

ARTIFICIAL INTELLIGENCE FOR EARLY DETECTION OF CROP DISEASES

Dr. Roaf Ahmad Parray

Scientist

Division of Agricultural Engineering

ICAR–Indian Agricultural Research Institute (ICAR-IARI)

New Delhi, India

Abstract

Crop diseases remain a major source of uncertainty in agricultural production because visible symptoms may be subtle at early stages, may resemble nutrient stress, and can spread before field scouting identifies a problem. Artificial intelligence (AI) offers a practical approach for improving early disease surveillance by combining computer vision, machine learning, mobile imaging, and precision-agriculture data. This paper presents a comparative analysis of AI approaches for the early detection of crop diseases, including conventional image-feature methods, convolutional neural networks (CNNs), transfer-learning models, object-detection systems, and multimodal models that combine images with weather, soil, or sensor information. The study uses a structured comparative research design based on published technical evidence and application requirements rather than claiming a new field experiment. Models are assessed through detection speed, diagnostic reliability, data requirements, robustness under real field conditions, device suitability, and interpretability. The analysis indicates that CNN and transfer-learning approaches are highly effective for leaf-image classification, while object-detection systems are more suitable when symptoms must be located within complex field scenes. Multimodal systems offer the greatest potential for early warning because they can connect visual symptoms with environmental conditions; however, they require more reliable data infrastructure and careful validation. The findings show that no single AI model is optimal for every crop, disease stage, or production setting. Effective deployment depends on diverse field datasets, human agronomic review, transparent confidence reporting, and integration with practical crop-management decisions. The study highlights AI as a decision-support technology that can strengthen timely monitoring, targeted intervention, and sustainable plant-health management.

Keywords: Artificial Intelligence, Crop Disease Detection, Deep Learning, Computer Vision, Precision Agriculture, Convolutional Neural Networks, Transfer Learning, Image Classification, Smart Farming, Plant Health Monitoring

1. INTRODUCTION

Crop production is strongly affected by fungal, bacterial, viral, and pest-related diseases that can reduce plant vigor, lower quality, and create avoidable treatment costs. Early diagnosis is therefore a central requirement of crop protection. In conventional practice, disease monitoring depends on periodic field inspection and the visual judgement of growers or agricultural specialists. Although expert scouting remains valuable, symptoms can emerge between inspection visits, and the process becomes difficult when farms are large, labor is limited, or several stress factors produce similar leaf discoloration and lesions. Artificial intelligence has emerged as a useful complement to crop scouting because digital images can capture disease-related patterns such as spots, chlorosis, mildew, necrosis, curling, texture change, and canopy

irregularity. Machine-learning systems can process these visual signals at a scale that would be difficult to achieve through manual inspection alone. Smartphones, field cameras, unmanned aerial systems, and edge devices further make it possible to collect observations directly from farms and deliver preliminary decision support close to the point of production.

Computer-vision research has moved from manually designed color and texture features toward deep-learning models that learn disease-relevant visual representations directly from images. Convolutional neural networks, transfer-learning models, object detectors, and transformer-based systems have expanded the range of crops and symptom types that can be examined. However, high performance on controlled laboratory datasets does not automatically guarantee dependable

performance in open-field conditions, where illumination, background clutter, cultivar variation, mixed infections, occlusion, and imaging quality can change substantially.

The practical objective is not only to classify a leaf as healthy or diseased. A useful early-detection system must help users identify the likely disease, locate the affected area where necessary, communicate model confidence, recognize cases requiring expert review, and provide a record that supports timely and responsible action. For this reason, AI must be evaluated not only by classification accuracy but also by field robustness, inference speed, interpretability, data requirements, and ease of deployment on available devices.

This study examines major AI approaches used for early crop disease detection and compares their suitability for image-based diagnosis and precision-agriculture decision support. It focuses on the strengths, limitations, and deployment conditions of different model types, with particular attention to the gap between controlled image

benchmarks and real agricultural environments.

2. LITERATURE REVIEW

Early work on automated plant disease diagnosis used image-processing methods that extracted color, shape, texture, and lesion features before applying classifiers such as support vector machines and artificial neural networks. These techniques can be useful in constrained tasks but often depend on careful feature design and can be sensitive to changes in lighting, crop variety, image quality, and field background.

Public plant-health datasets accelerated deep-learning research by enabling convolutional neural networks and transfer-learning models to learn disease-related visual features directly from images. More recent studies emphasize early symptoms, mobile capture, field deployment, object localization, and contextual agricultural data. The consistent finding is that model value depends on representative training data and validation across seasons, farms, cameras, and environmental conditions.

LITERATURE REVIEW SUMMARY TABLE

S.No.	Author / Year	Study Focus	Key Contribution	Limitations Identified
1	Hughes & Salathé (2015)	Open plant-health image repository	Established a widely used image resource for mobile disease-diagnosis research	Many images use controlled backgrounds and do not represent all field conditions
2	Mohanty et al. (2016)	Deep learning for leaf-image diagnosis	Demonstrated the feasibility of CNN-based crop disease classification	Model performance can fall when images differ from the training environment
3	Ferentinos (2018)	Multiclass CNN disease diagnosis	Compared deep-learning models across numerous plant-disease classes	Requires large, well-labelled datasets and validation beyond laboratory scenes
4	Picon et al. (2019)	Mobile capture for early wheat diseases	Evaluated early identification in real acquisition conditions	Crop and regional diversity remain limited in many field datasets
5	Barbedo (2018)	Factors affecting AI disease recognition	Explained the impact of dataset quality and image conditions on model reliability	No universal model can overcome poor data coverage or ambiguous symptoms

3. OBJECT OF STUDY

The primary focus of this research is to investigate and compare artificial intelligence approaches that can support early identification of crop diseases from visual and contextual agricultural data. The study considers how model choice affects the reliability, speed, transparency, and usability of disease-detection systems in practical crop-management environments. The principal objects of study are outlined below:

3.1 AI APPROACHES UNDER INVESTIGATION

- Traditional classifiers using engineered visual features
- CNNs for healthy and diseased leaf-image classification
- Transfer learning with ResNet, EfficientNet, and MobileNet
- Object detection for localizing lesions and symptomatic plant regions
- Multimodal models combining imagery with environmental crop data

3.2 AGRICULTURAL DISEASE CONTEXTS

- Leaf symptoms such as spots, chlorosis, mildew, blight, curling, and texture change
- Cereals, vegetables, fruit crops, legumes, and plantation crops
- Field images affected by lighting, shadows, background clutter, and occlusion
- Disease-risk contexts informed by weather, soil, and crop-stage signals

3.3 PERFORMANCE EVALUATION PARAMETERS

- Detection speed and inference efficiency
- Diagnostic reliability, confidence calibration, and early-symptom sensitivity
- Data requirements, label quality, and image diversity
- Robustness across farms, seasons, cultivars, and devices
- Device feasibility, interpretability, and decision-support usability

3.4 COMPARATIVE ANALYSIS FOCUS

- Controlled image classification versus real-world field deployment
- Image classification, symptom localization, and risk prediction
- Smartphone, edge-device, drone, and cloud implementation pathways

- Human review, uncertainty reporting, and responsible AI use

3.5 RESEARCH OBJECTIVE SCOPE

- To identify suitable approaches for early crop disease screening
- To explain trade-offs between speed, reliability, data, and robustness
- To highlight representative datasets and external validation
- To support transparent AI-assisted crop-health monitoring

4. RESEARCH METHODOLOGY

The present study adopts a comparative and evidence-based research methodology to analyse artificial intelligence approaches for early crop disease detection. The research framework is designed to compare models according to their technical characteristics and their practical value in agricultural monitoring, rather than to claim a new controlled field experiment. The methodology combines conceptual analysis of published research, known model behavior, and deployment requirements for crop-health decision support. The comparison is organized around the workflow of early disease detection: image or sensor acquisition, preprocessing, feature learning, classification or localization, confidence assessment, and communication of results to growers or agricultural advisors. Each selected approach is considered under common conditions, including variable illumination, symptoms at different stages, heterogeneous backgrounds, limited computing resources, and the need for timely intervention.

METHODOLOGY FRAMEWORK

1. The study uses a comparative design covering principal AI approaches.
2. Published evidence and computer-vision principles support qualitative synthesis.
3. All approaches are assessed for early disease screening and diagnosis support.
4. The analysis includes image-only and multimodal systems.
5. Field variability is treated as a core evaluation condition.
6. Comparisons distinguish classification, localization, and risk prediction.
7. Performance covers speed, reliability, data needs, robustness, devices, and interpretability.

8. Smartphone, edge-device, cloud, and drone workflows are considered.
9. No fabricated experimental measurements are presented.
10. Recommendations focus on AI that complements agronomic expertise.

5. DATA ANALYSIS

The data analysis section presents a comparative evaluation of AI approaches used for early crop disease detection. The analysis is based on reported model behavior, technical architecture, dataset requirements, and practical deployment considerations. The objective is to examine how each approach

performs in relation to response time, diagnostic reliability, field robustness, computational demand, and suitability for farmer- and advisor-facing crop-health monitoring.

Five major approaches are considered: traditional machine learning with engineered visual features, CNN-based classification, transfer learning, object detection, and multimodal AI. The comparison is qualitative because the performance of any individual model depends on crop species, disease class, image quality, label accuracy, data diversity, and the evaluation setting.

5.1 COMPARATIVE PERFORMANCE ANALYSIS

S.No.	Approach	Primary Application	Detection Speed	Diagnostic Reliability	Data Requirement	Field Robustness	Overall Suitability
1	Traditional ML + engineered features	Basic leaf-image screening	High	Medium	Low-Medium	Low	Moderate
2	Custom CNN classification	Leaf disease classification	High	High	Medium	Medium	Good
3	Transfer learning	Multicrop image diagnosis	High	Very High when validated	Medium	High	Very Good
4	Object detection	Locating lesions or symptomatic plants	Very High	High	High	High	Very Good
5	Multimodal AI (image + context)	Early risk and decision support	Medium	High but context-dependent	High	High	Excellent for supported settings

5.2 EXTENDED PERFORMANCE EVALUATION

- Traditional machine-learning models can offer rapid screening on limited hardware and may be suitable for narrowly defined tasks. Their main weakness is reliance on manually designed features, which can be sensitive to lighting, image noise, symptom variability, and differences between crops or cultivars.
- CNN-based classifiers learn visual features from images and are effective when datasets contain sufficient, well-labelled examples. They are a practical choice for diagnosis from isolated leaves or clearly framed plant images, but their

reliability can decrease when models encounter field backgrounds or disease manifestations not represented during training.

- Transfer learning is particularly valuable where agricultural datasets are too small to train a deep model from the beginning. Pretrained architectures can reduce training time and improve baseline performance, provided that fine-tuning and external validation are carried out using images that resemble the intended deployment setting.
- Object-detection systems are useful when diseases must be located within a full image rather than classified from a

cropped leaf. Their ability to identify symptom regions can improve interpretability and support targeted scouting, although accurate bounding-box or segmentation labels require greater annotation effort.

- Multimodal AI can combine images with contextual evidence such as humidity, temperature, rainfall, soil condition, crop growth stage, and local disease history. This approach is promising for early warning, but it depends on data governance, sensor quality, synchronization of data streams, and clear communication of uncertainty.

5.3 OBSERVATIONS FROM DATA ANALYSIS

- AI performance is problem-dependent; a model that is effective for one crop and disease may not generalize to another setting.
- Controlled leaf-image datasets are useful for model development, but field validation is essential before operational use.
- Transfer learning and object detection provide strong practical value when models must handle diverse images or localize symptoms.
- Early disease diagnosis requires attention to subtle symptoms, which may be confused with nutrient deficiency, drought stress, or physical damage.
- Data diversity, label quality, and validation across seasons are often more important than increasing model complexity alone.
- Human agronomic review remains necessary for low-confidence predictions, rare diseases, and decisions involving chemical treatment.
- Model transparency, confidence scoring, and record keeping improve the usefulness and accountability of AI-assisted recommendations.

6. DISCUSSION

The comparative analysis shows that AI can improve crop disease surveillance when it is designed as a decision-support system rather than as an isolated classification tool. The central benefit of AI lies in its ability to process large volumes of image and sensor information quickly, helping users recognize

visual patterns that may require timely attention. However, early detection is more demanding than late-stage diagnosis because disease symptoms may be small, incomplete, or visually similar to other forms of plant stress.

CNNs and transfer-learning models are appropriate for many image-classification applications because they can learn discriminative features from plant images and can be adapted to new tasks. Their value is greatest when the training data reflect the real deployment environment. A model trained mostly on clean leaf images may report high performance during internal testing but perform poorly on leaves photographed in shadows, under glare, behind other foliage, or with multiple symptoms. This domain shift remains one of the principal barriers to dependable agricultural AI.

Object-detection and segmentation methods extend the role of AI from identifying a disease label to locating the visual evidence that supports the prediction. This can be useful for field scouting, drone imagery, and farmer-facing mobile applications because highlighted symptom regions make results easier to interpret. Yet localization models require more detailed labels and careful evaluation to ensure that they are responding to true disease indicators rather than background patterns or camera artifacts.

Multimodal AI offers a broader direction for precision agriculture. Disease development is influenced by environmental and crop-management conditions, so combining imagery with weather, soil, and crop-stage data can improve early warning. Such systems should nevertheless be implemented cautiously. Data gaps, faulty sensors, incomplete local history, and unclear confidence estimates can produce misleading recommendations. Responsible deployment therefore requires data-quality checks, model monitoring, human review pathways, and communication that distinguishes screening from definitive plant-pathology diagnosis.

7. CONCLUSION

This study presented a comparative analysis of artificial intelligence approaches for early crop disease detection, including traditional machine-learning methods, CNN-based classifiers, transfer-learning models, object

detectors, and multimodal AI systems. The analysis shows that AI can strengthen plant-health monitoring by supporting timely image screening, symptom localization, disease-risk assessment, and more focused field scouting. The findings indicate that each approach has distinct strengths and limitations. Traditional machine-learning systems are comparatively light and accessible for narrow tasks, while CNNs and transfer-learning models are effective for image-based classification when reliable training data are available. Object-detection models are suitable for complex field scenes, and multimodal AI offers strong potential for early warning when contextual agricultural data can be collected and validated.

No single model is universally optimal across crop species, disease types, symptom stages,

or farm conditions. The practical performance of AI depends on representative datasets, external validation, confidence reporting, device constraints, and the availability of agronomic expertise. High benchmark scores should not be treated as proof of field readiness without testing across seasons and locations.

The study concludes that AI should be deployed as a transparent, evidence-based support tool within integrated crop-health management. Future work should prioritize diverse real-world datasets, low-cost edge deployment, explainable predictions, multimodal risk modelling, and collaborative validation with growers, plant pathologists, and agricultural extension services.

8. REFERENCES

1. Hughes, D. P., & Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv:1511.08060.
2. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, 1419.
3. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311-318.
4. Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. *Computers and Electronics in Agriculture*, 161, 280-290.
5. Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161, 272-279.
6. Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. *Biosystems Engineering*, 172, 84-91.
7. Barbedo, J. G. A. (2019). Plant disease identification from individual lesions and spots using deep learning. *Biosystems Engineering*, 180, 96-107.
8. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70-90.
9. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
10. Mahlein, A. K. (2016). Plant disease detection by imaging sensors: Parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease*, 100(2), 241-251.
11. Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases. *Computers and Electronics in Agriculture*, 72(1), 1-13.
12. Mahlein, A. K., Oerke, E. C., Steiner, U., & Dehne, H. W. (2012). Recent advances in sensing plant diseases for precision crop protection. *European Journal of Plant Pathology*, 133, 197-209.
13. Rumpf, T., Mahlein, A. K., Steiner, U., Oerke, E. C., Dehne, H. W., & Plümer, L. (2010). Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. *Computers and Electronics in Agriculture*, 74(1), 91-99.
14. Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. *Applied Artificial Intelligence*, 31(4), 299-315.

15. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, 2016, 3289801.
16. DeChant, C., Wiesner-Hanks, T., Chen, S., Stewart, E. L., Yosinski, J., Gore, M. A., Nelson, R. J., & Lipson, H. (2017). Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning. *Phytopathology*, 107(11), 1426-1432.
17. Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. *Frontiers in Plant Science*, 8, 1852.
18. Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors*, 17(9), 2022.
19. Geetharamani, G., & Arun Pandian, J. (2019). Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Computers and Electrical Engineering*, 76, 323-338.
20. Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, 267, 378-384.
21. Redmon, J., & Farhadi, A. (2018). YOLOv3: An incremental improvement. *arXiv:1804.02767*.
22. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770-778.
23. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. *Proceedings of the 36th International Conference on Machine Learning*, 6105-6114.
24. Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications. *arXiv:1704.04861*.
25. Dosovitskiy, A., Beyer, L., Kolesnikov, A., et al. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. *International Conference on Learning Representations*.
26. Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6, 60.
27. Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-CAM: Visual explanations from deep networks via gradient-based localization. *Proceedings of the IEEE International Conference on Computer Vision*, 618-626.
28. Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.
29. Oerke, E. C. (2006). Crop losses to pests. *Journal of Agricultural Science*, 144(1), 31-43.
30. Strange, R. N., & Scott, P. R. (2005). Plant disease: A threat to global food security. *Annual Review of Phytopathology*, 43, 83-116.