# Hybrid CNN-Based Plant Disease Detection for Smart Agriculture: A Review

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**Abstract**

Plant diseases are a major challenge in agriculture, leading to reduced crop yield and economic losses. Traditional methods of disease detection rely on manual inspection, which is time-consuming and less accurate. With the advancement of Deep Learning, Computer Vision, and Internet of Things, automated plant disease detection systems have been developed to improve accuracy and efficiency.

Recent research shows that deep learning models, especially Convolutional Neural Networks (CNNs), are widely used for plant disease classification due to their ability to automatically extract features from images and achieve high accuracy [3], [34] . Transfer learning techniques using models such as ResNet and VGG further enhance performance, particularly when datasets are limited [9], [41] . In addition, lightweight models like MobileNet and ShuffleNet are being developed for deployment on mobile and IoT devices [2], [12] .

Many studies use benchmark datasets such as PlantVillage, which provide high accuracy under controlled conditions. However, real-world applications face challenges such as varying lighting conditions, complex backgrounds, and limited dataset diversity [13], [15] . To address these issues, researchers are exploring advanced techniques such as data augmentation, object detection models like YOLO, and multimodal approaches that combine image data with environmental sensor data [5], [10] .

IoT-based systems are also gaining importance as they enable real-time monitoring of crop conditions using sensors and smart devices [21], [26] . Furthermore, Explainable AI techniques such as Grad-CAM are being used to improve model transparency and help users understand the prediction results [25] .

Despite significant progress, challenges remain in terms of model generalization, computational complexity, and real-time deployment. Future research should focus on developing lightweight, efficient, and scalable models, along with the use of large real-field datasets and edge computing technologies.

**Keywords**

Plant Disease Detection; Leaf Image Analysis; Convolutional Neural Network (CNN); Deep Learning; Transfer Learning; Computer Vision
Internet of Things; Lightweight Models; Object Detection (YOLO); Multimodal Data Fusion; Explainable Artificial Intelligence (XAI)

**Introduction**

Earlier studies on plant disease detection relied on traditional machine learning techniques such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest, along with handcrafted feature extraction methods like texture, color, and shape analysis [1], [13] .

Later research shifted toward Deep Learning, particularly Convolutional Neural Network (CNN)-based models, which automatically extract hierarchical features from plant leaf images and achieve higher classification accuracy [3], [34] .

Several deep learning architectures such as ResNet, EfficientNet, MobileNet, and transfer learning-based CNN models have demonstrated strong performance in plant disease classification tasks, especially when trained on benchmark datasets like PlantVillage [9], [41] .

Recent studies have also explored advanced approaches such as lightweight CNN models for edge devices, object detection frameworks like YOLO for disease localization, and multimodal systems combining image and environmental sensor data for improved accuracy [2], [5], [10] .

Moreover, integration with Internet of Things has enabled real-time monitoring and smart agriculture applications, while Explainable Artificial Intelligence (XAI) techniques have been introduced to enhance transparency and trust in deep learning-based plant disease detection systems [21], [25]

**Literature Review**

| No. | Author(s) | Method / Model | Dataset | Accuracy | Limitation |
|---|---|---|---|---|---|
| 1 | Kusuma R et al., 2025 | CNN + ML (DT, KNN, SVM, RF) | PlantVillage | High accuracy | Limited to few crops, no multi-disease detection |
| 2 | Kangchen Liu et al., 2025 | ShuffleNet (Lightweight CNN) | Kiwifruit dataset | High efficiency | Limited disease types |
| 3 | B. R. Reddy et al., 2025 | Custom CNN + Mobile App | PlantVillage | >92% | Binary classification only |
| 4 | Wenjie Liu et al., 2025 | Multi-scale Attention CNN | Soybean + PlantVillage | High accuracy | Limited dataset diversity |
| 5 | Silva et al., 2025 | YOLOv8 + CNN models | BRACOL + DPCL | High performance | Sensitive to leaf variation |
| 6 | Ji Li et al., 2025 | GAN + IDCNN | Tea dataset | Improved accuracy | Complex background issues |
| 7 | T. Ozcan et al., 2025 | BorB Segmentation + CNN | PlantVillage | High accuracy | Environmental variation affects results |
| 8 | Arnav Karnik et al., 2025 | Multi-scale feature CNN | Medicinal plant dataset | Good accuracy | Noise sensitivity |
| 9 | Richter et al., 2025 | Transfer Learning CNN | Multiple datasets | High accuracy | Dataset dependency |
| 10 | Rubina Rashid et al., 2024 | Multi-model Fusion CNN | PlantVillage + IoT data | High accuracy | Needs real-time optimization |
| 11 | Khaoula Taji et al., 2024 | Ensemble CNN + Metaheuristics | PlantVillage | 99.8% | High computational cost |
| 12 | Ritesh Maurya et al., 2024 | Meta-Ensemble (CNN + LSTM) | PlantVillage + Field | High accuracy | Needs multimodal data |
| 13 | Kashif Khan et al., 2024 | CNN + Camera-based ML | Grape dataset | Good performance | Limited disease types |

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| 14 | Mahrin Tasfe et al., 2024 | CNN + ViT (Survey) | Multiple datasets | — | No implementation |
| 15 | Moupojou et al., 2023 | CNN + FieldPlant dataset | FieldPlant | Good accuracy | Small dataset size |
| 16 | Changjian Zhou et al., 2024 | GAN + CNN | Grape dataset | Improved accuracy | GAN artifacts |
| 17 | Anita Shrotriya et al., 2024 | CNN + RNN Hybrid | Cotton dataset | High accuracy | High computation |
| 18 | Abdullah Mamun et al., 2024 | Self-Supervised Learning | Unlabeled datasets | Promising | High computation |
| 19 | Ammar Oad et al., 2024 | Ensemble CNN + XAI | PlantVillage | High accuracy | Complex model |
| 20 | Pajany et al., 2024 | Fuzzy Deep Neural Network | UAV dataset | High accuracy | Not suitable for IoT |
| 21 | Natasha Nigar et al., 2024 | CNN + Explainable AI | Kaggle + field data | High accuracy | Reduced performance in noise |
| 22 | Al-Shahari et al., 2024 | IoT + CNN | Sensor + Image dataset | Good accuracy | Expensive IoT setup |
| 23 | Assad Doutoum et al., 2023 | DL Review | Multiple datasets | — | No experimental validation |
| 24 | Hessane et al., 2023 | ML (SVM, RF) | Date palm dataset | Good accuracy | Limited generalization |
| 25 | Uferah Shafi et al., 2023 | CNN + U2-Net | Wheat dataset | ~96% | Single disease focus |

**Research Gap**

Despite significant progress in deep learning-based plant disease detection, several limitations still exist in current approaches.

Most existing methods rely heavily on Convolutional Neural Network (CNN)-based architectures, which primarily focus on extracting local spatial features from leaf images. However, these models often struggle to generalize in real-field environments due to variations in lighting, background complexity, and occlusions, limiting their practical applicability [13], [15] .

Furthermore, many studies depend on controlled datasets such as PlantVillage, which do not accurately represent real agricultural conditions. As a result, models trained on such datasets show reduced performance when applied to real-world scenarios [9], [15] .

Another major limitation is the limited use of multimodal data. Although environmental factors such as temperature, humidity, and soil conditions play a crucial role in disease development, many existing systems rely only on image-based inputs, leading to incomplete analysis [10], [26] .

In addition, deep learning models often require high computational resources, making them unsuitable for deployment on low-power Internet of Things devices and real-time applications [12] .

Finally, the lack of interpretability remains a challenge, as most models act as black-box systems, reducing user trust and limiting their adoption in practical agricultural environments. Although Explainable AI techniques have been introduced, they are still not widely integrated into existing systems [25] .

Therefore, there is a need to develop an advanced framework that integrates efficient Deep Learning models, real-field datasets, multimodal data fusion, lightweight architectures for edge deployment, and explainable AI techniques to improve accuracy, robustness, and usability in real-world agricultural applications.

**Methodology**

**1. Leaf Image Input Layer**

- Input consists of plant leaf images collected from datasets such as PlantVillage and real-field environments [1], [15]
- Images may include different crops such as tomato, potato, grape, and corn
- These images capture disease symptoms like spots, discoloration, and texture changes

Using diverse leaf images helps improve model accuracy and robustness in disease detection.

**2. Preprocessing & Image Enhancement**

- Image resizing, noise removal, and normalization are applied to standardize input images [1]
- Techniques such as Gaussian Blur and segmentation (RGB/HSV) are used to enhance disease regions
- Background removal helps focus on the leaf area

This step improves feature extraction and reduces unwanted noise.

**3. CNN-Based Feature Extraction Module**

- **Deep Learning** models (CNN) are used to automatically extract features from images [3], [34]
- Convolution and pooling layers extract:
  - Edges
  - Texture
  - Color patterns

CNN effectively identifies disease patterns such as leaf spots, lesions, and discoloration.

**4. Feature Optimization & Lightweight Model**

- Lightweight models such as MobileNet and ShuffleNet are used for efficient processing [2], [12]
- These models reduce computational complexity and are suitable for real-time applications

Important for deployment on mobile and IoT devices.

**5. IoT Sensor Data Integration**

- Environmental data such as:
  - Temperature
  - Humidity
  - Soil moisture

are collected using **Internet of Things** devices [10], [26] Combining image + sensor data improves disease prediction accuracy.

**6. Classification Layer**

The final classification layer categorizes plant diseases into different classes:

- Healthy
- Early-stage disease
- Specific disease types (e.g., leaf spot, blight, mildew)

Deep learning models achieve high accuracy in multi-class classification tasks [3], [34]

**7. Output & Visualization**

- The system displays:
  - Predicted disease
  - Confidence score
- Explainable AI techniques (e.g., Grad-CAM) highlight infected regions [25]

Helps users understand model predictions.

**Discussion**

Hybrid CNN-based approaches combined with IoT and advanced techniques provide several advantages over traditional machine learning models.

CNN networks effectively capture local spatial features such as leaf texture, color variation, and disease patterns, which are essential for accurate classification [3], [34] . However, standalone CNN models may struggle in real-field environments due to variations in lighting and background conditions.

The integration of Internet of Things enables real-time monitoring by incorporating environmental parameters such as temperature and humidity, which play a significant role in disease development [10], [26] . This combination improves the overall prediction accuracy and reliability of the system.

Furthermore, the use of lightweight deep learning models enhances system efficiency, making it suitable for deployment on mobile and edge devices [2], [12] .

In addition, techniques such as object detection and Explainable AI improve system performance by enabling disease localization and providing visual interpretation of results, which increases user trust and usability [5], [25] .

**Future Scope**

Future research in plant disease detection can focus on several advanced directions.

Researchers may explore advanced deep learning architectures such as Vision Transformers and hybrid models to improve feature representation and handle complex real-field conditions. Another important direction involves multi-class disease classification and severity prediction, which can help farmers take timely and effective actions for crop management [3], [34] .

Additionally, the use of multimodal data combining leaf images with environmental parameters such as temperature, humidity, and soil conditions can significantly enhance prediction accuracy and reliability [10], [26] .

Federated learning approaches can also be explored to allow data sharing across different agricultural regions while preserving data privacy. Integration of large-scale real-field datasets and self-supervised learning techniques may further improve model generalization [18] .

Finally, deploying these models in real-time agricultural environments using Internet of Things, cloud computing, and edge devices can improve accessibility, reduce latency, and support smart farming applications.

**Conclusion**

Plant disease detection using image-based analysis remains an important research area in smart agriculture. Deep learning techniques, particularly Convolutional Neural Network (CNN) models, have significantly improved disease classification accuracy and automated detection processes [3], [34] .

However, CNN models mainly focus on local image features and often face challenges in real-field conditions due to variations in lighting, background complexity, and dataset limitations [13], [15] .

The integration of Internet of Things with deep learning provides a promising solution by incorporating environmental data such as temperature and humidity, enabling more accurate and real-time disease prediction [10], [26] .

Furthermore, the use of lightweight models, multimodal data fusion, and Explainable AI techniques can enhance system efficiency, interpretability, and practical usability in agricultural environments [2], [25] .

Overall, combining deep learning with IoT and advanced techniques can significantly improve plant disease detection systems, making them more reliable, scalable, and suitable for real-world smart farming applications

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