NEW ERA AGRICULTURE MAGAZINE

Digital diagnostic for plant diseases: A foundation for sustainable agriculture

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Abstract:

Over the past two decades, digital plant pathology researchers have strived to integrate advanced technologies like sensors and machine learning into plant health monitoring and analysis. This integration has faced numerous obstacles due to the complexity of both greenhouse and field environments, which require different experimental approaches. The field's challenges are multifaceted: researchers must choose appropriate sensor technologies (such as thermal or hyperspectral imaging), determine suitable platforms for deployment (like drones, ground vehicles, or satellites), and consider the specific spatial and temporal requirements of each study. This is particularly complicated because each plant-pathogen system is unique, with distinct symptoms and interactions. The complexity increases when considering how plants, pathogens, and environmental factors interact across time and space. To better understand these relationships, researchers need extensive datasets. Modern machine learning, particularly deep learning, has emerged as a valuable tool for analyzing this complex data efficiently and objectively, potentially revealing previously unknown patterns in plant-pathogen-environment interactions. However, potential users often remain skeptical about these new technological approaches. To bridge this gap between research and practical application, scientists must clearly explain how biological mechanisms relate to machine learning findings, making their results accessible to non-experts. The authors propose creating a global network of experts and data sharing to establish a focused research agenda. This collaborative approach could accelerate progress in both research and practical applications. They suggest organizing international centers of excellence to minimize redundant research while promoting complementary studies. The review aims to examine past research achievements and persistent challenges, using this historical perspective to identify future challenges and propose a direction for digital plant pathology research in the coming decade.

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Introduction

Society's evolving focus on environmental sustainability, now called 'neo-ecology', is fundamentally transforming traditional agriculture. Current agricultural practices, including animal husbandry, crop farming, and plant disease management, are being reevaluated to align with environmental and human health protection goals, following 'agriculture green development' principles. With agriculture currently occupying 38% of Earth's available land (about 5 billion hectares), the sector faces a complex challenge: it must become more environmentally sustainable while simultaneously increasing productivity to feed a growing global population. This challenge has become even more pressing since the COVID-19 pandemic, which saw the number of undernourished people rise from 650 million (8.4%) to 811 million (9.9%). To ensure adequate food production, preventing avoidable crop losses is crucial. While integrated pest management (IPM) has helped limit losses in major food crops (wheat, rice, maize, potato, and soybean) to 20-40% from pathogens and pests, monitoring large agricultural areas remains problematic. Farmers often find it financially impractical to regularly inspect their extensive fields for diseases and other yield-reducing factors. Remote sensing technology offers a solution to this monitoring challenge by providing high-resolution temporal and spatial surveillance. This technology enables efficient identification of diseased plants, allowing for targeted ground analysis and treatment before significant financial losses occur or diseases spread into epidemics. The effectiveness of remote sensing in detecting plant diseases stems from how pathogens and pests alter the way light interacts with plant leaves and canopies. Remote sensing fundamentally involves using non-contact sensors, primarily optical devices like RGB cameras, multi- and hyperspectral sensors, thermal imaging, chlorophyll fluorescence detectors, and 3D imaging systems, to gather data about both natural and human-modified landscapes. These optical sensors enable non-destructive disease monitoring at various scales, complementing traditional monitoring methods that range from molecular testing to smartphone apps, while reducing the manual effort required for field disease detection. However, using remote sensing for field disease detection isn't as straightforward as it might seem. Plant diseases themselves are complex phenomena, characterized by uneven distribution within crop populations and dynamic behavior across time and space, resulting from interactions between living organisms in constantly changing environmental conditions.

The authors emphasize that digital plant pathology's primary objective must be addressing farmers' practical needs. Their paper aims to propose a new direction for research in this field by:

- Examining key milestones in digital plant pathology
- Exploring current imaging technologies and analysis methods
- Assessing the present state of applied digital plant pathology
- Evaluating whether automated disease detection has successfully improved upon manual detection methods

Digital plant pathology

As optical sensor technology advanced, Colwell made a breakthrough in 1956 by using military helicopters equipped with infrared cameras and spectrometers to detect wheat rust and other grain diseases from different viewing angles. His research explored various spectral band combinations and established a novel understanding of light-plant interactions, creating a theoretical foundation that remains crucial in today's digital plant pathology.

By 2000, scientists developed the concept of "foliar functional traits" as a key framework in terrestrial remote sensing, helping to understand both natural plant variations and stress responses. This led to the development of "spectranomics" - combining spectroscopy with chemistry and taxonomy. This approach is based on the principles that plants have distinct chemical and structural signatures, and that spectroscopic measurements can reveal their chemical makeup. Spectranomics enables non-invasive detection of disease-related changes in plants, both before and after symptoms appear visibly. Different wavelength ranges interact with specific aspects of plant biology: ultraviolet (100-380 nm) detects secondary metabolites, visible light (400-700 nm) reveals pigments, near-infrared (700-1000 nm) shows leaf structure, and short-wave infrared (1000-2500 nm) indicates chemical and water content. These spectral properties allow detection of various disease-induced changes in plants, including alterations in nutrients, water content, photosynthesis, and cell structure, explaining why remote sensing effectively detects plant diseases. The combined effect of the basic biochemical, structural, and physiological mechanisms underlying the diseased plant phenotype is evaluated by remote imaging spectroscopy. Although additional electromagnetic spectrum ranges might potentially yield intriguing data, it is frequently impossible to attribute the identified alterations to a particular source. For instance, thermal cameras may detect infrared (8–12 µm) light and provide a "calibrated" plant temperature. There is a close correlation between a plant's temperature and transpiration rate. This allows for the recording of the crop's or plant's water balance as well as the early identification of any drought stress. Despite having extremely high sensitivity, thermography and chlorophyll fluorescence sensors are unable to distinguish between biotic and abiotic stressors and, consequently, a causal relationship to a particular disease. Nonetheless, a particular characterisation of plant diseases can be made possible by a combination of sensors. Zarco-Tejada et al. (2018) were able to pre-symptomatically identify Xylella fastidiosa infection in olive trees in the last several years by using a radiative transfer and machine learning technique (Hernández-Clemente et al. 2019). This was accomplished by combining thermal, solar-induced fluorescence, and hyperspectral NIR data. The authors discovered that in order to differentiate asymptomatically infected plants from both symptomatic and healthy plants, spectral-plant trait changes in response to X. fastidiosa infection were crucial for both spectral stress indicators and pigment degradation traits, especially the chlorophyll degradation phaeophytinization-based spectral trait (NPQI). In their further research, the authors discovered that in irrigated almond fields, NPQI was only suggestive of asymptomatic X. fastidiosa infection. This ultimately resulted in the identification of distinct pathogen and host-specific spectral circuits that respond to biotic and abiotic stressors while producing a comparable visual expression. Despite the fact that bacterial infection and dryness both cause plants to wilt, spectroscopy may be used to identify the differences in the methods by which they do so. The authors subsequently improved their misclassification accuracy from 37% and 17% to 6.6% and 6.5%, respectively, by uncoupling the confounding interaction using the thermal crop water stress index (CWSI). The authors developed a robust disease detection and differentiation methodology for mapping asymptomatic X. fastidiosa infection in diverse crops at scale by evaluating spectrum trait measures that identified the underlying physiochemical cause of their diseased plant phenotype. This accomplishment supports and gives hope to further research aimed at identifying illnesses in multistress, real-world settings.

Data handling and machine learning

After collecting imaging data, researchers must develop comprehensive data analysis pipelines to extract meaningful information. The process involves several key steps:

First, the raw data must undergo preprocessing, which includes:

- De-noising and smoothing
- Calibration
- Image segmentation

- Outlier removal

These steps transform raw image data into features suitable for machine learning applications. This preprocessing stage is crucial but demanding, especially for different types of sensors used in greenhouse and field settings.

For hyperspectral measurements, researchers can either use:

1. Raw reflectance signals directly, or
2. Simplified vegetation indices like NDVI or OSAVI to reduce data complexity while maintaining predictive power

Field-based multispectral imaging presents additional challenges, requiring more extensive registration and calibration due to changing environmental conditions and larger areas of interest. 3D imaging techniques can help provide necessary calibration information in these situations.

The machine learning phase then gives meaning to the processed data. This typically involves supervised learning, where classifiers are trained to distinguish between different types of infections or diseases. The process requires:

- A labeled dataset split into three parts:
  - Training set (to generate the model)
  - Validation set (for fine-tuning)
  - Test set (for measuring accuracy)

While creating labeled datasets requires significant manual effort, machine learning's ability to learn analysis rules automatically has made it increasingly popular in plant science, contrasting with conventional methods that rely on predetermined analysis rules.

Digitalization in agricultural practice: are robots the better farmer?

Researchers have become more comfortable with unmanned aerial and terrestrial vehicles since the year 2000. These might be outfitted with reflectance-based disease detection sensors that have higher spatial resolutions, making it easier to distinguish between biotic and abiotic stress. According to West (2003), some systems achieved a work rate of three ha/h. However, consistent and high-quality data retrieval was being hampered by fluctuations in illumination intensity, sun/sensor alignment, and/or background soil reflection. Soil dust proved to be another issue, resulting in inaccurate detection and actual crop damage from the vehicle.

These days, mobile platforms like drones, automobiles, and robots can operate with a high degree of autonomy thanks to advancements in automation, mechatronics, sensors, electrical engineering, and artificial intelligence. The next technological advancement in agriculture is the use of autonomous robots with advanced sensor systems for automated mechanical weeding, spot-spraying of pesticides, and accurate fertilizing. According to Lowenberg- Deboer et al. (2020), automated robotic applications may even provide a substitute for human labor shortages, particularly for labor-intensive jobs like physical weeding or vegetable harvesting. Additionally, by taking into account regional heterogeneities in plant pest dispersion or input parameters like nutrients, water, and agrochemicals, automated systems redesigned agricultural production. Depending on the crop variety and cultivation system, many robotic applications for crop management have been developed. The use of UAVs in the field to release Trichogramma brassicae, a natural adversary of the European corn borer Ostrinia nubilalis, as a biological control in maize plants is one example. UAVs provide for a quick and useful application in open terrain as opposed to the manual use of "Trichogramma bags." Higher levels of automation are already in place in the greenhouse, such as robotic plant protection measures for tomatoes or robotic harvesting of vegetables like pepper. Field crops provide a diversity of obstacles as they might be randomly distributed (e.g., cereals) or grown in rows (e.g., corn, sugar beet, cauliflower). The selective elimination of weeds within and between crop rows utilizing actuators such mechanical weeding tools, lasers, stampers, or milling heads is an increasingly popular application. When trained laborers for manual weeding were unavailable during the COVID-19 pandemic, prototypes of these weeding robots increased public awareness (Mitaritonna and Ragot 2020). Robots that pull weeds are rapidly evolving, especially for row crops. These robots can be outfitted to handle various working concepts and are commercially accessible. The first idea relies on the seed pill's extremely precise GPS location An automated weeding system and orientation require precise sowing with very little mistake. With the exception of the vicinity of the seed, the entire field is weeded by the robots. The seeding phase has no bearing on the second idea. The robot can identify the crop rows and modify its position, direction, and navigation course by using digital cameras, a modified vision recognition system that primarily relies on neural networks, and a sizable underlying training dataset. Furthermore, the weeding instruments can be positioned in between or across rows.

Conclusion

Digital plant pathology has made significant strides, as this review has shown, but there is still much more to be done. The state-of-the-art must be frequently challenged, and new problems must be identified and resolved, in order to fully realize the potential. Pathosystems can be highly specialized and complex, thus current methods need to be critically assessed and adjusted based on the specifics of each pathosystem. It is essential to have generalized frameworks and models that are easy for farmers to understand and use. A global database containing spectrum disease and plant spectra could serve as an excellent starting point for the development of generalized models. The TRY plant trait database (www.try-db.org; Kattge et al. 2020) is an example of a database of this type from a different field. Having a uniform method for cleaning and uploading data may be one of the challenges of such a spectrum data collecting. Simple database access, acknowledgment of contributions, sustainable data storage, and funding for data curation over several years or decades are all requirements. It should also be mandatory to relate the supplied dataset to the sensor type, ambient circumstances, and other relevant metadata. Presently, a lot of papers offer analysis pipelines on a small number of isolated databases (such as Plant Village Data; https://www.kaggle.com/ emmar ex/ plant disea se), which are unrelated to the intricate situations seen in the field. Algorithms are frequently not novel, and biological interpretation is absent. Nonetheless, this need to be a requirement for new publications in the field of digital plant pathology. It is necessary to integrate the intricate facets of machine learning, sensors, and phytopathology. This intricacy could be captured and deconstructed with the aid of a worldwide database.

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