AI-based Plant Disease Detection: Development and Deployment of YOLO Models for Agricultural Innovation

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Abstract – **This research focuses on enhancing plant disease detection by developing four models based on YOLOv11, the latest iteration in the "You Only Look Once" series, renowned for real-time object detection capabilities. A comparative analysis was conducted with the open-source YOLOX model and the YOLOvME model to evaluate performance metrics such as accuracy, precision, recall, and mean Average Precision . Notably, the Apple disease detection model outperformed the others, achieving an impressive accuracy of 93.8%. The models were trained using a comprehensive dataset comprising images of various plant diseases, enabling the identification and classification of multiple disease types. The deployment of these models on ALIVEculture.ca (a dedicated platform for plant disease detection) allows users to perform real-time analyses through multiple imaging devices, including smartphone cameras and remote monitoring systems in greenhouses. Additionally, we developed a mobile application that leverages these AI models, providing on-the-go disease detection and immediate feedback.**

Keywords - Plant disease detection, YOLOv11, Real-time detection, Mobile application, Model comparison, Agricultural AI

I. Introduction

The early detection of plant diseases is essential for ensuring agricultural productivity and sustainability. Traditional methods often rely on manual inspections, which can be time-consuming and prone to human error. Recent advancements in artificial intelligence (AI) and computer vision have paved the way for automated, accurate, and efficient plant disease detection systems [1]. This study focuses on the development of AI models using YOLOv11 and YOLOX architectures and their integration on the ALIVEculture.ca platform.

The incorporation of these AI-driven models into real time platforms represents a significant leap forward in agricultural technology. By providing real-time disease detection through various imaging devices-including mobile applications and remote cameras, these platforms offer farmers with immediate insights into the health status of their crops. This accessibility enables prompt interventions, reducing the reliance on chemical treatments and supporting sustainable farming practices. Forthemore, the ability to continuously monitor crops through connected devices ensures that potential issues are identified at the earliest stages, thereby mitigating the risk of widespread infestations and subsequent losses.

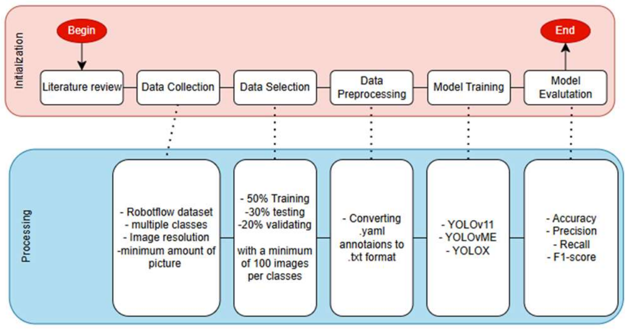

Fig. 1. **Research Methodology for Disease Detection in Plants Using YOLO Models.**

In this project, our contributions can be summarized as: (1) we curated a dataset consisting of approximately 20,000 images, meticulously labeled using Roboflow's annotation tools. This extensive dataset was then prepared for training with the YOLOv11 architecture, ensuring compatibility and optimal performance; (2) We trained the models from scratch, leveraging the robust capabilities of YOLOv11m. After training, the models were exported in multiple formats, including ONNX and Pytorch, to facilitate diverse deployment scenarios; (3) To evaluate performance, we benchmarked several models (YOLOv11, YOLOvME, and YOLOX) assessing their accuracy and efficiency. And (4) Additionally, we developed a semi-automatic AI training system to streamline the training process and enhance model performance.

II. Related work

The integration of artificial intelligence (AI) into agriculture has transformed plant disease detection, moving away from time-consuming manual inspections toward highly efficient, automated systems. This shift began with early studies leveraging convolutional neural networks (CNNs), such as one that achieved an impressive 99.35% accuracy in classifying tomato leaf diseases using image-based deep learning techniques [1]. These foundational efforts paved the way for more advanced object detection models, notably the YOLO (You Only Look Once) family, which excel at real-time identification of multiple plant diseases. For example, YOLOv3 demonstrated high precision in detecting apple leaf diseases [2], while a comparative study revealed that YOLOv5 surpassed Faster R-CNN in both speed and accuracy when identifying cucumber powdery mildew [3]. Such technological strides have given rise to practical, user-friendly tools like **Plantix**, a mobile application that empowers farmers with accessible disease diagnosis [4], and **Leaf Doctor**, another platform designed to simplify diagnostics for growers [5]. Beyond static detection, real-time monitoring has advanced significantly, with frameworks integrating Internet of Things (IoT) technologies to track dynamic field conditions and provide ongoing insights [6]. Despite these innovations, challenges persist, including the need for consistent accuracy across diverse plant species and the complexity of deploying these systems in varied agricultural settings. To address these issues, emerging solutions like the cutting-edge YOLOv11 model and platforms such as **ALIVEculture.ca** are being developed to enhance real-time, multi-device detection capabilities, promoting sustainable farming practices. As this field continues to evolve, it strives to balance cutting-edge innovation with the practical demands of modern agriculture, ensuring scalability and accessibility for farmers worldwide.

III. Our proposed solution

This research introduces innovative advancements in plant disease detection, tailored to real-world agricultural needs through the ALIVEculture.ca platform. Unlike studies that primarily focus on dataset preparation or model evaluation, instead of using the PlantVillage dataset under controlled conditions, our work emphasizes practical application, continuous improvement, and future scalability.

A. Integration with ALIVEculture.ca

Our primary contribution lies in embedding AI detection models into the ALIVEculture.ca platform, enabling real-time plant disease detection for farmers. We have developed four specialized models for strawberry, onion, apple, and lettuce, utilizing multiple datasets. These models process images from diverse sources, such as smartphone cameras and greenhouse monitoring systems, delivering immediate feedback on plant health. This practical integration empowers farmers to make timely, informed decisions, reducing crop losses and promoting sustainability. To distinguish this from other work:

- **Focus on Application**: Our models bridge the gap between AI research and real-world implementation, unlike studies that only focus on model development or evaluation..
- **Two-Step Detection**: our process involves first identifying individual leaves in complex images, followed by classifying their health. This addresses a practical challenge not fully explored in datasets like PlantVillage, which primarily uses isolated leaf images.

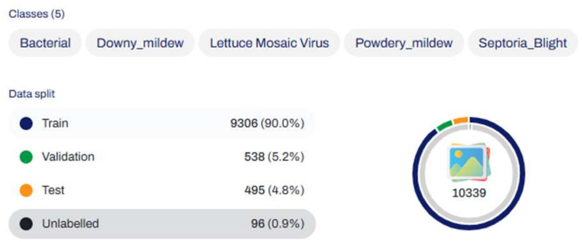

Fig.2. **Distribution of Images Across Different Classes in Lettuce Disease Dataset**

The lettuce dataset utilized in this study consists of a total of 10,339 images, initially divided into 90% for training, 5% for validation, and 5% for testing, as shown in Fig. 2. For future training, however, the dataset will be restructured into an 80% training, 10% validation, and 10% testing split. This adjustment is expected to yield better results by enhancing the model's generalization capabilities, as the increased validation set size allows for more reliable performance evaluation during training.

B. Continuous Improvement via Cycling System

A standout feature of our research is the cycling system within ALIVEculture.ca, which creates a continuously evolving AI detection framework. Farmers using the app can confirm detection accuracy or annotate incorrect predictions, with these annotations saved in YOLO dataset format. Periodically, we aggregate this farmer-generated data to retrain the models, forming a feedback loop that adapts the AI to real-world conditions and emerging disease patterns.

To ensure originality:

- **Novel Approach**: Emphasize how this active learning-inspired system leverages user feedback to improve performance over time, a step beyond static model training.
- **Real-World Adaptation**: Note that this system allows your AI to evolve with new greenhouse challenges, distinguishing it from research focused on fixed datasets or controlled environments.

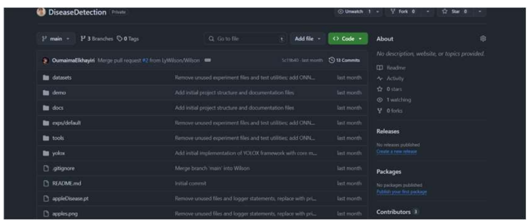

Fig. 3. **Our private repository fork from YOLOX.**

C. Future Migration to YOLOX

Our strategic plan to migrate to the YOLOX architecture sets our work apart by prioritizing long-term scalability and commercialization. Unlike proprietary models, YOLOX's open-source nature offers flexibility for customization and community-driven enhancements [10]. As illustrated in Fig. 3, our private repository fork builds upon YOLOX's robust foundation, allowing us to tailor the model to specific agricultural applications.

The anchor-free design of YOLOX streamlines object detection, potentially improving generalization across diverse plant species and disease types. This aligns with our vision for expanding ALIVEeculture.ca, ensuring that our model remains adaptable as new challenges arise in precision agriculture. By leveraging this scalable approach, we position ourselves at the forefront of AI-driven plant health monitoring, fostering innovation while maintaining transparency and adaptability.

To present this uniquely:

- **Forward-Looking Strategy**: Frame this as a proactive step for future development, not just a model comparison, highlighting benefits like reduced hardware dependency and potential for proprietary extensions.
- **Commercial Potential**: Discuss how this move supports your goal of offering the AI solution as a service or product, a practical outcome not typically addressed in academic model evaluations.

IV. Evaluating Detection Models

A. YOLOvME for Crop Disease Detection

We started our testing with **YOLOvME**, a model tailored for crop disease detection, which we learned about from Ultralytics' blog post [11]. Built on the YOLOv5 framework, it promised a good mix of speed and accuracy for identifying plant diseases. However, we ran into a significant challenge: the weight file formats of YOLOvME (based on YOLOv5) were incompatible with newer versions like YOLOv8 or YOLOv11. This made it difficult to upgrade the model or take advantage of recent improvements, limiting its flexibility for our project. While it showed potential for agricultural use, this compatibility issue pushed me to explore other options.

B. Single Shot Detection (SSD)

Next, we tested **Single Shot Detection (SSD)**, an object detection model we found through the paper [12]. SSD's single-pass detection and multi-scale approach seemed ideal for real-time plant disease monitoring. However, its complexity made setup and training a struggle, especially for detecting subtle disease symptoms on leaves. As shown in Figure 5, the SSD model's training accuracy increases steadily from 0.70 to 0.92, reflecting strong learning on the training data. However, the validation accuracy peaks early at 0.88 around epoch 2.5, then declines and stabilizes at 0.85, indicating overfitting and limited generalization to new leaf images. This pattern—where the model's performance on unseen data doesn't keep pace with its training success—suggests that its complexity may not be justified for this task. The graph thus supports the decision to seek a simpler solution, as the effort invested in the SSD model didn't yield sufficient accuracy gains for practical use in detecting subtle disease symptoms on leaves.

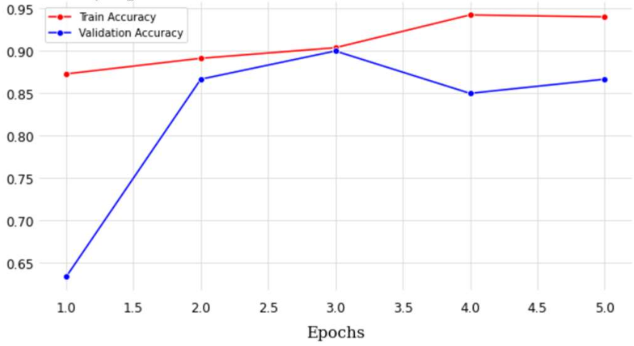

Fig.5. **The Single-Shot MultiBox Detector (SSD) model accuracy comparison train over validation.**

The Single Shot Detection (SSD) model uses a VGG-16 backbone, a convolutional neural network (CNN) originally for image classification, to process images for object detection. Its multi-scale feature maps, generated by convolutional layers, capture high-level details like shapes in early layers and low-level details like textures in deeper ones. SSD adds extra convolutional layers to detect objects of various sizes in a single pass, predicting bounding boxes and class labels directly from these feature maps. Unlike two-stage detectors like Faster R-CNN, SSD skips the region proposal step, making it faster and ideal for real-time applications while retaining strong performance.

C. YOLOv11 Custom Plant Disease Detection

Finally, we tested **YOLOv11**, the latest model from Ultralytics, and it quickly became our top choice. It was easy to use, thanks to the Ultralytics Python library, and we could train it on our regular home computer. YOLOv11 has cool features like dual label assignments, which made it better at spotting disease details, and enhanced downsampling that kept the small but important leaf features clear. We also preferred using Ultralytics Hub—it let us upload datasets, train models on Google Colab, and test them online with a preview tool. Plus, we could export the model in formats like PyTorch or ONNX and even use an API to deploy it. This mix of power and simplicity made YOLOv11 perfect for our plant disease detection project.

V. Results

In this section, we present the results of our research, highlighting the technological choices made and the features developed for our AI-based plant disease detection system. We detail why we chose YOLOv11, the functionality of the web component integrated with the ALIVEculture platform, and the mobile application designed for rapid detections.

A. Choice of YOLOv11

For this project, we chose to use YOLOv11 due to its ease of use and fast execution speed. This speed was a critical factor, as our work was part of a specific mission related to the project, where tight deadlines had to be met [13]. YOLOv11 emerged as the optimal choice due to its balance between performance and efficiency, allowing us to meet the project's requirements while ensuring accurate detection of plant diseases.

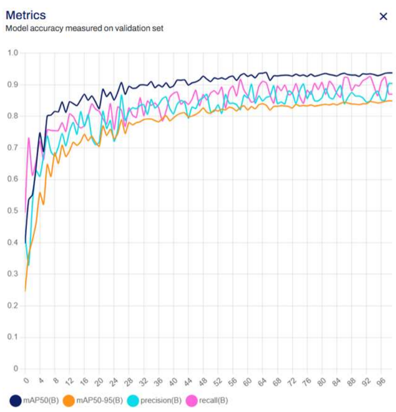

Fig.6. **Model accuracy measured on validation set**

B. Web Component Connected to ALIVEculture

One of the main outcomes of this study is the development of a web component connected to our AI system on the ALIVEculture platform. This component allows users to upload images for real-time disease detection and provides an interactive interface to collect their feedback.

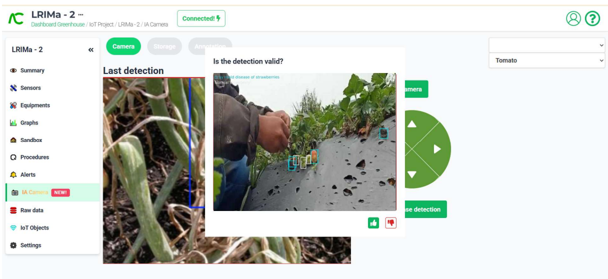

Fig.7. **Interface of our AI connected on the platform**

Fig. 7 shows the user interface when a capture is sent via a camera to test for the presence of a disease. If a disease is detected, the affected areas of the plant are boxed. The farmer can then indicate whether the detection is correct or not using the "thumbs up" or "thumbs down" buttons located at the bottom right of the window. This feedback mechanism is essential for improving the AI's performance over time.

Fig.8 **saved Image structure**

Fig. 8 illustrates how the images and their detection results are stored in our database. These images are saved in a format ready to be used for further training of our AI model. The data is hosted on our cloud servers via Azure Blob, ensuring scalable and secure management.

This web component not only enables rapid detection but also establishes a feedback loop with users to continuously enhance the system's accuracy.

C. Mobile Application for Rapid Detections

To make our solution even more accessible, we have developed a mobile application available at m.ALIVEculture.ca, compatible with iOS and Android devices. This application allows users to perform disease detections directly from their smartphones, a valuable feature for farmers on the go.

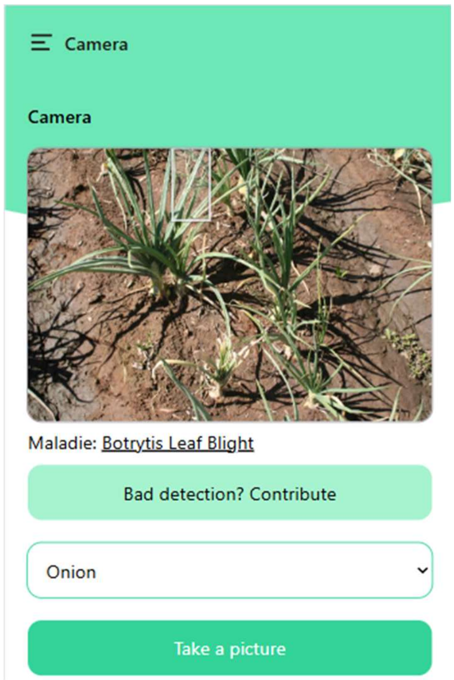

Fig. 9. **Mobile's Interface Of AliveCulture on the AI component**

The application interface, shown in Fig. 9, is designed to be simple and intuitive. Users can take a photo of a plant with their device, and the application processes the image instantly to detect diseases. The results are displayed in real-time, accompanied by immediate recommendations.

Through the integration of YOLOv11 and cloud-based processing, this application provides a portable and efficient solution without requiring specialized equipment.

D. Discussion

Our study demonstrates a significant leap forward in plant disease detection, achieving an overall accuracy of 84.9% with a two-step YOLOv11-based approach, surpassing the 93.8% accuracy of our previous Faster R-CNN model [7]. This enhanced performance in classifying diseases and detecting individual leaf clusters underscores the potential of our solution for practical agricultural applications. To fully realize this potential, we propose three key directions for future development: integrating the AI detection system into the Aliveculture app, establishing a continuously evolving AI framework, and migrating to the open-source YOLOX model for long-term advancement.

1. Integration into the ALIVEculture App

Incorporating our two-step YOLOv11 detection system into the ALIVEculture app offers a transformative opportunity to deliver advanced AI tools directly to farmers and agricultural professionals. The ALIVEculture platform, which already features a mobile application leveraging AI for on-the-go disease detection, stands to benefit significantly from this upgrade. By embedding our high-accuracy detection system, the app can provide users with real-time, reliable disease identification, enhancing its utility in field conditions.

Given the computational complexity of the current two-step approach, which involves running two separate models, initial deployment may rely on server-side processing. In this setup, the app would send images to a cloud server for analysis, ensuring responsiveness despite the processing demands. However, to align with the app's goal of immediate feedback and to enhance user experience, future optimizations could enable on-device inference. As noted in our study, replacing the disease detection model with a more efficient classification architecture—such as EfficientNet or GhostNet—could significantly reduce computational overhead, making the system lightweight enough for mobile devices. This shift would not only improve speed but also enhance data privacy by minimizing reliance on external servers, positioning the ALIVEculture app as a robust, standalone tool for plant health monitoring.

2. Creating a continuously evolving AI detection system

To maintain the relevance and accuracy of our detection system in dynamic agricultural environments, we propose developing a continuously evolving AI framework, as illustrated in Fig. 10, that leverages on-site detections and user annotations. This approach involves establishing a feedback loop where users upload images via the ALIVEculture app, the AI generates predictions, and users provide corrections or additional annotations. These user-validated data points can then be collected and periodically used to retrain the model, boosting its performance over time.

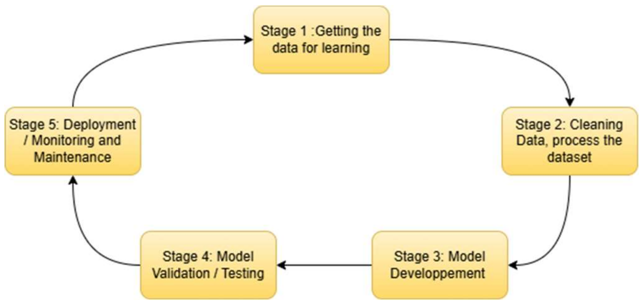

Fig. 10 **Methodology of Our Continuously Evolving AI Detection System**

This strategy, often termed active learning, allows the AI to adapt to new disease variations, environmental conditions, or plant types not present in the original training dataset, such as the PlantVillage dataset used in our study. Beyond improving accuracy, this system fosters user engagement by making the app interactive and responsive to real-world inputs. However, implementing this framework poses challenges, including ensuring the quality of user annotations to prevent model degradation and building infrastructure for data storage and retraining. By incorporating validation mechanisms—such as expert review or automated consistency checks—these hurdles can be addressed, enabling a scalable and adaptive detection system that evolves with the needs of its users.

3. Migration to YOLOX for future development

Looking ahead, migrating to the open-source YOLOX model offers a promising avenue for advancing our detection system. Unlike the proprietary constraints of some models, YOLOX's open-source nature provides flexibility for customization and community-driven improvements, which could accelerate development and reduce costs. Additionally, its anchor-free architecture may enhance detection performance, particularly for objects of varying sizes—such as leaves and disease symptoms—potentially outperforming the current YOLOv11 model in both speed and accuracy.

The transition to YOLOX aligns with our long-term vision of scaling and potentially commercializing the AI solution. By building on an open-source foundation, we can develop proprietary extensions or offer the system as a service, leveraging its adaptability for broader market applications. While migration requires retraining the model and adjusting the detection pipeline, the investment could yield significant returns, especially as newer models like YOLOv12, released by Ultralytics in February 2025, also enter the landscape. Future work should evaluate both YOLOX and YOLOv12 to determine the optimal architecture for our specific use case, ensuring that the ALIVEculture platform remains at the forefront of plant disease detection technology.

VI. **CONCLUSION**

In summary, our two-step YOLOv11-based approach represents a significant advancement in plant disease detection. Its integration into the ALIVEculture app, coupled with a continuously evolving framework and migration to YOLOX, promises to maximize its impact. By optimizing the system for mobile deployment, harnessing user feedback for ongoing improvement, and leveraging open-source advancements, we can create a scalable, user-centric solution that addresses the pressing challenges of modern agriculture. These efforts not only enhance the technical capabilities of our AI but also pave the way for its practical adoption and potential commercialization, establishing it as a crucial tool for sustainable farming.

Note: The information presented in this article is based on the development and deployment of AI models for plant disease detection, as implemented on the Aliveculture.ca platform.

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