Towards Trustworthy Multi-modal Foundation Models for Plant Disease Management

Yunqi Li, Xinlin Chen, Qun Liu, Yuewei Lin, Wei Xu
{yli12, xchen7, qunliu, ywlin, xuw}@bnl.gov
Brookhaven National Laboratory

Topic: Trustworthy AI, Multimodal Modeling

Background: Crops (Plants) are constantly attacked by various pathogens, such as fungi, oomycetes, bacteria, viruses, and nematodes, threatening food and energy security by causing detrimental crop (plants) diseases, generating tremendous quality concerns and yielding losses worldwide [1]. Overall, 94% of ethanol in the United States is produced from corn, which is then mixed with U.S. gasoline to reduce air pollution. Plant disease management aims to develop strategies for detecting, preventing, and controlling plant diseases Advanced AI/ML models can provide powerful insights into plant disease prediction, yet ensuring these models are trustworthy is crucial for their effective application.

Biological data are heterogenous, large-scale, and naturally biased due to limited experimental conditions and data acquisition mechanisms, making it rather challenging to maintain AI-ready data for plant disease management. The emergence of Foundation Models (FMs) [2] offers a unique opportunity to enhance the trustworthiness through generating high-quality synthetic data, integrating diverse data modalities, and enabling more reliable decision-making. Additional efforts are still required to tackle the trustworthy issues of the FMs in multiple dimensions such as interpretability, robustness, and uncertainty, thereby advancing AI-driven solutions to support DOE's bioenergy and environmental missions.

Challenge 1: Managing Multi-Modal and Biased Data in Plant Disease Detection. Detecting plant disease requires dealing with a diverse array of data types, including genetic, phenotypic, environmental, and multi-omics data. These datasets are often multi-modal, unbalanced, biased, or incomplete that make analysis and integration difficult. Transforming such heterogeneous data into an AI-ready structure is a significant challenge, as it involves addressing inconsistencies in modality, scale, and quality while ensuring the data is suitable for machine learning models. Effectively overcoming these obstacles is a mandate to enable reliable and actionable insights for plant disease detection.

Opportunity: Harnessing Foundation Models for Multi-Modal Integration and Data Generation. Multi-modal foundation models (FMs) present a transformative opportunity to tackle these challenges. Firstly, FMs can effectively integrate multi-modal data, such as image, sequence, and phenotypic data into a cohesive framework by leveraging text information as a bridge. This integration allows for a more comprehensive understanding of plant-pathogen interactions, revealing patterns and insights that may be hidden when data is considered in isolation. Secondly, when faced with limited or unbalanced data across different modalities, FMs can generate high-quality synthetic datasets to fill these gaps, providing a richer and more robust foundation for AI-driven solutions in plant disease management [3].

Challenge 2: Lack of Robustness and Adaptability in Plant Disease Management. Many current plant disease prediction models are static and typically trained on common crops and pathogens, making them unsuitable for a broader application. This lack of generalizability limits their robustness when faced with dynamic plant disease management challenges. For instance, the progression of plant diseases varies based on region, climate conditions, and pathogen strains. Additionally, plant diseases evolve through the co-evolution of hosts and pathogens. In multifactorial plant disease management, robust and adaptable models are essential for long-term effectiveness and stakeholder trust [4].

Opportunity: FM-based Continuous Learning for Robustness and Adaptability. Continuous learning methods help models to incrementally incorporate new data, improving model robustness and adaptability to dynamic plant disease management challenges. Multi-modal FMs can enhance continuous learning by efficiently processing and integrating diverse, real-time biological data, such as climate changes, environmental shifts, and pathogen dynamics [5]. By learning from both structured data (e.g., genomic sequences, sensor data) and unstructured sources (e.g., research papers, expert knowledge), FMs can adapt to evolving conditions and address regional, seasonal, and co-evolutionary variations in plant diseases, ensuring models remain robust and accurate over time.

Challenge 3: Lack of Model Interpretability in Plant Disease Diagnosis. The diagnosis of plant diseases is a complex process that relies on the combined analysis of phenotypic data, physiological data, and multi-omics data. Effective plant disease prediction depends on understanding the intricate relationships between these diverse data types and the observable model outcomes. However, model opacity—where the decision-making process is not clearly understood—can raise concerns about the reliability of model outcomes, where deviations and errors in the diagnosis of plant diseases could lead to irreversible impacts on the defense against plant diseases and serious economic losses.

Opportunity: Improving FM Model Interpretability with Explainable AI (XAI). Multi-modal FMs can integrate diverse data types, such as genetic, visual, and textual information, enabling a holistic view of plant health dynamics. Existing XAI techniques like feature attributions and latent space understanding [6] must be extended for FM interpretation. Cross-attention can be developed to highlight different modalities' influence and interaction. An approach assisting the loss function design can be essential to incorporate multi-modal data. Finally, making the XAI scalable is also preferred due to an FM's size.

Timeliness: Recent increases in the severity of plant diseases and pests, coupled with the looming threat of global food shortages, highlight the urgent need for improved trustworthy plant disease management. Fortunately, recent breakthroughs in AI, particularly multimodal foundational models, present new opportunities to tackle this critical issue. These advanced models seamlessly integrate real-time multi-modal data to address past limitations in robustness and adaptability, enabling a system-level understanding of complex biological data with greater interpretability and reliability. Trustworthy AI for plant disease management can transform bioenergy agriculture by enabling evidence-based decisions, adaptable models, and broader applicability across crops. These advancements directly support DOE's mission for sustainable agriculture, biosecurity, and economic resilience.

Reference:

[1] Zhu Feng, et al. “Join the green team: Inducers of plant immunity in the plant disease sustainable control toolbox.” J Adv Res. (2024)

[2] Zhou, Ce, et al. "A comprehensive survey on pretrained foundation models: A history from bert to chatgpt." *arXiv preprint arXiv:2302.09419* (2023).

[3] Long, Lin, et al. "On llms-driven synthetic data generation, curation, and evaluation: A survey." *arXiv preprint arXiv:2406.15126* (2024).

[4] Li Yunqi, et al. “Causal factorization machine for robust recommendation.” In Proceedings of the 22nd ACM/IEEE Joint Conference on Digital Libraries. (2022).

[5] Yang, Yutao, et al. "Recent Advances of Foundation Language Models-based Continual Learning: A Survey." *arXiv preprint arXiv:2405.18653* (2024).

[6] Xu, Wei, et al. “Studying the Impact of Latent Representations in Implicit Neural Networks for Scientific Continuous Field Reconstruction.” AAAI co-held XAI4Sci workshop (2024).