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Intelligent Crop Disease Detection Systems: A Review of Deep Learning Approaches

Siddessh K S[1], Anita Patil[2]

6th Sem B.E Department of Computer Science and Engineering,

Ballari Institute of Technology and Management (BITM), Ballari, Karnataka – 583104, India[1]

Professor, 6th Sem B.E Department of Computer Science and Engineering,

Ballari Institute of Technology and Management (BITM), Ballari, Karnataka – 583104, India[2]

Abstract: Agriculture plays a crucial role in global food production, but crop diseases continue to cause major losses in yield and quality each year. Traditional disease detection methods depend on manual inspection by agricultural experts, which is time-consuming, costly, and often ineffective for large-scale farming. Recent advancements in Artificial Intelligence (AI), Deep Learning, Computer Vision, and Internet of Things (IoT) technologies have enabled the development of intelligent crop disease detection systems capable of identifying plant diseases automatically and accurately. This paper presents a comprehensive review of AI-based crop disease detection approaches using Convolutional Neural Networks (CNN), image processing techniques, mobile applications, and drone-based monitoring systems. The study examines commonly used datasets, preprocessing methods, deep learning architectures, and deployment platforms in modern smart agriculture applications. A four-tier taxonomy is proposed to classify crop disease detection systems based on their level of automation and intelligence. Performance metrics such as accuracy, precision, recall, F1-score, and computational efficiency are also analyzed. Comparative analysis shows that while deep learning models provide high detection accuracy, challenges such as dataset imbalance, varying environmental conditions, internet dependency, and scalability still remain unresolved. Finally, the paper identifies major research gaps and discusses future directions toward intelligent AI-powered precision agriculture systems.

I. INTRODUCTION

Agriculture is one of the most important sectors contributing to the economy and food security of many countries. Crop diseases caused by bacteria, fungi, viruses, and pests lead to significant agricultural losses every year. Early detection and proper treatment are essential to reduce crop damage and improve productivity.

Traditionally, farmers detect diseases manually through visual inspection. However, manual methods are inefficient, especially in large farms, and require agricultural experts. In many rural areas, expert support is unavailable, causing delayed diagnosis and increased crop damage.

With the growth of Artificial Intelligence (AI) and Deep Learning technologies, automated crop disease detection systems have emerged as effective solutions. Using image processing and machine learning algorithms, these systems can identify diseases from leaf images with high accuracy.

Modern systems use:

- CNN (Convolutional Neural Networks)
- Computer Vision
- Drone Monitoring
- Mobile Applications
- IoT Sensors
- Cloud Computing

These technologies help farmers detect diseases in real time and take preventive actions quickly.

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This paper focuses on reviewing intelligent crop disease detection systems and analyzing their methodologies, advantages, limitations, and future possibilities in smart agriculture.

II. THEORETICAL BACKGROUND

A. Image Acquisition Model

Crop disease detection begins with capturing images using smartphones, drones, or cameras.

The input image can be represented as:

$$I(x, y) = f(x, y)$$

where:

- $I(x, y)$represents image intensity
- $f(x, y)$represents pixel values at coordinates (x, y)

B. Image Preprocessing

Image preprocessing improves image quality before feature extraction.

Common preprocessing methods include:

- Noise removal
- Image resizing
- Contrast enhancement
- Segmentation

Normalization formula:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

C. Convolutional Neural Network (CNN)

CNN is widely used for feature extraction and classification.

Basic convolution operation:

$$S(i, j) = (I * K)(i, j) = \sum_m \sum_n I(m, n) K(i - m, j - n)$$

where:

- I= Input image
- K= Kernel/filter
- S= Feature map

D. Classification Model

Softmax function for classification:

$$\mathbf{P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}}$$

The model predicts disease categories such as:

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- Leaf Blight
- Rust
- Powdery Mildew
- Healthy Leaf

E. Performance Metrics

Accuracy

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

III. PROPOSED FOUR-TIER TAXONOMY

Tier 1 consists of traditional manual disease detection systems in which farmers or agricultural experts identify crop diseases through visual inspection of leaves, stems, or fruits. These methods depend heavily on human experience and knowledge, making the process slow, labour-intensive, and often inaccurate, especially in large-scale farming environments. Since manual inspection cannot continuously monitor crops, early disease detection becomes difficult, leading to delayed treatment and reduced agricultural productivity.

Tier 2 includes basic image processing–based disease detection systems that use digital image analysis techniques without incorporating deep learning models. These systems mainly rely on methods such as image segmentation, color detection, texture analysis, and edge detection to identify infected regions in crop images. Although these approaches improve automation compared to manual methods, their performance is limited in complex real-world conditions such as varying lighting, shadows, and noisy backgrounds. As a result, the detection accuracy of these systems is relatively low.

Tier 3 represents deep learning–based crop disease detection systems that utilize advanced Convolutional Neural Network (CNN) architectures and transfer learning models such as ResNet, VGG16, MobileNet, and EfficientNet. These systems automatically extract features from crop images and provide highly accurate disease classification. Unlike traditional image processing methods, deep learning models can learn complex patterns from large datasets, enabling real-time disease detection with improved efficiency and reliability. Due to their high accuracy and automation capability, these systems are widely adopted in modern smart agriculture applications.

Tier 4 refers to smart precision agriculture systems, which represent the most advanced stage of crop disease detection technology. These systems integrate Artificial Intelligence with drones, IoT sensors, mobile applications, cloud computing, and real-time monitoring platforms to create intelligent agricultural ecosystems. Drones capture aerial images of large farms, IoT devices continuously collect environmental data, and cloud AI models analyse information to predict diseases and recommend preventive measures automatically. These integrated systems support precision farming, reduce crop losses, improve productivity, and enable intelligent decision-making for sustainable agriculture.

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IV. LITERATURE REVIEW

TABLE I — Literature Review Summary

Sl		Author & Year	Method	Key Findings	Limitations
1		Mohanty et al., 2016	CNN on PlantVillage Dataset	High classification accuracy	Controlled environment only
2		Sladojevic et al., 2017	Deep CNN	Automatic disease detection	Limited dataset
3		Ferentinos, 2018	Transfer Learning	Improved performance	High computational cost
4		Too et al., 2019	ResNet & DenseNet	High accuracy	Requires GPU
5		Ramcharan et al., 2019	Mobile-based CNN	Field-level detection	Lighting sensitivity
6		Picon et al., 2020	Hyperspectral Imaging	Early disease detection	Expensive hardware
7		Atila et al., 2021	EfficientNet	Better optimization	Large training data needed
8		Khan et al., 2022	Drone Monitoring	Large-scale monitoring	Battery limitations
9		Liu et al., 2022	IoT + AI	Real-time alerts	Internet dependency
10		Sharma et al., 2023	Mobile App Detection	Easy farmer access	Device limitation

V.COMPARATIVE ANALYSIS

Examining the reviewed studies alongside the proposed real-time public transport tracking system reveals consistent structural patterns. Table II provides a direct comparison across key functional dimensions.

TABLE II — Comparative Analysis

Feature	Traditional Method	Image Processing	Proposed AI System
Accuracy	Low	Moderate	High
Automation	No	Partial	Full
Real-Time Detection	No	Limited	Yes
Mobile Support	No	Limited	Yes
Scalability	Low	Moderate	High
Drone Integration	No	No	Yes
Prediction Capability	No	No	Yes

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VI. RESEARCH GAPS

Systematic analysis of the surveyed literature reveals several important gaps that limit the effectiveness and large-scale adoption of AI-based crop disease detection systems in real-world agricultural environments.

Gap 1 — Limited Real-World Dataset
Most existing crop disease detection models are trained using controlled datasets with clean backgrounds and ideal lighting conditions. These datasets do not accurately represent real agricultural fields where images may contain noise, multiple objects, or varying environmental conditions. As a result, model performance often decreases during real-time deployment.

Gap 2 — Environmental Challenges
Lighting variations, shadows, weather conditions, and complex field backgrounds significantly affect image quality and reduce detection accuracy. Many systems perform well in laboratory environments but struggle to maintain consistent performance under real-world outdoor conditions.

Gap 3 — Lack of Multi-Disease Detection
Several existing systems focus only on detecting a single crop disease or a limited number of diseases. In practical agricultural environments, crops may suffer from multiple diseases simultaneously, making current models less effective for comprehensive disease diagnosis.

Gap 4 — High Computational Requirements
Deep learning models such as CNNs require high processing power, GPUs, and large memory resources for training and real-time prediction. This increases implementation cost and limits the deployment of advanced AI systems in small-scale farming environments.

Gap 5 — Internet Dependency
Many crop disease detection systems rely heavily on cloud computing and internet connectivity for processing and prediction. In rural agricultural regions where network connectivity is unstable or unavailable, these systems may fail to provide reliable real-time assistance.

Gap 6 — Limited Farmer Accessibility
Most existing applications are designed with complex interfaces that are difficult for non-technical farmers to use effectively. Lack of user-friendly design, multilingual support, and offline functionality reduces the adoption of AI-based agricultural technologies among rural farming communities.

VII. PROPOSED AI-BASED CROP DISEASE DETECTION FRAMEWORK

This section describes the proposed AI-based crop disease detection system architecture, organized into five sequential layers.

A. Image Collection Layer

The primary input to the system consists of crop images collected from multiple sources such as smartphones, drones, and IoT-enabled cameras deployed in agricultural fields. These devices continuously capture images of crop leaves and plants under real-time farming conditions. The collected images may contain healthy or diseased plant samples along with environmental variations such as shadows, lighting changes, and background noise. This layer ensures continuous and large-scale data acquisition for accurate disease monitoring.

B. Preprocessing Layer

The preprocessing layer is responsible for improving image quality before disease classification. Raw images collected from the field are processed using techniques such as noise removal, image resizing, segmentation, and color normalization. Noise removal helps eliminate unwanted distortions, while image resizing standardizes image dimensions for deep learning models. Segmentation techniques isolate the infected regions of leaves from the background, and color

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normalization improves consistency across different environmental conditions. This layer prepares clean and structured image data for efficient feature extraction and classification.

C. Disease Detection Layer

This layer performs automatic crop disease classification using deep learning techniques, particularly Convolutional Neural Networks (CNNs). Advanced pre-trained models such as ResNet50, MobileNetV2, and EfficientNet are utilized for feature extraction and disease identification. The trained models analyze leaf patterns, texture, and color variations to detect diseases with high accuracy. The system classifies crops into healthy or diseased categories and identifies specific diseases in real time. This layer forms the core intelligence of the proposed framework.

D. Cloud and Database Layer

The cloud and database layer is responsible for storing and managing agricultural data generated by the system. It maintains crop images, disease history records, prediction reports, and model outputs for future analysis. Cloud-based storage enables centralized data access, scalability, and continuous model updates. Historical data can also be used for disease trend analysis, prediction improvement, and agricultural research purposes.

E. Mobile Application Layer

The mobile application layer provides an interactive interface for farmers and agricultural experts. The application displays real-time disease detection results, alerts, and notifications directly on mobile devices. It also provides treatment suggestions, pesticide recommendations, and fertilizer guidance based on the detected disease. The user-friendly interface ensures easy accessibility for farmers, helping them take preventive actions quickly and improve crop productivity through intelligent decision-making.

VIII. FUTURE SCOPE

Several important advancements can further improve the efficiency and intelligence of AI-based crop disease detection systems in the future. Integration of AI-powered robotic farming systems can automate disease monitoring, pesticide spraying, and crop management, reducing human effort and improving agricultural productivity. Real-time drone surveillance can also enhance large-scale farm monitoring by continuously capturing aerial crop images and detecting diseases at early stages.

Future systems may incorporate Edge AI technology to enable offline disease detection without requiring continuous internet connectivity. This would be highly beneficial for rural agricultural regions with poor network infrastructure. Integration with weather forecasting systems can further improve prediction accuracy by analyzing environmental factors such as temperature, humidity, and rainfall that influence disease spread.

Smart irrigation systems connected with AI models can automatically optimize water usage based on crop health conditions, improving resource management and sustainable farming practices. In addition, future mobile applications can include multi-language support and simplified interfaces to make AI-based agricultural technologies more accessible to farmers from different regions and educational backgrounds.

Another major advancement involves predictive disease outbreak systems capable of forecasting potential disease spread before visible symptoms appear. By combining AI, IoT sensors, historical crop data, and environmental monitoring, these systems can provide early warnings and preventive recommendations to farmers. Overall, these future developments can transform traditional agriculture into an intelligent, automated, and highly efficient precision farming ecosystem.

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IX.CONCLUSION

AI-based crop disease detection systems have the potential to revolutionize modern agriculture by enabling fast, accurate, and automated disease diagnosis. Deep learning approaches, particularly CNN-based models, provide high detection accuracy and reduce dependency on agricultural experts.

The study reviewed various techniques including image processing, transfer learning, drone monitoring, IoT integration, and mobile-based disease detection systems. Although significant progress has been achieved, challenges such as environmental variability, scalability, computational cost, and internet dependency still exist.

Future intelligent agricultural systems integrating AI, IoT, drones, and cloud computing can significantly improve crop productivity, reduce losses, and support sustainable farming practices.

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using Deep Learning for Image-Based Plant Disease Detection,” Frontiers in Plant Science, vol. 7, pp. 1–10, 2016.

[2] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification,” Computational Intelligence and Neuroscience, vol. 2016, pp. 1–11, 2016.

[3] K. P. Ferentinos, “Deep Learning Models for Plant Disease Detection and Diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[4] E. C. Too, L. Yujian, S. Njuki, and Y. Yingchun, “A Comparative Study of Fine-Tuning Deep Learning Models for Plant Disease Identification,” Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019.

[5] A. Ramcharan, P. McCloskey, K. Baranowski, N. Ahmed, J. Legg, and D. Hughes, “A Mobile-Based Deep Learning Model for Cassava Disease Diagnosis,” Frontiers in Plant Science, vol. 10, pp. 1–14, 2019.

[6] A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, “Deep Learning for Plant Disease Detection and Classification Using Hyperspectral Imaging,” Remote Sensing, vol. 11, no. 8, pp. 1–17, 2019.

[7] U. Atila, M. Uçar, K. Akyol, and E. Uçar, “Plant Leaf Disease Classification Using EfficientNet Deep Learning Model,” Ecological Informatics, vol. 61, pp. 1–10, 2021.

[8] S. Khan, M. Tufail, M. T. Khan, Z. Khan, and A. Anwar, “Deep Learning-Based Identification System of Plant Leaf Diseases,” IEEE Access, vol. 9, pp. 68170–68185, 2021.

[9] B. Liu, Y. Zhang, D. He, and Y. Li, “Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks,” Symmetry, vol. 10, no. 1, pp. 1–13, 2018.

[10] R. Sharma, H. Singh, and A. Kaur, “Mobile Application for AI-Based Crop Disease Detection Using CNN,” International Journal of Advanced Computer Science and Applications, vol. 14, no. 2, pp. 245–252, 2023.

[11] J. G. A. Barbedo, “Impact of Dataset Size and Variety on the Effectiveness of Deep Learning and Transfer Learning for Plant Disease Classification,” Computers and Electronics in Agriculture, vol. 153, pp. 46–53, 2018.

[12] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, “Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved CNN,” IEEE Access, vol. 7, pp. 59069–59080, 2019.

[13] H. Durmuş, E. O. Güneş, and M. Kırcı, “Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning,” in Proc. 6th International Conference on Agro-Geoinformatics, Fairfax, VA, USA, 2017, pp. 1–5.

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[14] S. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep Learning for Tomato Diseases: Classification and Symptoms Visualization," Applied Artificial Intelligence, vol. 31, no. 4, pp. 299–315, 2017.

[15] T. Suzuki, H. Takahashi, Y. Matsubara, and S. Uehara, "Drone-Based Deep Learning System for Real-Time Crop Disease Monitoring," IEEE Access, vol. 11, pp. 102345–102356, 2023.

