International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

AI-Powered Crop Disease Detection And Smart Recommendation Systems: A Review Of Deep Learning, Mobile Deployment And Decision Support For Farmers

Dhole Siddharth Dnyaneshwar; Prof. N. G. Rokade; Prof. M. C. Kolse; Prof. S. K. Said
Department Of Artificial Intelligence And Data Science Jaihind College Of Engineering Pune, Maharashtra, India;

Abstract—Plant diseases, unpredictable weather and soil problems cause major yield losses every year, and farmers in many regions still depend on visual inspection or delayed expert visits to identify diseases. Late detection often leads to excessive use of chemical sprays, which raises costs and harms the environment. This paper reviews AI-powered systems that detect crop diseases early from leaf images and provide smart recommendations for treatment and crop management. The review examines image datasets such as PlantVillage and PlantDoc, convolutional neural networks and transfer learning for disease classification, object-detection models for locating lesions in field images, and lightweight networks for offline smartphone use. It also covers how detection results can be combined with weather, soil and crop-stage information to recommend targeted, dose-appropriate interventions and preventive practices. A five-layer architecture comprising data acquisition, preprocessing, a detection engine, a recommendation engine and a farmer-facing application is proposed. The paper identifies research gaps such as the drop in accuracy from laboratory to field images, limited regional crop coverage and the lack of explainable advice, and it concludes that a multilingual, mobile-first assistant combining disease detection with context-aware recommendations can reduce losses and chemical overuse.

Index Terms—Crop disease detection, plant pathology, deep learning, convolutional neural networks, transfer learning, precision agriculture, recommendation system, smart farming

I. INTRODUCTION

Agriculture supports the livelihoods of a large part of India's population, yet pests and pathogens destroy a significant fraction of the harvest. Savary *et al.* [1] estimated global yield losses from pathogens and pests for five major food crops and found them to be substantial, with the highest losses in regions already facing food insecurity. For a smallholder farmer, a single uncontrolled outbreak can wipe out a season's income.

Traditionally, diagnosis depends on the farmer's experience or a visit by an agricultural officer, which may take days. During this delay, the disease spreads, and uncertain farmers often apply broad-spectrum chemicals as a precaution. This increases costs, contributes to pesticide resistance and contaminates soil and water.

The spread of smartphones in rural areas creates an opportunity: a photograph of an affected leaf can be analysed instantly by an AI model. This paper reviews research on AI-based crop disease detection and recommendation, proposes an integrated architecture, and identifies gaps that must be addressed for real-world impact.

II. THEORETICAL BACKGROUND

2.1 Image-Based Disease Recognition

Most crop diseases produce visible symptoms such as spots, lesions, discoloration, wilting or mildew on leaves. Convolutional Neural Networks (CNNs) learn hierarchical visual features directly from images [2], making them well suited to recognizing these patterns. Transfer learning reuses networks pre-trained on large image collections and fine-tunes them on plant images, which reduces the amount of labelled data required.

2.2 Smart Recommendation

Detection alone does not tell a farmer what to do. A recommendation engine combines the diagnosis with crop type, growth stage, weather forecast and soil information to suggest treatment, timing and preventive steps. Fig. 1 classifies the AI functions involved.

© 2026 IJSRET

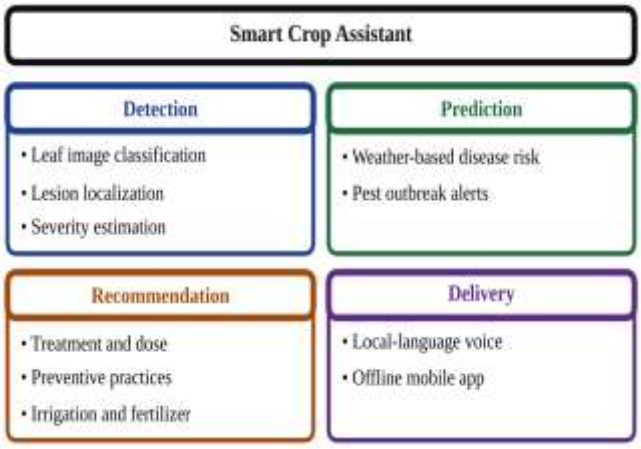


Fig. 1. AI functions in a crop disease detection and recommendation system.

III. SURVEY OF EXISTING APPROACHES

Hughes and Salathé [3] released PlantVillage, an open repository of tens of thousands of labelled leaf images covering many crop–disease pairs, which became the standard benchmark. Using this dataset, Mohanty *et al.* [4] trained AlexNet and GoogLeNet models and reported very high accuracy on held-out images, but accuracy fell sharply on images taken under different conditions, revealing a domain gap between laboratory and field.

Ferentinos [5] trained several CNN architectures on a larger set of images including field photographs and confirmed that deep models can achieve high accuracy across many species. Too *et al.* [6] compared fine-tuned VGG, Inception, ResNet and DenseNet models and found that DenseNet offered strong accuracy with fewer parameters. Ramcharan *et al.* [7] applied transfer learning to cassava diseases and later demonstrated the approach on mobile devices in East Africa, showing feasibility for low-resource settings.

To address field conditions, Singh *et al.* [8] created PlantDoc, a dataset of real-world images with cluttered backgrounds, and showed that models trained only on laboratory images perform poorly on it. Fuentes *et al.* [9] used object detectors such as Faster R-CNN to locate and classify tomato diseases and pests within whole-plant images.

Barbedo [10] analysed factors limiting deep learning for plant pathology, including dataset size, symptom variability, multiple simultaneous diseases and image-capture conditions. Broader reviews by Kamilaris and Prenafeta-Boldú [11] and Liakos *et al.* [12] place disease detection within the wider landscape of AI in agriculture, including yield prediction and soil management. Table I summarizes the key studies.

TABLE I Summary of Literature Survey

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[3]	Hughes and Salathé, 2015	PlantVillage open image repository	Large labelled dataset for many crops	Uniform laboratory backgrounds
[4]	Mohanty et al., 2016	AlexNet and GoogLeNet on PlantVillage	Very high accuracy on test split	Large drop on field-like images
[5]	Ferentinos, 2018	Several CNN architectures	High accuracy across many species	Limited regional diversity
[6]	Too et al., 2019	Fine-tuned VGG, ResNet, DenseNet	DenseNet best accuracy-to-parameter ratio	Laboratory images only
[7]	Ramcharan et al., 2017	Transfer learning for cassava	Feasible mobile diagnosis in the field	Single crop
[8]	Singh et al., 2020	PlantDoc in-field dataset	Exposed lab-to-field domain gap	Relatively small dataset
[9]	Fuentes et al., 2017	Faster R-CNN and other detectors	Locates tomato diseases and pests	Heavy for mobile devices
[10]	Barbedo, 2018	Analysis of limiting factors	Identified data and symptom variability issues	No new model proposed
[11]	Kamilaris and Prenafeta-Boldú, 2018	Survey of deep learning in agriculture	Mapped applications and techniques	Survey; no recommendations engine

© 2026 IJSRET

IV. COMPARATIVE STUDY

Table II compares common models. Larger networks provide high accuracy but are difficult to run on low-end phones, while MobileNet and EfficientNet offer an excellent accuracy-to-size ratio. Object detectors are preferred when images contain several leaves or multiple diseases.

TABLE II Comparison of Detection Models

Model	Accuracy	Model Size	Mobile Use
VGG-16	High	Very large	Poor
ResNet-50	High	Large	Moderate
DenseNet-121	High	Medium	Moderate
MobileNet	Good	Small	Excellent
EfficientNet-B0	High	Small	Very good
YOLO / Faster R-CNN	High (localization)	Medium–Large	Moderate

V. RESEARCH GAPS

The following gaps are identified:

- High laboratory accuracy does not transfer to field images with varying light, backgrounds and multiple leaves.
- Datasets under-represent regional crops and diseases important to Indian farmers.
- Few systems link diagnosis to context-aware, dose-specific recommendations.
- Explanations of why a disease was predicted are rarely shown, limiting farmer trust.
- Many applications require internet access and support only English.

5.1 Aims And Objectives

The objectives of this review are:

- To review deep learning methods and datasets for crop disease detection.
- To compare classification and detection models in terms of accuracy and suitability for mobile deployment.
- To propose an integrated architecture combining detection with smart recommendations.
- To identify methods for explainable and multilingual farmer advice.
- To discuss challenges and future directions for field-scale adoption.

VI. PROPOSED ARCHITECTURE

Fig. 2 presents the proposed architecture. It is designed to work offline on a smartphone for detection, while using the cloud when available for recommendations that need weather data and for model updates.

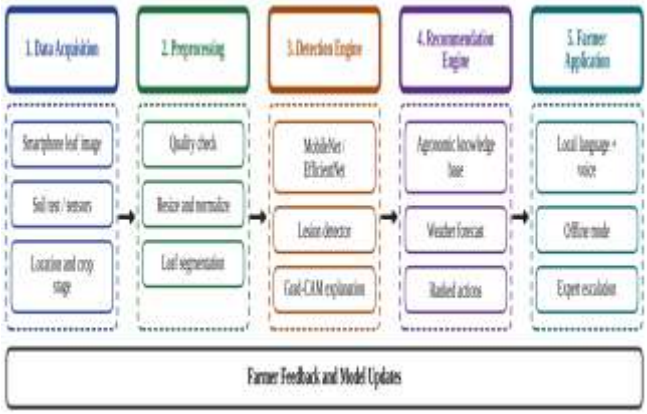


Fig. 2. Proposed architecture of the AI-powered crop disease detection and recommendation system.

6.1 Data Acquisition Layer

Farmers capture leaf images with a smartphone camera. Optional inputs include soil test results, field location, crop variety and sowing date, as well as data from low-cost soil-moisture sensors.

6.2 Preprocessing Layer

Images are checked for blur and brightness, resized, normalized and, where needed, segmented to isolate the leaf from the background. Data augmentation is used during training to simulate field variability.

6.3 Detection Engine

A lightweight CNN such as MobileNet [13] or EfficientNet [14] classifies the disease and outputs a confidence score. An optional detector localizes multiple lesions. Grad-CAM [15] highlights the leaf regions that influenced the prediction.

6.4 Recommendation Engine

A knowledge base of agronomic practices is combined with the diagnosis, crop stage, weather forecast and soil data. Rules and a learned ranking model recommend actions such as removal of infected leaves, biological controls, appropriate fungicide and dose, irrigation changes or consultation with an expert.

6.5 Farmer Application Layer

Results are presented in the farmer's language with images, voice output and simple steps. Farmers can report outcomes, which are used to improve both models.

© 2026 IJSRET

VII. PROCESS FLOW AND EVALUATION

The workflow of the system is shown in Fig. 3. Transfer learning minimizes the categorical cross-entropy loss over C disease classes:

$$L = -\Sigma_c y_c \cdot \log(p_c) \quad (1)$$

where y_c is the true label and p_c the predicted probability for class c. When the maximum probability is below a threshold, the application asks for a clearer image or refers the case to an expert rather than guessing.

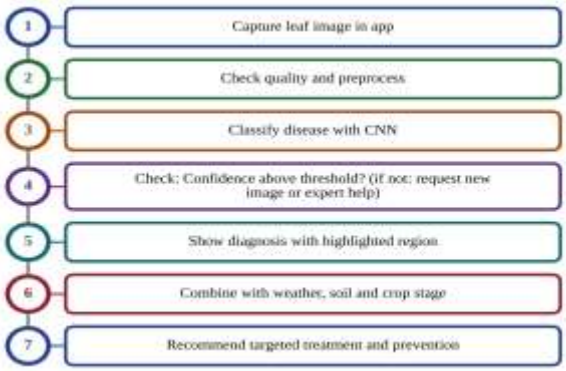


Fig. 3. Workflow from image capture to recommendation.

A disease-risk index can be computed from weather variables such as humidity and leaf wetness duration, which are known to favour fungal infections, allowing preventive alerts even before symptoms appear.

VIII. LIMITATIONS AND FUTURE SCOPE

Table III lists the main challenges. Future research should build large regional field datasets through farmer participation, use drones and multispectral imaging for field-scale monitoring, apply federated learning to improve models without collecting farmers' data centrally, and integrate market and advisory services. Big-data platforms for smart farming [16] can connect these elements into a single service.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Lab-to-field gap	Field images, augmentation, domain adaptation
Regional crop coverage	Farmer-contributed, expert-verified data
Low connectivity	On-device models; sync when online
Trust in advice	Grad-CAM highlights; expert escalation
Chemical overuse	Dose-specific, threshold-based recommendations

IX. CONCLUSION

AI-based crop disease detection has advanced from laboratory demonstrations to practical mobile tools. The reviewed literature shows that CNNs with transfer learning achieve high accuracy, but performance in the field depends on representative data and robust preprocessing. Combining detection with context-aware recommendations, explainable outputs and multilingual interfaces turns a classifier into a useful farming assistant that can help farmers act early, apply chemicals only when needed and protect both their income and the environment.

9.1 Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

REFERENCES

1. S. Savary et al., “The global burden of pathogens and pests on major food crops,” Nat. Ecol. Evol., vol. 3, no. 3, pp. 430–439, 2019.
2. Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.
3. D. P. Hughes and M. Salathé, “An open access repository of images on plant health to enable the development of mobile disease diagnostics,” arXiv:1511.08060, 2015.
4. S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Front. Plant Sci., vol. 7, Art. no. 1419, 2016.
5. K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Comput. Electron. Agric., vol. 145, pp. 311–318, 2018.
6. E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, “A comparative study of fine-tuning deep learning models for plant disease identification,” Comput. Electron. Agric., vol. 161, pp. 272–279, 2019.
7. A. Ramcharan et al., “Deep learning for image-based cassava disease detection,” Front. Plant Sci., vol. 8, Art. no. 1852, 2017.
8. D. Singh et al., “PlantDoc: A dataset for visual plant disease detection,” in Proc. 7th ACM IKDD CoDS and 25th COMAD, 2020, pp. 249–253.
9. A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, “A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition,” Sensors, vol. 17, no. 9, Art. no. 2022, 2017.

© 2026 IJSRET

10. J. G. A. Barbedo, “Factors influencing the use of deep learning for plant disease recognition,” Biosyst. Eng., vol. 172, pp. 84–91, 2018.
11. A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” Comput. Electron. Agric., vol. 147, pp. 70–90, 2018.
12. K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, “Machine learning in agriculture: A review,” Sensors, vol. 18, no. 8, Art. no. 2674, 2018.
13. A. G. Howard et al., “MobileNets: Efficient convolutional neural networks for mobile vision applications,” arXiv:1704.04861, 2017.
14. M. Tan and Q. V. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proc. Int. Conf. Mach. Learn. (ICML), 2019, pp. 6105–6114.
15. R. R. Selvaraju et al., “Grad-CAM: Visual explanations from deep networks via gradient-based localization,” in Proc. IEEE ICCV, 2017, pp. 618–626.
16. S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, “Big data in smart farming—A review,” Agric. Syst., vol. 153, pp. 69–80, 2017.

© 2026 IJSRET