

Artificial Intelligence (AI): A Path to Future's New Horizon in Disease Detection

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Artificial Intelligence (AI) has transformative potential in revolutionizing plant disease detection, with a focus on enhancing agricultural sustainability. By employing advanced machine learning and deep learning techniques, AI facilitates predictive modelling based on environmental data and precise image recognition of disease symptoms. This proactive approach enables timely intervention, mitigating crop losses and bolstering food security, especially in regions such as India. AI driven decision support systems empower farmers with personalized recommendations, optimizing resource allocation and reducing reliance on fungicides. Through accessible knowledge sharing platforms, AI democratizes agricultural expertise, empowering farmers to combat plant diseases effectively and safeguard their livelihoods.

Introduction

Unforeseen crop loss due to delayed disease detection is becoming a major challenge in front of sustainable agriculture. When diseases go unnoticed or untreated, they can spread rapidly throughout a crop, causing widespread damage and yield reduction. One major consequence of delayed detection is the inability to implement timely control measures such as fungicide application or crop rotation. As a result, pathogens are allowed to proliferate unchecked, causing extensive damage to plant tissues and compromising the overall health of the crop. Studies has estimated that delayed detection of plant diseases can result in substantial crop losses ranging from 20% to 40% annually (Jones and Smith, 2019). For instance, a study conducted by the Food and Agriculture Organization (FAO) reported that delayed detection of wheat rust led to a 25% reduction in global wheat yields (FAO, 2018).

Early disease detection is paramount in agriculture as it enables timely intervention, reducing crop losses, safeguarding farmers' livelihoods, and ensuring food security. In India, where agriculture plays a vital role in the economy and sustenance of millions, the importance of early disease detection cannot be overstated. However, the current scenario of disease detection in India presents several challenges.

One of the significant challenge is the lack of widespread access to advanced diagnostic tools and technologies, particularly in rural areas where the majority of farmers reside. Traditional methods of disease detection, such as visual observation, are still commonly used, but they often lack precision and can lead to misdiagnosis or delayed detection (Kumar *et al.*, 2018). There is also a shortage of trained personnel capable of accurately identifying and diagnosing plant diseases, further hindering early detection efforts (Chandra *et al.*, 2020).

The huge diversity of crops cultivated in India presents a complex landscape for disease management. Each crop is susceptible to a myriad of pathogens, making comprehensive monitoring and surveillance a daunting task. Limited resources and infrastructure further exacerbate the difficulties in implementing effective disease detection and management strategies.

Artificial Intelligence (AI) holds tremendous promise as a ray of hope for addressing the challenges of disease detection in agriculture, particularly in a country like India. With its ability

to analyze vast amounts of data quickly and accurately, AI offers innovative solutions to improve early disease detection and management.

One way AI can revolutionize disease detection is through the development of predictive models that leverage data on environmental conditions, crop characteristics, and disease dynamics to forecast disease outbreaks. By analysing historical data and real-time information from various sources such as weather stations, satellite imagery, and crop sensors, AI algorithms can identify patterns and trends indicative of disease presence or risk. These predictive models can alert farmers and agricultural authorities to potential outbreaks before they occur, allowing for proactive intervention measures to be implemented (Ramesh *et al.*, 2020).

Image recognition technologies have the potential to enhance the accuracy and efficiency of disease diagnosis. By analysing images of plant symptoms captured by drones, smartphones, or other imaging devices, AI algorithms can identify specific disease symptoms with high precision, enabling rapid and accurate diagnosis even in remote or resource-constrained settings. This can significantly reduce the reliance on human expertise for disease identification and empower farmers to take timely action to mitigate the spread of diseases (Bhattacharya *et al.*, 2021).

Also, The AI enabled platforms and mobile applications can facilitate knowledge sharing and capacity building among farmers by providing access to educational resources, training modules, and expert advice on disease detection and management. By democratizing access to agricultural expertise and information, these technologies can empower farmers, particularly those in remote or marginalized communities, to effectively tackle plant diseases and protect their crops.

AI as technology

Artificial Intelligence (AI) is a branch of computer science that aims to create systems capable of performing tasks that typically require human intelligence. One of the key technologies within AI is machine learning, which enables computers to learn from data and improve their performance over time without being explicitly programmed (Russell and Norvig, 2021).

Machine learning algorithms can be broadly categorized into supervised learning, unsupervised learning, and reinforcement learning (Goodfellow *et al.*, 2016). In supervised learning, algorithms are trained on labelled data, where each input is associated with a corresponding output. The algorithm learns to map inputs to outputs by identifying patterns and relationships in the data.

Unsupervised learning involves training algorithms on unlabelled data to identify hidden patterns or structures within the data (Bishop, 2006). Clustering algorithms, such as k-means clustering and hierarchical clustering are examples of unsupervised learning techniques commonly used for tasks such as customer segmentation and anomaly detection.

Reinforcement learning is a type of machine learning where an agent learns to interact with an environment to achieve a specific goal (Sutton and Barto, 2018). The agent receives feedback in the form of rewards or penalties based on its actions, and it learns to optimize its behaviour over time to maximize cumulative rewards. Reinforcement learning has applications in robotics, gaming, and autonomous systems.

Deep learning is a subfield of machine learning that focuses on neural networks with multiple layers (LeCun *et al.*, 2015). Deep learning algorithms, known as deep neural networks, are capable of learning hierarchical representations of data, which enables them to capture

complex patterns and relationships in large datasets. Convolutional Neural Networks (CNNs) are widely used in computer vision tasks, such as image classification and object detection, while Recurrent Neural Networks (RNNs) are commonly used in natural language processing tasks, such as language translation and sentiment analysis.

In the context of disease detection, AI technologies, particularly machine learning and deep learning, have shown great promise in improving the accuracy and efficiency of diagnosis (Topol, 2019). By analyzing large volumes of data, including medical images, genetic data, and clinical records, AI algorithms can identify patterns and biomarkers indicative of disease presence or risk.

Transforming the plant disease detection

Artificial Intelligence (AI) has the potential to revolutionize plant disease detection by offering innovative solutions to improve accuracy, efficiency, and scalability. With the increasing availability of data and advances in AI technologies, such as machine learning and computer vision, researchers and agricultural stakeholders are exploring new approaches to detect and manage plant diseases more effectively.

One way AI can transform plant disease detection is through the development of predictive models that leverage data on environmental conditions, crop characteristics, and disease dynamics. By analysing large datasets collected from sources such as satellite imagery, weather stations, and field sensors, AI algorithms can identify patterns and correlations indicative of disease presence or risk. These predictive models can enable early detection of plant diseases, allowing farmers to implement timely intervention measures to prevent or mitigate crop losses (Mohanty *et al.*, 2016).

Image recognition technologies powered by AI can enhance the accuracy and efficiency of disease diagnosis by analysing images of plant symptoms captured by drones, smartphones, or other imaging devices. Convolutional neural networks (CNNs), a type of deep learning algorithm, can learn to recognize specific disease symptoms with high precision, enabling rapid and accurate diagnosis even in remote or resource-constrained settings. By automating the process of disease identification, AI can help farmers make informed decisions about disease management strategies, such as selecting appropriate treatments or implementing quarantine measures (Fuentes *et al.*, 2017).

Decision support systems driven by AI can assist farmers in making proactive management decisions by providing personalized recommendations based on real-time data and predictive analytics. These systems can analyse diverse datasets, including historical disease incidence, crop health monitoring, and agronomic practices, to generate tailored recommendations for disease prevention and control. By leveraging AI technology, farmers can optimize resource allocation, minimize pesticide use, and maximize crop yields while reducing the risk of disease outbreaks (Liu *et al.*, 2019).

Numerous platforms and mobile applications can facilitate knowledge sharing and capacity building among farmers by providing access to educational resources, training modules, and expert advice on disease detection and management. By democratizing access to agricultural expertise and information, these technologies can empower farmers, particularly those in remote or marginalized communities, to effectively tackle plant diseases and protect their crops (Singh *et al.*, 2019).

Image recognition: from pixel to plant health

An image recognition system for disease detection in plants is a powerful tool that focuses on collecting data on various diseases affecting plants and training models to accurately detect these diseases. This system utilizes advanced techniques, including CNN, to analyze images of plant leaves and identify symptoms associated with different diseases (Mohanty *et al.*, 2016). Here's how such a system works:

Collection of disease data and model training: The image recognition system begins by collecting a diverse dataset of images depicting plants affected by various diseases. These images serve as the training data for the AI model. The model learns to distinguish between healthy plants and those exhibiting symptoms of disease by analysing patterns and features present in the images.

Utilization of CNN for recognition and classification: CNNs are employed in the image recognition system for their effectiveness in recognizing patterns in visual data. These neural networks are trained to automatically extract relevant features from plant images and classify them based on the presence or absence of disease. Additionally, CNNs can be adapted for smartphone-based applications, enabling on-the-go detection by capturing images of plant leaves and analysing them for signs of disease based on size, colour and texture.

Workflow of disease detection: The image recognition system follows a systematic workflow for disease detection, which includes several key steps:

- **Image Acquisition:** Images of plant leaves are captured using cameras or smartphones.
- **Pre-processing:** The captured images undergo pre-processing techniques to enhance their quality and remove noise.
- **Segmentation:** The images are segmented to isolate the regions of interest, such as the plant leaves, from the background.
- **Feature extraction:** Relevant features, such as texture, shape, and colour information, are extracted from the segmented regions.
- **Classification:** The extracted features are inputted into the trained CNN model, which classifies the images into categories based on the presence of disease.
- **Prediction:** The system provides predictions regarding the presence of disease and, if applicable, identifies the specific disease affecting the plant.
- **Outcome and recommendations:** The image recognition system enables users to determine whether a crop is infected with a disease and provides valuable insights into the severity and type of disease (Fig. 1). By analysing the colours and patterns developed due to the disease, the system can classify the specific disease affecting the plant. Based on the severity of the disease, the system suggests various remedies and management strategies to mitigate its impact on crop yield.

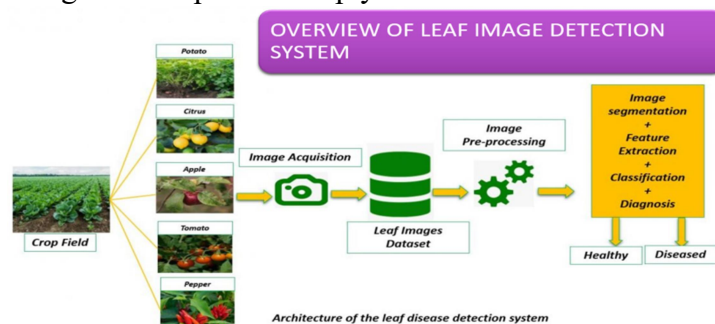


Fig.1. Overview of leaf image detection system

Smart farming solution: integrating machine learning with IoT sensors

Smart farming solutions that integrate machine learning with IoT sensors offer advanced capabilities for monitoring, analysing, and optimizing agricultural processes. These solutions leverage data collected from various sensors deployed in the field to provide real time insights and decision support for farmers. One notable case study demonstrating the effectiveness of such an approach is the research conducted by Patil *et al.*, 2016, titled "Early Detection of Grape Diseases Using Machine Learning and IoT."

In their study, Patil *et al.*, 2016 developed a model for early detection of grape diseases by integrating Wireless Sensor Network (WSN), IoT and statistical modelling, specifically Hidden Markov Model. The model utilized inputs from sensors measuring temperature, relative humidity, and leaf wetness, which were then converted into digital format for analysis.

The data collected from these sensors were transmitted to a central server using Zig-Bee wireless communication protocol and stored in a database for further processing (Table 1). By continuously monitoring environmental parameters and plant health indicators, the system gathered a large volume of data over time, creating a valuable dataset for analysis.

Using machine learning techniques, particularly Hidden Markov Models, the researchers classified grape diseases based on various parameters derived from the sensor data. By analysing patterns and deviations in the collected data, the model was able to detect early signs of diseases affecting the grapevines.

The integration of machine learning with IoT sensors enabled the system to provide timely alerts to farmers, allowing them to take proactive measures to prevent the spread of diseases and minimize crop losses. By leveraging real-time data and predictive analytics, farmers could optimize their farming practices, such as adjusting irrigation schedules, applying targeted treatments, or implementing preventive measures, to maintain crop health and maximize yields.

Table 1. Weather data obtained from Zig-bee wireless communication protocol

Disease name	Temperature ($^{\circ}$ C)	Relative humidity (%)	LH (hrs)
Bacterial leaf spot	25-30	80-90	-
Powdery mildew	21-27	>48	-
Downey mildew	17-35	>48	2-3
Anthraxnose	24-26	-	12
Bacterial canker	25-30	>80	-
Rust	24	75	-

Source: Patil *et al.*, 2016

Smart application in disease detection

Smart applications in disease detection leverage technology to provide farmers with valuable tools and resources for identifying and managing crop diseases effectively. Several notable examples include:

Plant doctor: A joint venture between green savers and the United Nations, plant doctor offers a comprehensive platform for diagnosing plant diseases and providing recommendations for treatment and management.

Rice doctor: Developed by the International Rice Research Institute (IRRI), Lucid team at the University of Queensland, Australia, Philippine Rice Research Institute (PhilRice), and Research



Institute for Rice, Indonesia, Rice Doctor is a smartphone application designed to assist rice farmers in diagnosing and managing rice diseases.

Plantix: Developed by Progressive Environmental and Agricultural Technologies (PEAT), Germany, in collaboration with ICRISAT, CIMMYT, FAO, and PJTSAU, Plantix is an AI-powered mobile app that helps farmers identify plant diseases, pests, and nutrient deficiencies using image recognition technology.

Crop doctor: Developed by IGKV-NIC, Raipur, Chhattisgarh, Crop Doctor is an application that provides farmers with information on crop diseases, their symptoms, and recommended management practices.

Leaf doctor: A collaborative effort between Cornell University and the University of Hawaii at Manoa, College of Tropical Agriculture and Human Resources, Leaf Doctor is a smartphone application that assists farmers in diagnosing and managing leaf diseases in various crops.

Ricexpert: Developed by ICAR-National Rice Research Institute (NRI), Cuttack, Ricexpert is an online platform that provides rice farmers with information and advisory services related to rice diseases and pest management.

Pestoz - Identify plant diseases: created by Agro Connect India Pvt. Ltd., Chhattisgarh, Pestoz is a mobile application designed to help farmers identify and manage plant diseases through image recognition and expert advice.

Remote sensing technologies: Eyes in the sky

Remote sensing (RS) technologies play a crucial role in disease detection by providing non-invasive methods for obtaining information about plants or crops. RS involves capturing data on an object, such as vegetation, by measuring the electromagnetic energy reflected, backscattered, or emitted by the Earth's surface. These measurements are then processed and analysed to retrieve valuable information about the observed object, such as plant health (Jensen, 2007).

RS is an indirect assessment technique that enables the monitoring of vegetation conditions from a distance, allowing for the evaluation of spatial extent and patterns of vegetation characteristics and plant health. When plants are stressed, such as by disease, they exhibit protection mechanisms that lead to suboptimal growth. These stress-induced changes manifest as alterations in variables like leaf area index (LAI), chlorophyll content, or surface temperature, resulting in a spectral signature distinct from that of healthy vegetation.

The RS scientific community defines plant disease monitoring through three main stages:

- **Detection:** Identifying deviations from healthy vegetation.
- **Identification:** Diagnosing specific symptoms and differentiating between various diseases.
- **Quantification:** Measuring disease severity, such as the percentage of leaf area affected.

Different sensors and techniques are required to detect plant responses to various diseases and assess disease severity accurately. These may include multispectral or hyperspectral sensors, thermal imaging, or LiDAR (Light Detection and Ranging), each offering unique capabilities for capturing and analysing plant health indicators (Fig. 2).

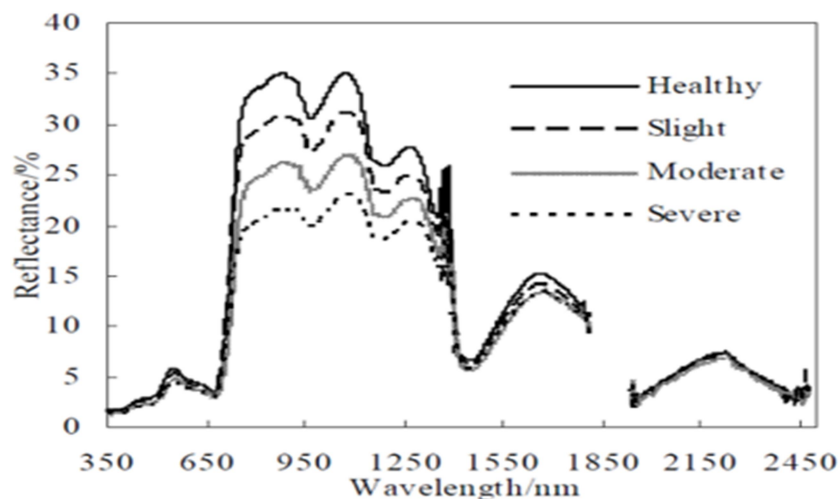


Fig. 2. The spectral reflectance of healthy wheat and wheat infected by leaf rust pathogen at damage levels
(*Source:* Geobotanical Study of Some Areas South-Western Mosul by using Remote Sensing and ASD Dataset - Scientific Figure on Research Gate)

Challenges and future opportunities

AI presents immense potential as a path to the future's new horizon in disease detection, it also comes with its set of challenges and future opportunities. The integration of AI technologies, such as machine learning and computer vision, has already shown remarkable progress in revolutionizing disease detection across various sectors, including agriculture.

However, challenges remain, including the need for robust data infrastructure, addressing ethical considerations surrounding data privacy and bias, and ensuring equitable access to AI-enabled solutions, particularly in underserved communities. Additionally, the complexity of disease dynamics and the ever-evolving nature of pathogens require continuous innovation and adaptation of AI models and algorithms to stay ahead of emerging threats. Despite these challenges, the future holds promising opportunities for leveraging AI in disease detection. Advancements in sensor technologies, data analytics, and computational power offer new avenues for improving the accuracy, efficiency, and scalability of disease detection systems. Collaborative efforts between researchers, policymakers, industry stakeholders, and communities are essential to harnessing the full potential of AI in addressing global plant health challenges.

It can empower individuals and communities with actionable insights and decision support tools to enhance disease prevention, early detection, and management. By fostering interdisciplinary collaborations and investing in research and development, we can unlock the transformative power of AI to create a healthier and more resilient future for all.

Conclusion

AI is opening new horizons in the detection of diseases in agricultural crops, offering innovative solutions that enhance precision and efficiency in farming. By integrating AI with advanced imaging and sensor technologies, farmers can now detect crop diseases at an early stage. This early detection allows for timely interventions, reducing crop loss and improving yield quality. Furthermore, AI-driven tools can analyze vast datasets from various sources, including weather patterns and soil conditions, to predict potential disease outbreaks, enabling proactive measures. As AI continues to evolve, it promises to transform agriculture by ensuring healthier crops, optimizing resource use, and contributing to global food security.