

# **TRANSFORMING PLANT HEALTH WITH AI-POWERED DISEASE DIAGNOSIS**

**Neha A<sup>1</sup> , Sreechithra M S<sup>1</sup> , Sherin A Salam2\* and Heera G 2**

*<sup>1</sup>M.Sc. (Ag.) Plant Pathology, College of Agriculture, Vellayani, Thiruvananthapuram 695522 <sup>2</sup>Assistant Professor, Department of Plant Pathology, College of Agriculture, Vellayani, Thiruvananthapuram- 695522 \*Corresponding Author Mail ID: [sherin.salam@kau.in](mailto:sherin.salam@kau.in)*

#### **Introduction**

In developing nations, plant diseases incite an approximate annual loss of 10% leading to severe financial setbacks for farmers and generating social instability in regions that rely heavily on specific crops. Every year a yield loss of 40% is recorded in economically important crops due to the combined effect of pests and disease (Baldi and La Porta, 2020). The financial impact of plant diseases is substantial, with an annual estimated loss of \$220 billion (FAO, 2019). Moreover, by 2050 the global population is expected to reach 9.7 billion, enhancing the demand for food that will exacerbate the importance of addressing the socioecological and economic ramifications of plant diseases (FAO, 2024)

Plant diseases occurring in the field or post-harvest can lead to substantial yield and financial losses for the global agriculture sector. Sustainable agriculture relies mainly on effective monitoring of plant health and early disease detection. Currently, no commercially available sensors are capable of assessing plant health in real time. The primary method for monitoring plant stress is scouting, which is costly, time-consuming, and labour-intensive. Molecular techniques like polymerase chain reaction (PCR) used to identify plant diseases require detailed collection and sample

processing procedures. Detection of plant health issues and diseases at early stages is critical for improving productivity and managing diseases through targeted interventions, such as the application of fungicides, pesticides, or disease-specific chemicals to control pathogens and vectors.

Recent developments in artificial intelligence (AI) and machine learning techniques revolutionizing plant pathology through the integration of various sensors, drones, robots, and intelligent monitoring systems are employed. For phenotyping plant stress, diagnosing, and assessing the severity of plant diseases in both field and horticultural crops computer vision techniques are used. The development of IOT-based sensors is enhancing research on host-pathogen interactions and facilitating early identification and prediction of plant diseases by detecting biomarkers such as volatile organic compounds. Unmanned aerial vehicles (UAVs) are now employed for precise phenotyping of orchards and targeted application of fungicides and other plant protection chemicals. Additionally, AI and smartphonebased diagnostic tools are gaining traction globally, particularly in remote areas where laboratory access is limited (Prabha *et al*., 2021).

# **Methods for Identifying Plant Pathogens**

#### **1.Visual Observation**

The initial step in diagnosing plant health issues involves comparing a sick plant to a healthy one within the same growing environment. Key observations include changes in root systems, plant height, colour, leaf shape, leaf density etc. Use of a magnifying lens to inspect for mycelium, sporangiophores, or sclerotia in diseased areas, such as necrotic spots on stems or leaves. The presence of these indicators may suggest a pathogenic fungus. Often, visual observation can help identify whether the pathogen is a worm, fungus, bacteria, or virus based on symptoms. However, it is usually not sufficient for a definitive diagnosis (Khakimov et al., 2021).

#### **2. Microscopy**

Precision microscopes are essential for detailed diagnosis. After visual inspection, diseased plant samples are taken to a lab for microscopic analysis. Examining structures such as hyphae, microsclerotia, conidiophores, conidia, and bacterial cell clusters under the microscope can help diagnose the specific pathogen affecting the plant (Khakimov et al., 2021).

### **3. Mycological Diagnosis**

The "moist chamber" method is used for growing fungi from infected plant parts under controlled conditions. Infected plant samples (e.g., fruit slices, leaves, or roots) are placed on sterile blotting paper in Petri dishes and incubated at 24-28°C. (for Phytophthora species it is 17-20oC). This method promotes fungal growth, allowing for the identification of the fungus, including its genera and species, through microscopic examination of the hyphae, macroconidia, and microconidia (Khakimov et al., 2021).

#### **4. Biological Assays or Indicator Plant Tests**

These tests are often used alongside other diagnostic methods to detect phytoplasmas and plant viruses. Indicator plants and trees are employed for biological testing. Mechanical inoculation or injection of a typical buffer suspension is used to infect indicator plants. Additionally, micro-grafting techniques are employed on indicator trees and shrubs to simulate infection. These tests are conducted in controlled environments to assess the presence of the pathogens (Khakimov et al., 2021).

# **Why choose Artificial intelligence for Plant disease detection?**

Plant Pathologists usually rely on conventional methods to identify plant diseases but they are resource-intensive, timeconsuming, and require special knowledge. To address the challenges mentioned above that are prevalent in modern agricultural settings, computer-aided automated studies such as machine learning and deep learning can be instrumental in facilitating precise, rapid, and early identification of diseases. The benefits of using these technologies are found in their capacity to produce results quickly and accurately by using image processing and computerized detection methods. Artificial intelligence (AI) methods in agriculture can save labor expenses, eliminate time wastage, and improve crop quality and production overall. By employing the early data regarding crop health and the precise location of diseases, the deployment of appropriate management measures can aid in the implementation of disease control plans.

# **Automated Plant Disease Detection Using Artificial Intelligence, Machine Learning, and Deep Learning**

Automated detection of plant diseases is becoming increasingly crucial for preventing frequent crop diseases and minimizing associated losses. AI-powered systems follow a structured process that begins with capturing and recording plant images through various sensors deployed in agricultural fields. These images are then processed and segmented to be used as input for machine learning algorithms. The algorithms analyse the images to predict whether the leaves are healthy or infected with the disease. This automation streamlines the detection process, improving efficiency and accuracy in managing plant health.



### **Plant Image Acquisition**

During this stage, capturing highresolution plants' images are captured using digital cameras or smartphones, supporting formats such as PNG, JPG, and TIF. These images, consisting of binary data, are then processed and analyzed on a computer. If the initial images do not meet processing standards, image-enhancing techniques are applied to improve quality. Accurate image acquisition is critical for effective disease classification, as machine learning (ML) models

rely on these images for training. Numerous datasets, such as PlantVillage and IPM Images, provide examples of both healthy and diseased plant leaves for comprehensive analysis.

#### **Image Pre-processing**

Raw images often contain noise, blur, or irrelevant background elements that hinder accurate disease classification. To address this, pre-processing techniques clean and format the images, removing unwanted artifacts and standardizing them for further analysis. This step is essential for ensuring that the images are suitable for the next stages of segmentation and feature extraction.

#### **Image Segmentation**

Segmentation divides an image into specific regions or components in order to facilitate the analysis of specific features. This process helps to isolate and differentiate between healthy and infected areas of the plant, which is crucial for accurately classifying diseased leaves. By focusing on relevant parts of the image, segmentation enhances the precision of disease detection.

### **Feature Extraction**

Feature extraction involves identifying and quantifying characteristics of the plant images related to their health status. Key attributes such as shape, colour, and texture are used as feature descriptors. This process transforms raw data into meaningful and relevant features that can be used for classification. In the context of machine learning, feature engineering is essential for converting unprocessed data into a set of informative characteristics that the model can use to assess plant health and identify diseases.

#### **Machine Learning Algorithms in AI**

To comprehend the impact of AI on plant disease detection, it's essential to understand the Machine learning (ML). which is a, a subset of AI that aims to equip computers with the ability to learn from experience, utilizing diverse methods tailored to specific tasks and problems.

#### **Supervised Learning**

This approach involves training a system using input data paired with corresponding output values. The goal is to predict outputs based on new inputs. Supervised learning is commonly used for classifying plant diseases using labeled datasets.

#### **Unsupervised Learning**

Unlike supervised learning, unsupervised learning identifies hidden patterns in data without predefined inputoutput pairs. This method is useful for discovering underlying structures in the data that are not labelled.

#### **Semi-Supervised Learning**

This is a combination of both labeled and unlabelled data, leveraging the strengths of both mentioned above to improve model performance.

ML tasks generally fall into two categories, classification and regression. The classification was meant to assign inputs to predefined categories, such as different plant disease types. whereas, regression predicts continuous numerical values, which might be used for estimating disease severity. Common ML algorithms include random forests, decision trees, k-nearest neighbors, artificial neural networks, support vector machines, linear regression, and naive Bayes.

#### **Deep Learning Models**

Deep learning (DL), a specialized branch of AI and ML, has significantly advanced fields such as image classification, object recognition, and natural language processing. By utilizing neural networks for automatic feature extraction, deep learning minimizes the necessity for manual feature engineering and boosts precision in applications such as image recognition

# **DL development can be categorized into two eras**

**First Era (1943-1998):** Marked by early innovations like backpropagation and foundational architectures such as LeNet.

**Second Era (2006-present):** Characterized by breakthroughs such as deep belief networks, autoencoders, and convolutional neural networks (CNNs). These modern algorithms are applied across diverse sectors, including autonomous vehicles, healthcare, and finance. **Limitations**

AI and image processing offer significant advantages in the detection of plant diseases, but they also face challenges. Here, image processing can effectively identify disease-affected areas but often struggles with issues like noise and complex backgrounds. Although computer vision is pivotal in agriculture, real-time ML systems for disease detection are still scarce. The effectiveness of disease control also hinges on the appropriate use of chemical treatments, as misuse can damage crops and harm the environment. Advanced automated systems are necessary to address these challenges. Early disease detection is critical, yet there is a need for userfriendly mobile apps and websites that can provide accessible real-time diagnostic tools. While efficient disease identification models exist, they require thorough validation for

deployment on mobile and web platforms. Drones, despite their high cost, are increasingly used for monitoring and treatment in agriculture.

# **Future aspects of AI in Plant disease detection**

Hence, it proposed a framework that integrates AI models, trained on extensive plant disease databases which could validate the learning techniques when transferred. This framework envisions deploying these models on mobile apps or drones, allowing for realtime image capture and analysis. By combining AI with IoT sensors, the framework aims to improve the accuracy and accessibility of plant disease detection. This approach seeks to advance the field by providing more efficient and practical solutions for monitoring and managing plant health.

#### **Conclusion**

Effective crop cultivation relies heavily on precisely detecting and classifying plant diseases. Annual disease detection presents challenges, such as accounting for diverse agricultural practices, distinguishing between the various types of diseases and recognizing similar symptoms of different diseases. This process demands significant time, resources, and expertise, all of which could impact crop quality and productivity considerably.

To overcome these challenges, AI techniques offer a promising solution for automated disease identification. By leveraging AI, it is possible to streamline the detection process, improve accuracy, reduce the time, resources required, ultimately enhancing crop health and productivity.

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