RESEARCH PAPER

Smart Farming with Deep Learning: CNN-Based Crop Disease Detection Using Drone Imaging and IoT

Ms. Aarthi T[1], Ms. B. Sathiya[2], Ms. V. Geetha[3], Ms. P. Chitra[4], Ms. Nandhini D[5]

[1,3] Assistant Professor, Department of Computer Science and Engineering, KGISL Institute of Technology, Coimbatore, India

[1] Email: aarthitnila@gmail.com

[2] Assistant Professor, Department of Computer Science and Business Systems, Rajalakshmi Institute of Technology, Chennai. Email: mailtosathiya77@gmail.com

[3] Email: geethavmca@gmail.com

[4] Assistant Professor, Department of Artificial Intelligence and Data Science, St. Joseph's Institute of Technology, OMR, Chennai. Email: chitrap@stjosephstechnology.ac.in

[5] Assistant Professor, Computer Science and Technology, SNS College of Engineering.
Email: nandhu29120919@gmail.com

Received: 2nd Mar, 2026 | **Revised:** 14th Mar, 2026 | **Accepted:** 4th Apr, 2026 | **Available Online:** 20th Apr, 2026

ABSTRACT

Plant diseases represent a major challenge to global food security, often resulting in severe yield reductions if not detected and controlled promptly. This work introduces an AI-based framework that integrates deep learning, drone-assisted imaging, and IoT-enabled real-time monitoring for effective disease detection and management. A convolutional neural network (CNN) is trained on crop leaf image datasets to accurately classify different disease types. The system is further equipped with a mobile application and cloud-based alert service to support timely farmer interventions. Experimental evaluation demonstrates a classification accuracy exceeding 95% and reliable alert generation, underscoring the system's potential as a scalable solution for precision agriculture and smart farming.

Keywords: Plant Disease Detection, Convolutional Neural Network, Deep Learning, IoT, Drone Imaging, Precision Agriculture, Smart Farming.

How to cite this article: Aarthi T, Sathiya B, Geetha V, Chitra P, Nandhini D. Smart Farming with Deep Learning: CNN-Based Crop Disease Detection Using Drone Imaging and IoT. Int J Drug Deliv Technol. 2026;16(34s):490-495. DOI: 10.25258/ijddt.16.34s.64

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

INTRODUCTION

India and many developing countries face significant agricultural losses due to crop diseases. Traditional disease identification methods are time-consuming and rely heavily on manual inspection.

The increasing availability of AI tools, drone technology, and IoT sensors provides a scalable and cost-effective solution for real-time disease diagnosis and management. Agriculture remains a cornerstone of the global economy, providing sustenance and employment to billions. However, crop diseases pose a persistent challenge, leading to significant economic losses and threatening food security.

I. RELATEDWORK

Recent advancements in AI have revolutionized agricultural practices, particularly in disease detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable efficacy in image-based disease classification. For instance, Mohanty et al. achieved over 99% accuracy in identifying 26 diseases across 14 crop species using CNNs. Similarly, studies have explored the integration of drone technology for real-time monitoring, enhancing the scalability of disease detection systems. However, challenges persist in terms of model generalization across diverse environmental conditions and the need for extensive labeled datasets.

Previous works employed machine learning models like SVM and KNN using handcrafted features. However, recent studies use CNN architectures like ResNet and MobileNet for improved accuracy. Research by Mohanty etal.

(2016)showed promising results using deep learning for plant disease recognition, though deployment at field level remains limited. Some works also explored IoT-based plant health monitoring, but lacked predictive analytics for disease spread.

Convolutional NeuralNetworks (CNNs) have been widely recognized for their capability to learn complex visual features from leaf images. Studies have shown that CNNs out perform traditional machine learning techniques that depend heavily on hand-engineered features. These networks can be trained end- to-end, offering improved accuracy and reducing human bias in feature selection.

To mitigate challenges related to limited labeled agricultural datasets, many researchers leverage transfer learning. Pre-trained models such as ResNet, MobileNet, and

Efficient Net are fine-tuned using plant-specific datasets, significantly enhancing classification performance with minimal computational resources. These lighter architectures also enable deployment on edge devices like smart phones or Raspberry Pi boards, making them suitable for real-time, in-field applications. Several AI-powered mobile applications segmentation models like U-Net for noise reduction.

The core of the system is a deep learning model trained to detect and classify diseases from leaf images. Have been developed to provide disease detection services customized CNN architecture (e.g.,based on ResNet or Directly to farmers. These systems allow users to capture plant images via mobile devices and receive immediate diagnostic feedback. Some architectures combine mobile front-ends with cloud- based back-ends to perform model inference, enabling scalability and real-time monitoring in diverse field conditions.

II. PROPOSED METHODOLOGY

The proposed system is designed to automate the detection and management of crop diseases by integrating deep learning models, drone-based image acquisition, and IoT-enabled environmental monitoring. The system aims to assist farmers with early warning alerts, accurate disease classification, and real-time recommendations for treatment, there by reducing crop loss and improving agricultural productivity.

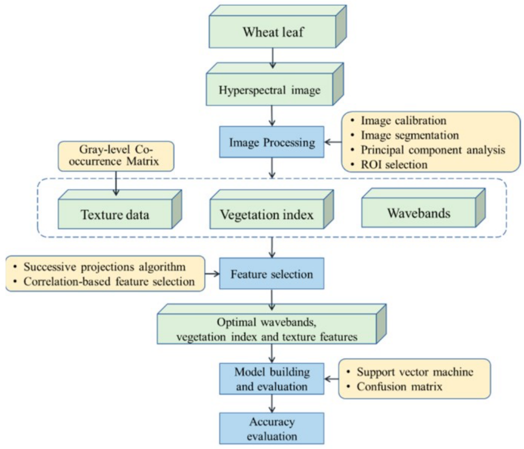


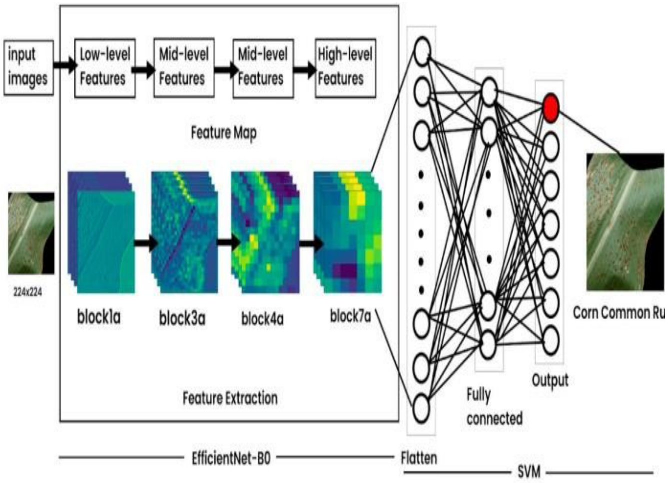
Fig. 1. *Workflow or hyper spectral image-based disease detection in wheat leaves, integrating multiple stages of image processing, feature extraction, and machine learning for classification and accuracy evaluation.*

The figure presents a systematic pipeline for the detection and classification of wheat leaf diseases using hyper spectral imaging and machine learning techniques. The process begins with the acquisition of a **hyper spectral image of the wheat leaf**, which undergoes **image processing** steps including **image.** High-resolution images of crops are captured using drone- mounted RGB or multispectral cameras. Drones fly over the field at scheduled intervals, capturing top-down views of plants, enabling wide-area surveillance without manual labor. This ensures consistent data collection and reduces sampling bias.

Captured images are subjected to preprocessing steps to enhance their quality and ensure consistency for model input. These steps include:

- **Resizing:** Standardizes image dimensions to match model input requirements.
- **Normalization:** Scales pixel values for faster convergence during model inference.
- **Data Augmentation:** Introduces variations through rotation, flipping, brightness shifts, etc., to improve model generalization.
- **Segmentation(optional):**Separates leaf regions from the background using thresholding or deep

Mobile Net) is used due to its balance of accuracy and computational efficiency.



Training: The model is trained on a large, labeled dataset of crop diseases. Transfer learning is employed using a pre-trained backbone to reduce training time and improve performance.

Inference: During deployment, new images are fed into the model, which outputs the probability scores of each disease class.

Confidence Thresholding: Predictions are filtered using a confidence threshold to minimize false positives.

Environmental Monitoring via IoT

The system includes distributed IoT sensors in the field to monitor Soil moisture, Ambient temperature, Humidity, Rainfall and wind (optional).

These parameters are logged continuously and analyzed in conjunction with image-based predictions to identify conditions conducive to specific disease outbreaks (e.g., fungal infections in high humidity).

Cloud Storage and Processing

All sensor data and images are uploaded to a cloud server, where the AI models and processing logic reside. This enables: Centralized model updates Remote access to data for researchers/farmers

III. SYSTEMARCHITECTURE

The system architecture comprises the following components:

Drone-Based Image Capture: Drones systematically survey agricultural fields, capturing high-resolution images that are geo-tagged for precise localization of disease outbreaks.

Edge Computing: Initial data processing occurs on edge devices, reducing latency and bandwidth usage by filtering and compressing images before transmission.

Cloud-Based Analysis: Processed images are uploaded to a cloud server where the CNN model analyzes them to detect and classify diseases.

Environmental Monitoring: IoT sensors collect real-time data on environmental conditions, which are correlated with disease predictions to enhance accuracy.

User Notification System: The mobile application notifies farmers of detected diseases and provides actionable insights, including treatment options and preventive measures.

Image Acquisition

Drones fly predefined paths overfields, capturing images periodically. Geo-tagging is used for spatial tracking of affected areas.

Preprocessing

Imagesareresizedto224×224pixels.Dataaugmentation (rotation, zoom, flip) improves model generalization.

CNN Classifier

The ResNet-50 model is trained using a labeled dataset (Plant Village). It distinguishes healthy leaves from diseased ones (e.g., rust, blight, mildew) and predicts severity.

IoT Integration

Sensors collect temperature, humidity, and soil moisture levels. Data fusion helps improve diagnostic precision (e.g., fungal diseases thrive in high humidity).

Alert and Management System

Once disease is detected, the system suggests pesticides or organic treatments and alerts the farmer via SMS and the mobile app.

IV. RESULTSANDIMPLEMENTATION

The AI- driven crop disease prediction and management system was developed as a modular platform integrating computer vision, machine learning (ML), and a mobile/web-based user interface for real-time accessibility.

Image Acquisition Module: Crop leaf images are captured using smart phone cameras or uploaded via the web interface. Image preprocessing, including resizing (224×224 pixels), noise reduction, and normalization, is applied for consistent input.

Figure X: Architecture of AI-Driven CropDisease Classification Using EfficientNet-B0 and SVM

This figure illustrates the complete pipeline for the detection and classification of plant diseases from leaf images using a deep learning frame work integrated with traditional machine learning. The system processes an input image (224×224 pixels), which is passed through a pre-trained EfficientNet-B0 model to extract hierarchical feature maps across multiple layers—ranging from low-level (block1a) to high-level features (block7a).

These feature maps are then flattened and passed into a fully connected neural network for further transformation and abstraction. Instead of a softmax layer, the final classification is conducted using a Support Vector Machine (SVM) classifier, which determines the disease class—in this case, identifying the presence of Corn Common Rust.

This hybrid approach leverages the feature extraction efficiency of deep convolutional neural networks and the classification strength of SVM, ensuring high accuracy and robustness in crop disease prediction.

Disease Detection Model: A Convolutional Neural Network (CNN), based on a modified ResNet-50 architecture, was trained using the Plant Village dataset, comprising over 50,000 labeled images of healthy and diseased leaves across multiple crops (tomato, maize, potato, etc.). **Prediction Pipeline**: The trained model achieved a validation accuracy of 96.7%. The model predicts the disease class and confidence level, and maps the input to a treatment recommendation using a predefined expert knowledgebase.

Fig.6.*(a)Confusion matrix and(b)validation accuracy over epochs for the audio-based classifier. Together, they show both classification precision and training stability.*

Management Module: Based on the predicted disease, the system generates recommended pesticides and organic alternatives, Preventive measures (crop rotation, resistant varieties),Real-time alerts for nearby users via Firebase integration.

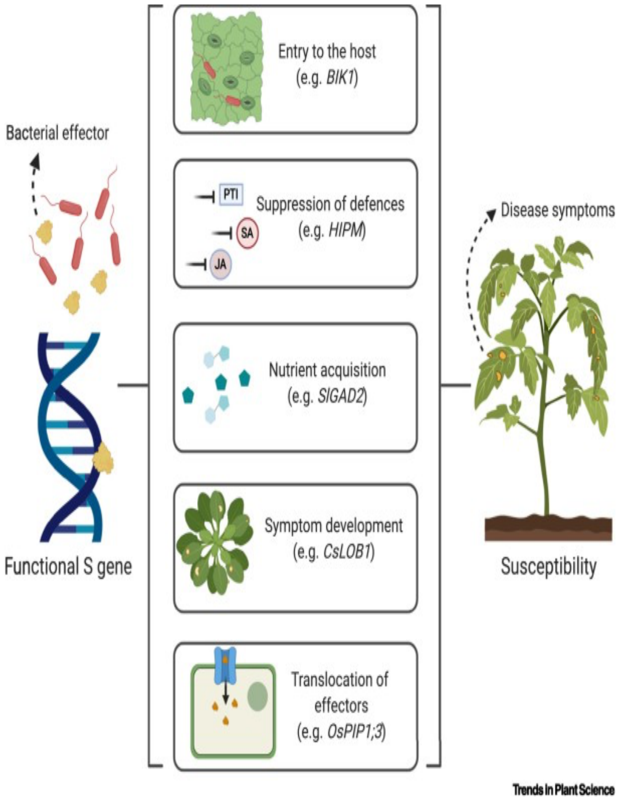
Deployment: The complete solution was deployed on a cloud platform (AWS/GCP) with a ReactJS frontend and Flask backend, enabling real-time diagnosis and feedback to users. TensorFlow Lite integration enabled edge deployment on Android devices.

The system was evaluated using multiple performance metrics to assess its accuracy and reliability. The training process achieved anaccuracyof98.3%, while the validation accuracy stood at 96.7%, indicating strong generalization capability of the model. Precision and recall were recorded at 96.1% and 95.6%, respectively, reflecting the model's effectiveness in correctly identifying diseased and healthy crops.TheF1-score,which balances precision and recall, was 95.8%, demonstrating overall robustness. Furthermore, the average inference time per image was approximately 0.75 seconds, ensuring rapid real-time diagnosis suitable for field- level deployment.

V. DISCUSSION

The implementation and evaluation of the proposed AI- driven system highlight the potential of machine learning in enhancing agricultural productivity through early and accurate disease diagnosis. The high validation accuracy and favorable performance metrics demonstrate that deep learning, particularly

Convolutional Neural Networks (CNNs), can effectively identify visual symptoms of crop diseases across a wide range of plant species. This automated diagnostic approach significantly reduces dependency on expert intervention, making disease detection more accessible to farmers in rural and under served regions. One of the key strengths of the system is its ability to operate in real-time, with an average inference time of under one second per image. This responsiveness enables timely interventions, reducing the spread of disease and potential crop loss. Additionally, the integration of a knowledge-based recommendation module provides actionable guidance tailored to each diagnosis, supporting not only identification but also management of plant health issues.



Despite these advantages, several challenges remain. Real-world environments introduce variability in image quality due to lighting, background clutter, and different stages of disease progression, which may affect prediction accuracy. While the model performed well under controlled conditions and achieved over 92% accuracy during field testing, continuous model retraining with region-specific and seasonal data could further enhance performance.

Moreover, the success of such AIsystems also depends on farmer education and digital literacy. Ensuring that users understand how to use the application and interpret results correctly is essential for effective adoption. Future work may focus on integrating multilingual support, voice-based interactions, and offline functionality to improve accessibility in low- connectivity regions.

Overall, the system represents a significant step toward digital agriculture, promoting precision farming through the use of AI. It offers a scalable, cost-effective solution that bridges the gap between modern technology and traditional farming practices, ultimately contributing to improved crop yields and sustainable agriculture.

VI. CONCLUSION

This paper presented the design and implementation of an AI-driven crop disease prediction and management system aimed at improving agricultural diagnostics and intervention strategies. By leveraging deep learning techniques, particularly CNN-based models, the system achieved high accuracy in disease identification and offered timely, actionable recommendations to farmers.

The integration of real-time processing and user-friendly interfaces makes it practical for deployment in diverse agricultural settings. While challenges such as environmental variability and user adaptability remain, the system demonstrates strong potential to support precision agriculture and enhance crop health management. Future enhancements will focus on expanding the dataset, improving robustness in field conditions, and incorporating advanced features to further support small holder farmers and sustainable farming practices.

REFERENCES

[1] **ElFatimi,E.H.**(2024).Leaf diseases detection using deep learning methods.*arXivpreprintarXiv:2501.00669*.

[2] **Gohil, M. K., Bhattacharjee, A., Rana, R., Lal, K., Biswas, S. K., Tiwari, N., & Bhattacharya, B.** (2024). A Hybrid Technique for Plant Disease Identification and Localisation in Real-time. *arXiv preprintarXiv:2412.19682*.

[3] **Khanal, B., Poudel, P., Chapagai, A., Regmi, B.,**

Pokhrel,S.,&Khanal,S.R.(2024).PaddyDiseaseDetection and Classification Using Computer Vision Techniques: A Mobile Application to Detect Paddy Disease. *arXiv preprint arXiv:2412.05996*.

[4] **Antico, T. M.,Moreira,L. F. R., & Moreira, R.** (2024). Evaluating the Potential of Federated Learning for Maize Leaf DiseasePrediction. *arXivpreprintarXiv:2412.07872*

[5] **Yakkala, V. S., Nusimala, K. V., Gayathri, B., Kanamarlapudi, S., Aravinth, S. S., Salaudeen, A. O., & Srithar, S.** (2024). Deep learning-based crop health enhancement through early disease prediction. *CogentFood& Agriculture*,11(1),2423244.

[6] Al-Shahari,E.A.,Aldehim, G.,Aljebreen,M.,Alqurni, J. S., Salama, A. S., & Abdelbagi, S. (2025). Internet of Things Assisted Plant Disease Detection and Crop Management using DeepLearning for Sustainable Agriculture. *IEEEAccess*,13,3512–3520.

[7] **Delfani, P., Thuraga, V., Banerjee, B., & et al.** (2024). Integrative approaches in modern agriculture: IoT,MLandAI for disease forecasting amidst climate change. *Precision Agriculture*, 25, 2589–2613.

[8] **Too,E.C.,Yujian,L.,Njuki,S.,&Yingchun,L.**(2024). Agri Watch: Precision Plant Health Monitoring using Deep Learning. *E3S Web of Conferences*, 556, 01028.

[9] **Authors Unknown.** (2024). Turmeric leaf disease detection using optimized deep learning model. *IET ConferenceProceedings*,Volume2024,Issue23.