FLORA, FAUNA, FOOD, FOREST & FARMING
Share Knowledge • Inspire Nature • Shape Future
ISSN: XXXX-XXXX | Volume: 01, Issue: 03 (October, 2026) | https://fffff.in

Role of AI in Plant Disease Detection

*Dr. Chahat Kaundal[1], Rajesh Kumar[2] and Dr. Aman Sharma[3]
[1]YP-II, ICAR-Indian Institute of Wheat and Barley Research, Karnal, Haryana, India
[2]Horticulture Development Officer, Head Office, Navbahar, Shimla, Himachal Pradesh, India
[3]Research Scholar, Dr. YS Parmar University of Horticulture and Forestry, Nauni, Solan, Himachal Pradesh, India
*Corresponding Author's email: chahat.k4128@gmail.com

Plant diseases can reduce yield, quality and farm income, particularly when diagnosis is delayed. Artificial intelligence (AI), especially machine learning and computer vision, can screen plant images and other sensor data for disease-related patterns. These tools may speed up preliminary diagnosis, but their reliability depends on representative data, image quality and validation under real field conditions. AI is best used as decision support alongside farmer experience and plant-health expertise.

How the technology works

Developers collect images of healthy plants and plants with confirmed diseases, label them and train a model to recognise patterns in colour, texture and lesions. A user can then submit a new image and receive a predicted class or confidence score. More advanced systems combine images with weather, crop stage or time-series observations. The quality of the output depends on the correctness of labels and how well the training data represent the user's field.

Applications and benefits

Smartphone tools can help farmers screen common symptoms and decide when to seek expert advice. Drone imagery can flag unusual patches across large fields, though it may detect general stress rather than a specific pathogen. AI can assist researchers in scoring disease severity, monitoring outbreaks and evaluating resistant varieties. Timely alerts may reduce unnecessary pesticide use, but only when recommendations are accurate and locally appropriate.

Limitations

Laboratory images may be clearer than field images, where lighting, dust, overlapping leaves and mixed stresses complicate detection. Nutrient deficiencies, drought, herbicide injury and pests can resemble disease symptoms. Models may perform poorly on unfamiliar crops or regions and can return confident but incorrect results. Smartphone access, connectivity, language, privacy and affordability also shape adoption. Some cases still require laboratory confirmation.

Building trustworthy systems

Training data should cover different varieties, locations, seasons and field conditions. Independent field trials should report false positives, false negatives and performance for each relevant disease. Systems should communicate uncertainty and provide access to human review. Local-language interfaces, farmer training, privacy safeguards and regular updates are essential as pathogens and practices change.

Choosing the right evaluation metrics

A disease-detection model should be evaluated with more than overall accuracy. Precision indicates how often a positive prediction is correct, while recall indicates how many actual positive cases are detected. False negatives may allow disease to spread; false positives may cause unnecessary spraying or expense. The balance between these errors depends on the crop, disease severity and available response. Evaluation should therefore report class-wise results and explain the consequences of mistakes.

From detection to recommendation

Identifying a likely disease is only one step. Farmers also need to know whether the diagnosis is sufficiently certain, what confirmation may be needed and which management practices are appropriate. Recommendations should follow integrated pest management principles, considering resistant varieties, sanitation, crop rotation, biological controls and approved treatments where justified. An AI system should not automatically recommend a pesticide without accounting for local registration, crop stage, label directions and safety requirements.

Equity and local knowledge

Digital tools are more useful when farmers can use them in their own language and under realistic connectivity conditions. Community-based extension workers can help interpret results and collect feedback about model failures. Farmers should understand that photographs may contain location or other sensitive information and

should be told how data are stored and used. Systems that learn from local observations can improve, but data-sharing arrangements should be transparent and fair.

Implementation pathway

A practical deployment should begin with a defined crop and a limited set of locally important diseases. Developers should work with plant pathologists and extension services, test the tool across farms and seasons, and compare its advice with expert diagnosis. Results should be monitored after launch, with a process for reporting errors and updating the model. This measured approach is more dependable than promoting a general-purpose app as universally accurate.

Choosing the right evaluation metrics

A disease-detection model should be evaluated with more than overall accuracy. Precision indicates how often a positive prediction is correct, while recall indicates how many actual positive cases are detected. False negatives may allow disease to spread; false positives may cause unnecessary spraying or expense. The balance between these errors depends on the crop, disease severity and available response. Evaluation should therefore report class-wise results and explain the consequences of mistakes.

From detection to recommendation

Identifying a likely disease is only one step. Farmers also need to know whether the diagnosis is sufficiently certain, what confirmation may be needed and which management practices are appropriate. Recommendations should follow integrated pest management principles, considering resistant varieties, sanitation, crop rotation, biological controls and approved treatments where justified. An AI system should not automatically recommend a pesticide without accounting for local registration, crop stage, label directions and safety requirements.

Equity and local knowledge

Digital tools are more useful when farmers can use them in their own language and under realistic connectivity conditions. Community-based extension workers can help interpret results and collect feedback about model failures. Farmers should understand that photographs may contain location or other sensitive information and should be told how data are stored and used. Systems that learn from local observations can improve, but data-sharing arrangements should be transparent and fair.

Implementation pathway

A practical deployment should begin with a defined crop and a limited set of locally important diseases. Developers should work with plant pathologists and extension services, test the tool across farms and seasons, and compare its advice with expert diagnosis. Results should be monitored after launch, with a process for reporting errors and updating the model. This measured approach is more dependable than promoting a general-purpose app as universally accurate.

Conclusion

AI can make plant-health screening faster and more accessible, but it cannot replace all expert diagnosis. Its strongest role is to combine computational speed with local agronomic knowledge, confirmatory testing where needed and appropriate crop management. Representative data, field validation and equitable access are the foundations of useful AI tools.