgraded robot captured thousands of high-resolution images during the summer 2024 field season under various weather conditions. These images were used to retrain deep learning models with a focus on detecting complex PVY symptomologies such as mosaic patterns and necrotic streaks. Through careful data curation, class balancing, and augmentation, the object detection model (YOLOv8) achieved an mAP (mean Average Precision) of 75% on test datasets, showing strong reliability under field conditions.

Grower-Focused Mobile App: A mobile application was developed to translate model predictions and robot-gathered data into actionable field maps. The app displays real-time, geo-referenced markers of PVY-infected plants and supports decision-making by providing precise coordinates and visual cues for targeted rogueing. This simplifies disease management for producers, helping mitigate the spread of PVY and improve yield outcomes.

Material and Methods

Autonomous Robot Design

To resolve the weather vulnerability identified in Year 1, the robot's structure was re-engineered with fully waterproof compartments, enclosing batteries, processing units, and other sensitive electronics. Durable materials and modular construction support easy maintenance and field-readiness. Protective casings also offer dust and debris shielding, extending equipment longevity.

Imaging System

The image acquisition system was overhauled with several key improvements:

- **Curtains and Boom Design**: Light-blocking curtains were mounted around cameras to reduce glare during mid-day operations. The camera boom, now foldable and field-deployable, supports up to five camera modules, maximizing coverage. This design is adaptable via a three-point hitch, allowing vertical adjustments based on the plant growth stage to ensure consistent image framing and focus. (Figure 1)

Figure 1. Foldable curtain design for easy transportation

- **Lighting**: Each camera includes a dedicated LED light, activated during image capture to provide consistent illumination. This resolves issues from low light, variable shadows, and overexposed surfaces. (Figure 2)

Figure 2. LED lights capture images with consistent lighting.

- **Camera System**: The switch from rolling shutter to global shutter cameras eliminated motion-related artifacts, ensuring high clarity at faster robot speeds or rough terrains. (Figure 3)

- **Data Processing and Transmission**: Cameras operate with independent single-board computers, each equipped with wireless connectivity. These boards handle local image pre-processing and immediately upload tagged images to a central cloud server for analysis, improving scalability and data integrity.

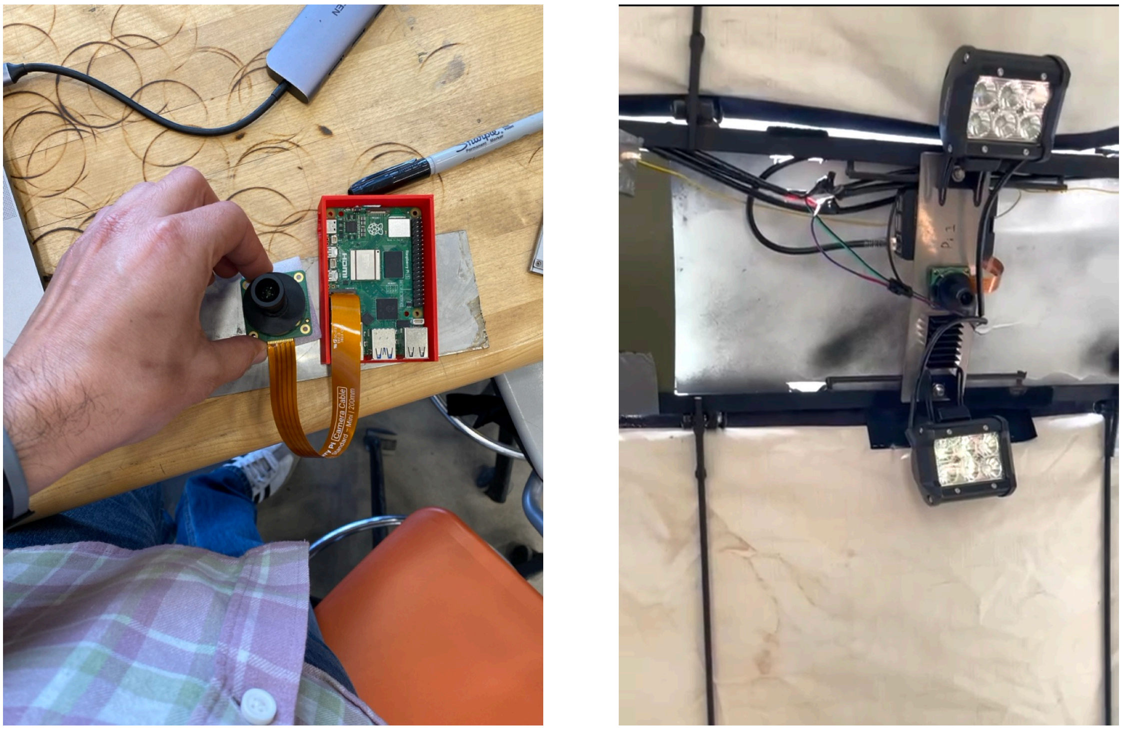

Figure 3. Global Shutter camera along with LED lights.

- **Localization and Communication**

RTK GPS modules paired with traditional GPS significantly improved positional accuracy to centimeter-level resolution. This enhancement supports precise geotagging of PVY-infected plant locations. The addition of Starlink Internet provided robust, high-bandwidth data transmission, allowing real-time model inference and cloud-based data access from any field location. (Figure 4)

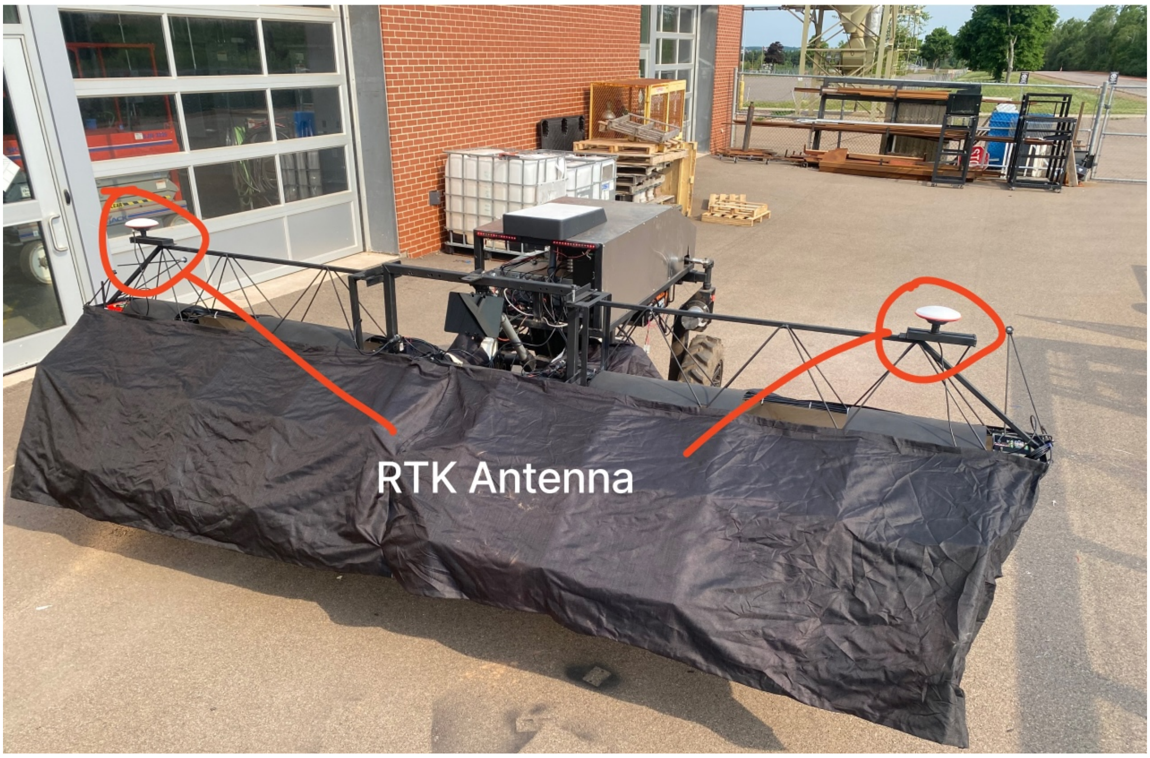

Figure 4. RTK modules and antennas.

Data Collection, Preprocessing, and Model Training

Image Acquisition

Data were collected from multiple field sites across Prince Edward Island during varying daylight and weather conditions. The dataset consists of thousands of annotated images showing healthy and PVY-infected plants. These were essential for training object detection models to recognize both subtle and advanced symptom presentations. (Figure 5)

Figure 5. Field data collection

Preprocessing and Labeling

Images were preprocessed by resizing from 1456 × 1088 to 640 × 640 pixels to match YOLOv8's input. Adjustments in brightness, contrast, and saturation preserved critical features such as discoloration and crinkling patterns. To prevent overfitting and improve generalizability, extensive data augmentation (cropping, rotation, flipping, color jitter, Gaussian noise) was applied. Manual annotations using LabelImg and Roboflow were converted into YOLO format with normalized bounding boxes.(Figure 6)

Figure 6. Data labelling, bounding boxes around symptomatic leaves

Model Training and Evaluation

The YOLOv8 model was trained for 200 epochs, using a learning rate schedule to balance training stability and convergence. Evaluation on an independent dataset showed a consistent downward trend in focal and box loss, indicating successful learning of difficult cases. Metrics such as precision, recall, and F1-score indicated balanced performance, with a mAP50 of ~75%. The model demonstrated strong reliability in detecting PVY under varied conditions, though minor validation fluctuations pointed to opportunities for fine-tuning in future iterations.

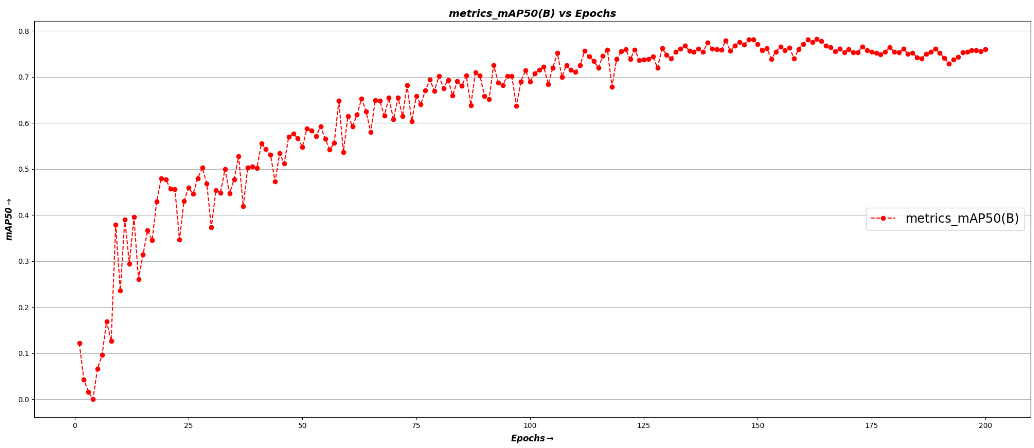

Figure 7. Mean Average Precision 50 vs Epochs

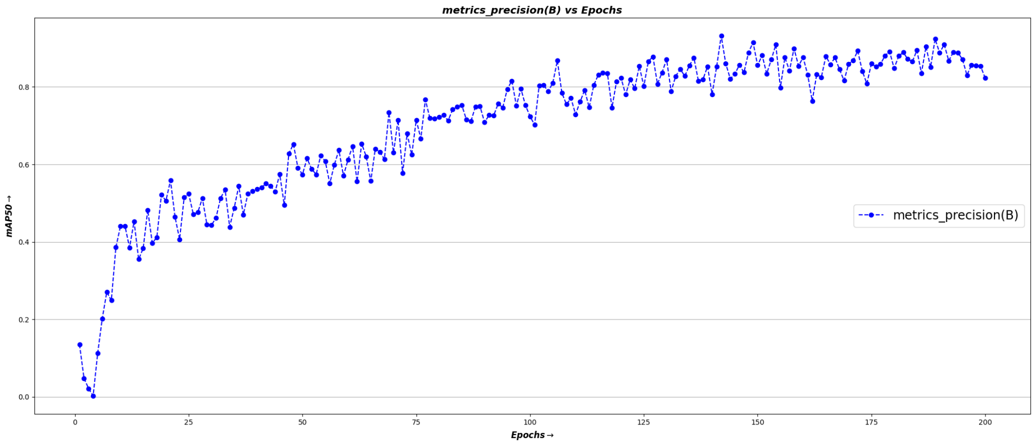

Figure 8. Precision 50 vs Epochs

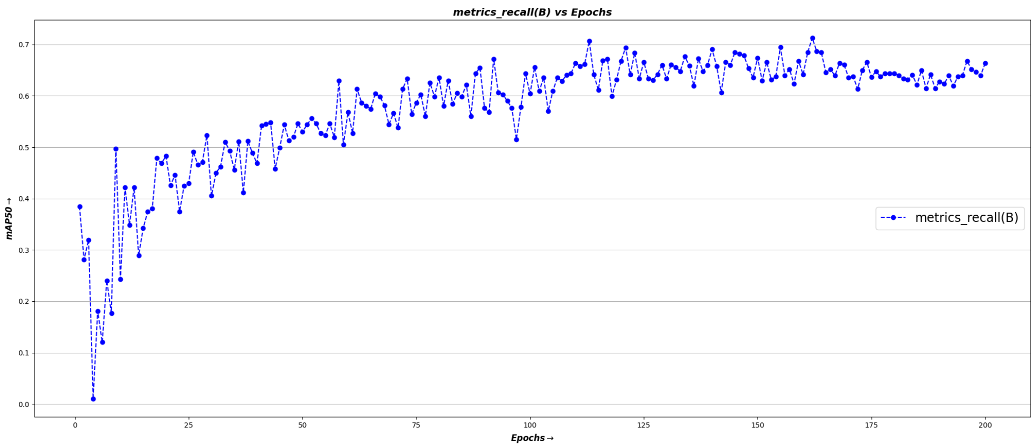

Figure 9. Recall 50 vs Epochs

Infestation Map

The mobile app developed concurrently with robot hardware and AI model improvements, acts as the grower's interface for disease mapping. It converts robot-collected geo-tagged image data into visual field maps showing infected plant locations with high spatial accuracy. Features include:

- Real-time updates via cloud sync
- Interactive field navigation
- Symptom image previews per marked location

By translating technical outputs into accessible, visual insights, the app bridges the gap between AI-based detection and on-farm decision-making. (Figure 10)

Figure 10. Infestation Map

Conclusion and Future Work

The second year of the project delivered key advancements in autonomous field scouting, PVY detection accuracy, and grower-focused decision tools. Notable achievements include:

- Major redesign and waterproofing of the autonomous robot
- Enhanced imaging with lighting, shutter upgrades, and adjustable boom
- Expanded and diversified dataset for more robust AI training
- Precision localization using RTK and real-time cloud connectivity
- A functional mobile app that empowers growers to act swiftly and accurately

Looking ahead, the next project phase will introduce:

- **Onboard Real-Time Inference**: Faster processing through onboard GPU integration will eliminate the need for remote cloud inference, improving speed and independence.
- **Integrated Spraying Module**: A mechanical spraying system will mark infected plants directly in the field for easy identification by workers, enabling immediate intervention.

These future capabilities aim to create a fully autonomous, intelligent system for early detection, precise mapping, and effective control of PVY in potato farming operations.