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# Image-Based Deep Learning Approach for Crop Disease Detection: A Schematic Review

**Rishabh Verma**
M. Tech. Scholar, Department of Electronics and Communication Engineering, Lakshmi Narain College of Technology Excellence, Bhopal
**Dr. Deepak Soni**
Associate Professor, Department of Electronics and Communication Engineering, Lakshmi Narain College of Technology Excellence, Bhopal

**Abstract**
Crop diseases significantly affect agricultural productivity, food quality, and economic stability worldwide. Early and accurate detection of plant diseases is essential for reducing crop losses and improving agricultural sustainability. Traditional disease identification methods mainly rely on manual inspection by agricultural experts, which is time-consuming, labor-intensive, and often inaccurate under large-scale farming conditions. In recent years, image-based deep learning techniques have emerged as powerful tools for automated crop disease detection due to their high accuracy, feature extraction capability, and real-time analysis performance. This schematic review presents a comprehensive overview of image-based deep learning approaches used for crop disease detection and classification. The study discusses various deep learning architectures, including Convolutional Neural Networks (CNN), Transfer Learning models, Recurrent Neural Networks (RNN), and hybrid deep learning frameworks applied to plant disease identification using leaf images. The review also highlights different stages involved in disease detection such as image acquisition, preprocessing, segmentation, feature extraction, classification, and performance evaluation. Publicly available datasets, data augmentation techniques, and evaluation metrics such as accuracy, precision, recall, and F1-score are also analyzed. Furthermore, the paper discusses the advantages, limitations, and challenges associated with deep learning-based crop disease detection systems, including dataset imbalance, environmental variations, computational complexity, and real-time deployment issues. The study concludes that image-based deep learning approaches have significant potential for developing intelligent and automated agricultural monitoring systems capable of improving crop health management and sustainable farming practices.

**Keywords**: Crop Disease Detection, Deep Learning, Convolutional Neural Network (CNN), Image Processing, Precision Agriculture, Plant Disease Classification

## I. INTRODUCTION

Agriculture plays a vital role in the economic development and food security of many countries worldwide. Crop productivity and quality are highly influenced by environmental conditions, soil fertility, irrigation practices, and plant health. Among these factors, crop diseases are one of the major causes of agricultural losses, significantly affecting crop yield, food quality, and farmers' income. Plant diseases caused by fungi, bacteria, viruses, and pests can spread rapidly and severely damage agricultural production if not identified and controlled at an early stage [1].

Traditionally, crop disease detection is performed through manual observation and laboratory analysis by agricultural experts. Although these methods can provide accurate diagnosis, they are often time-consuming, labor-intensive, costly, and unsuitable for large-scale agricultural monitoring. In many rural areas, the lack of expert availability further delays disease identification, resulting in reduced productivity and economic losses. Therefore, there is a growing need for automated, accurate, and real-time crop disease detection systems [2, 3].

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have transformed the field of precision agriculture. Among these technologies, image-based deep learning approaches have emerged as powerful tools for automated crop disease detection and classification. Deep learning models, especially Convolutional Neural Networks (CNNs), can automatically extract important features from plant leaf images and accurately identify disease patterns without manual feature engineering. These techniques provide high detection accuracy and can process large volumes of agricultural image data efficiently [4].

Image-based crop disease detection systems generally involve several stages, including image acquisition, preprocessing, segmentation, feature extraction, classification, and performance evaluation. High-resolution images of infected plant leaves are captured using cameras, smartphones, drones, or sensors. The collected images are then processed using deep learning algorithms to detect disease symptoms such as spots, discoloration, lesions, and texture abnormalities. Transfer learning models such as VGG16, ResNet, InceptionNet, and MobileNet are widely used for improving classification performance and reducing training complexity [5, 6].

Deep learning-based disease detection offers several advantages over traditional techniques, including high accuracy, automatic feature learning, reduced human intervention, and real-time monitoring capability. These systems support precision agriculture by enabling early disease diagnosis and timely treatment, thereby minimizing crop damage and improving agricultural productivity. Furthermore, the integration of deep learning with Internet of Things (IoT), cloud computing, and smart farming technologies has enhanced the development of intelligent agricultural monitoring systems [7].

Despite significant progress, several challenges still exist in image-based crop disease detection systems. Variations in lighting conditions, complex backgrounds, dataset imbalance, low-quality images, overlapping symptoms, and computational complexity can affect the performance of deep learning models. In addition, the availability of large and diverse labeled datasets remains a major limitation for training robust disease classification systems [8, 9].

This schematic review aims to provide a comprehensive overview of image-based deep learning approaches for crop disease detection. The study discusses different deep learning architectures, datasets, image processing techniques, evaluation metrics, advantages, limitations, and future research directions associated with intelligent crop disease monitoring systems. The review highlights the growing importance of deep learning technologies in modern agriculture for improving crop health management and ensuring sustainable farming practices.

## II. LITERATURE REVIEW

**J. Pierre Nyakuri et al. [1],** presented a comprehensive review of state-of-the-art deep learning algorithms used for Internet of Things (IoT)-based crop pest and disease detection systems. The study discussed the integration of IoT devices such as sensors, drones, and smart cameras with deep learning techniques for real-time agricultural monitoring. Various convolutional neural network (CNN) architectures and transfer learning models were analyzed for identifying crop diseases and pests with high accuracy. The authors highlighted the importance of cloud computing and edge computing in supporting intelligent agricultural systems. The paper also discussed challenges such as dataset limitations, computational complexity, network connectivity, and scalability issues in practical IoT-based crop disease detection systems.

A. S. Doutoum et al. [2], reviewed different deep learning approaches for leaf disease detection and classification. The authors explained how image processing and CNN-based models are widely used for identifying disease symptoms from plant leaf images. The study compared several deep learning architectures including AlexNet, ResNet, VGGNet, and MobileNet based on classification accuracy and computational efficiency. The review highlighted the role of preprocessing techniques such as segmentation, resizing, and data augmentation in improving model performance. The authors concluded that deep learning models significantly outperform traditional machine learning methods in automated plant disease detection.

Ekanayaka et al. [3], proposed a machine learning-based crop disease prediction and alert system for early disease diagnosis in agriculture. The study focused on using machine learning algorithms to predict crop diseases based on environmental conditions and crop symptoms. The authors emphasized the importance of real-time alert systems for supporting farmers in disease management and reducing crop losses. Different supervised learning algorithms were discussed for disease prediction and classification. The paper highlighted that integrating prediction systems with mobile and web applications can improve accessibility and agricultural decision-making.

Kalaivani et al. [4], introduced smart agriculture systems using federated and centralized artificial intelligence models for real-time crop disease diagnosis. The study compared centralized AI frameworks with federated learning approaches for agricultural data processing and disease classification. The authors explained that federated learning improves data privacy and security by allowing decentralized model training without sharing sensitive agricultural data. Deep learning models were implemented for accurate disease detection from crop images. The paper concluded that federated AI systems provide efficient and secure solutions for intelligent agriculture and real-time disease monitoring.

Chowdhury et al. [5], developed “Proprietor,” a smartphone-based farmer assistance application designed to support crop planning, disease diagnosis, agricultural expert search, and crop recommendation. The application utilized deep learning techniques for crop disease identification through image analysis. The study emphasized the importance of mobile technology in providing accessible agricultural support to farmers. Features such as crop suggestions, disease information, and expert consultation improved the usability of the system. The paper demonstrated that smartphone-based intelligent farming applications can enhance agricultural productivity and support sustainable farming practices.

In [6], the authors proposed an IoT-based plant disease identification and crop management system using deep learning techniques for sustainable agriculture. The system integrated sensors, IoT devices, and deep learning models for continuous monitoring of crop health and environmental conditions. CNN-based image classification techniques were used to identify plant diseases from leaf images in real time. The study highlighted the benefits of combining IoT with AI technologies for precision agriculture and efficient crop management. The paper also discussed challenges related to sensor accuracy, network connectivity, and implementation costs.

Xiaoxue et al. [7], reviewed the applications of knowledge graphs in crop pest and disease management. The study analyzed how knowledge graph technologies can organize agricultural information, improve disease diagnosis, and support intelligent decision-making systems. The authors discussed various data sources used in constructing agricultural knowledge graphs, including sensor data, expert knowledge, and image datasets. Trend analysis showed increasing interest in integrating artificial intelligence and semantic technologies for agricultural monitoring. The paper concluded that knowledge graphs can improve the efficiency and accuracy of crop disease management systems.

R. E. Schapire et al. [8], provided an overview of the boosting approach in machine learning and explained its importance in improving classification performance. The study discussed boosting algorithms such as AdaBoost, which combine multiple weak classifiers to create a strong predictive model. The author highlighted the advantages of boosting methods in reducing classification errors and improving model accuracy. This approach has been widely applied in image classification and agricultural disease detection tasks. The paper established boosting as an effective technique for enhancing machine learning performance in complex classification problems.

Ben-Hur et al. [9], introduced the concept of support vector clustering based on Support Vector Machine (SVM) theory. The study demonstrated how clustering techniques can identify patterns and classify complex datasets effectively. The authors explained the mathematical foundations of SVM and its applications in pattern recognition and image analysis. The paper contributed significantly to machine learning research and provided a strong basis for later applications of SVM in crop disease classification and agricultural image processing.

Otukei et al. [10], conducted a comparative study on land cover classification using decision trees, support vector machines, and maximum likelihood algorithms. The study evaluated the performance of different machine learning techniques in remote sensing and image classification applications. The authors found that support vector machines and decision trees produced better classification accuracy compared to conventional methods. The paper highlighted the importance of advanced machine learning algorithms in image-based environmental and agricultural analysis. Their findings supported the application of machine learning methods in crop monitoring and disease detection systems.

## III. CROP DISEASE

Crop disease refers to any harmful condition caused by pathogens such as fungi, bacteria, viruses, nematodes, or environmental factors that negatively affect the growth, quality, and productivity of crops. These diseases damage different parts of plants including leaves, stems, roots, fruits, and seeds, leading to reduced agricultural yield and economic losses for farmers. Crop diseases can spread rapidly through air, water, soil, insects, contaminated tools, and infected seeds. Early detection and proper management of crop diseases are essential for maintaining plant health, improving food production, and ensuring sustainable agriculture.

Types of Crop Diseases

1. Fungal Diseases: Caused by fungi and are the most common plant diseases.
   Examples:
   - Rust disease
   - Powdery mildew
   - Leaf spot
   - Wilt disease
2. Bacterial Diseases: Caused by harmful bacteria affecting plant tissues.
   Examples:
   - Bacterial blight
   - Citrus canker
3. Viral Diseases: Caused by plant viruses and usually spread by insects.
   Examples:
   - Mosaic disease
   - Leaf curl disease
4. Nematode Diseases: Caused by microscopic worms present in soil.
   Examples:
   - Root-knot disease
5. Environmental Diseases: Caused by unfavorable environmental conditions such as nutrient deficiency, excess moisture, drought, or temperature stress.

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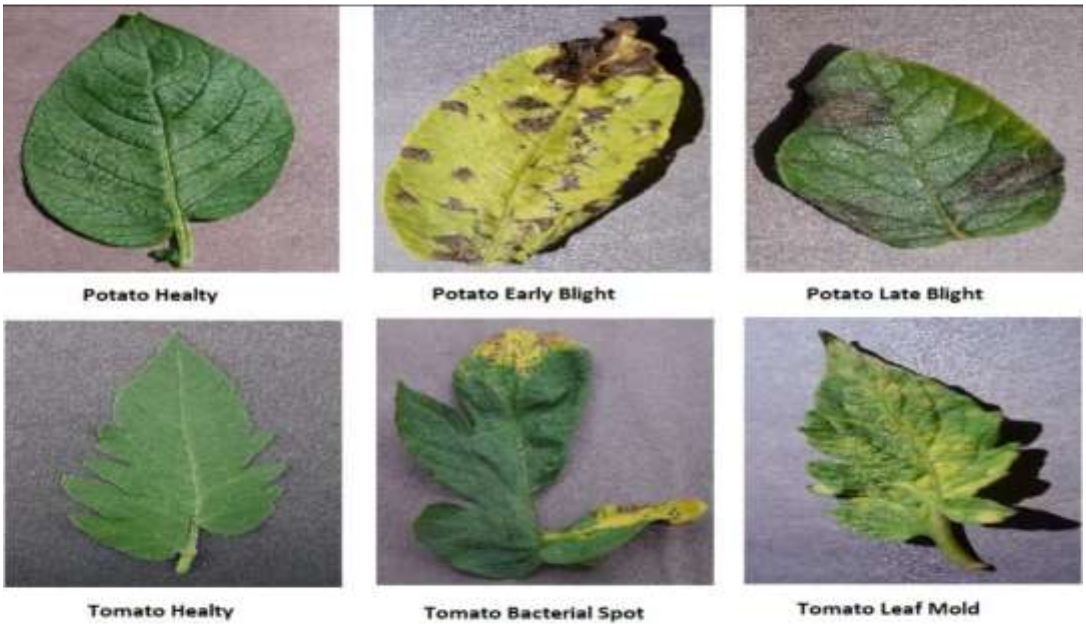


Figure 1: Potato Crop Disease

## IV. IMAGE PROCESSING

Image processing is a technique used to analyze, enhance, manipulate, and extract useful information from digital images using computer algorithms. It plays an important role in fields such as medical imaging, agriculture, satellite imaging, security systems, robotics, and artificial intelligence. In agriculture, image processing is widely used for crop disease detection, plant monitoring, weed identification, and yield analysis.

In crop disease detection systems, image processing helps in identifying disease symptoms from plant leaf images by analyzing color, texture, shape, and pattern variations. It improves the quality of images and extracts important features that are later classified using machine learning or deep learning algorithms.

Steps Involved in Image Processing

1. Image Acquisition

The first step involves capturing images using cameras, smartphones, drones, or sensors. High-quality images of crop leaves are collected for disease analysis.

2. Image Preprocessing

Preprocessing improves image quality and removes unwanted noise. Common preprocessing techniques include:

- Image resizing
- Noise removal
- Contrast enhancement
- Color conversion
- Filtering

3. Image Segmentation

Segmentation divides the image into meaningful regions to isolate infected areas from healthy portions of the leaf. Techniques include:

- Thresholding
- Edge detection
- Region-based segmentation
- Clustering methods

4. Feature Extraction

Important features such as color, texture, shape, and lesion patterns are extracted from segmented images for disease analysis.

5. Image Classification

Machine learning or deep learning models classify the image into healthy or diseased categories. Common algorithms include:

- CNN
- SVM
- Random Forest
- KNN

## V. DEEP LEARNING

Deep Learning is a subfield of Artificial Intelligence and Machine Learning that uses artificial neural networks with multiple hidden layers to automatically learn patterns and features from large amounts of data. It enables computers to perform tasks such as image recognition, speech recognition, natural language processing, and disease detection with high accuracy.

Deep learning models are inspired by the structure and functioning of the human brain. These models process data through interconnected layers of neurons, where each layer extracts important features from the input data. Unlike traditional machine learning methods, deep learning automatically performs feature extraction without requiring manual intervention.

In agriculture, deep learning is widely used for crop disease detection, yield prediction, weed identification, soil analysis, and smart farming applications. Image-based deep learning models can analyze plant leaf images and accurately identify diseases by detecting symptoms such as spots, discoloration, and texture changes.

Working Process of Deep Learning

1. Input Layer: Receives input data such as images, text, or sensor data.
2. Hidden Layers: Perform feature extraction and pattern learning using mathematical computations.
3. Output Layer: Produces the final prediction or classification result.

Common Deep Learning Architectures

- CNN: Mainly used for image processing and crop disease detection.
- RNN: Used for sequential and time-series data analysis.
- ResNet: Deep neural network architecture with skip connections.

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- VGG16: Popular CNN model for image classification.
- MobileNet: Lightweight deep learning model for mobile and embedded systems.

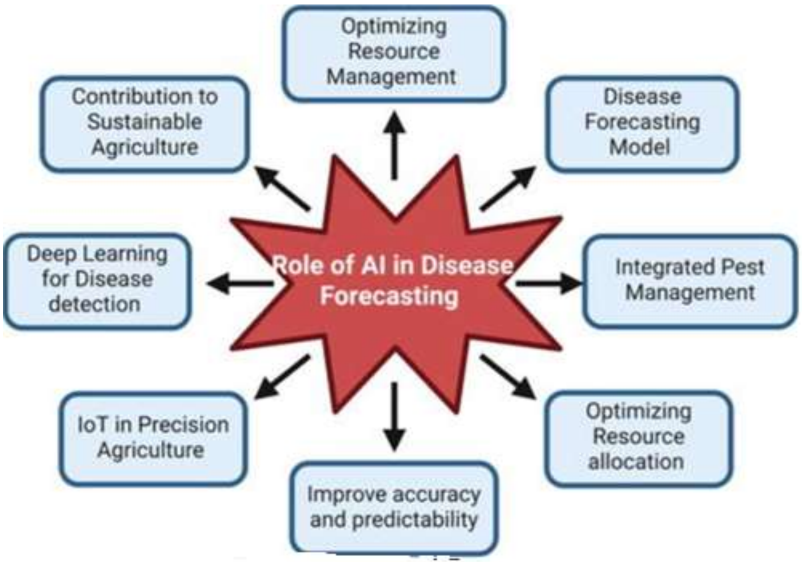


Figure 2: Deep Learning

## VI. CONCLUSION

Image-based deep learning approaches have emerged as highly effective and intelligent solutions for automated crop disease detection and classification in modern agriculture. The integration of deep learning techniques with image processing has significantly improved the accuracy, speed, and reliability of disease identification compared to traditional manual inspection methods. Deep learning models such as CNN, ResNet, VGG16, and MobileNet have demonstrated excellent performance in recognizing complex disease patterns from plant leaf images.

The review highlighted that image processing techniques including preprocessing, segmentation, feature extraction, and classification play an important role in improving disease detection efficiency. The use of publicly available datasets, transfer learning models, IoT devices, drones, and smartphone-based applications has further enhanced the development of intelligent agricultural monitoring systems. These technologies support precision agriculture by enabling early disease diagnosis, reducing crop losses, minimizing pesticide usage, and improving overall crop productivity.

Despite the significant advancements, several challenges still exist in practical implementation. Issues such as insufficient labeled datasets, environmental variations, poor image quality, computational complexity, and real-time deployment limitations can affect the performance of deep learning models. In addition, the requirement for high computational resources and large training datasets remains a major concern for large-scale agricultural applications.

Overall, image-based deep learning techniques provide a promising and sustainable solution for smart farming and automated crop health management. Future research should focus on developing lightweight, cost-effective, and highly accurate deep learning models that can operate efficiently in real-world agricultural environments. The integration of artificial intelligence, cloud computing, IoT, and mobile technologies is expected to further improve crop disease detection systems and contribute significantly to sustainable and precision agriculture practices in the future.

## REFERENCES


[1] J. Pierre Nyakuri, C. Nkundineza, O. Gatera and K. Nkurikiyeyezu, "State-of-the-Art Deep Learning Algorithms for Internet of Things-Based Detection of Crop Pests and Diseases: A Comprehensive Review," in *IEEE Access*, vol. 12, pp. 169824-169849, 2024, doi: 10.1109/ACCESS.2024.3455244.

[2] A. S. Doutoum and B. Tugrul, "A Review of Leaf Diseases Detection and Classification by Deep Learning," in *IEEE Access*, vol. 11, pp. 119219-119230, 2023, doi: 10.1109/ACCESS.2023.3326721.

[3] E. M. H. I. Ekanayaka and P. P. N. V. Kumara, "Machine Learning Approach for New Crop Disease Predict and Alert System: A Review," *2022 International Conference on Emerging Techniques in Computational Intelligence (ICETCI)*, Hyderabad, India, 2022, pp. 45-49, doi: 10.1109/ICETCI55171.2022.9921364.

[4] A. Kalaivani, V. Asha, J. Sathya, R. Kumar, R. N. T and R. Jain, "Smart Agriculture: Federated and Centralized Ai Models for Real-Time Crop Disease Diagnosis," *2025 6th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2025, pp. 1325-1329, doi: 10.1109/ICIRCA65293.2025.11089601.

[5] M. Chowdhury, M. O. Rahman and S. Alam, "Proprietor: A Farmer Assistance Smartphone Application with Crop Planner, Crop Disease Help, Agri-expert Search, and Crop Suggestion Features," *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10725364.

[6] T. V, P. S. R, T. s. S, V. S and V. R, "Sustainable Agriculture Through IoT Based Plant Disease Identification and Crop Management Using Deep Learning," *2025 International Conference on Innovative Trends in Information Technology (ICITIIT)*, Kottayam, India, 2025, pp. 1-6, doi: 10.1109/ICITIIT64777.2025.11041594.

[7] L. Xiaoxue, B. Xuesong, W. Longhe, R. Bingyuan, L. Shuhan and L. Lin, "Review and Trend Analysis of Knowledge Graphs for Crop Pest and Diseases," in *IEEE Access*, vol. 7, pp. 62251-62264, 2019, doi: 10.1109/ACCESS.2019.2915987.

[8] R. E. SCHAPIRE, "The boosting approach to machine learning: An overview" in Nonlinear estimation and classification, New York: Springer, pp. 149-171, 2003.

[9] A. Ben-HUR, D. Horn, H. T. Siegel MANN, V. VAPNIK, "Support vector clustering", Journal of machine learning research, vol. 2, pp. 125-137, Dec 2001.

[10] J. R. OTUKEI, T. BLASCHKE, "Land cover change assessment using decision trees support vector machines and maximum likelihood classification algorithms", International Journal of Applied Earth Observation and Geo information, vol. 12, pp. S27-S31, 2010.

[11] PANIGRAHI, S. & Ting K.C. (1998) Artificial Intelligence for Biology and Agriculture, Kluwer Academic Press).

[12] S. C. Mukhopadhyay, *Smart Sensing Technology for Agriculture and Environmental Monitoring*, vol. 146. Springer Berlin Heidelberg, 2012. doi:10.1007/978-3-642-27477-6.

[13] German, L. A., Ramisch, J. J., & Verma, R. (Eds.). (2010). *Beyond the biophysical: Knowledge, culture, and power in agriculture and natural resource management*. Springer Science+Business Media. https://doi.org/10.1007/978-90-481-8826-08. Won Don Lee (2009). The Development and Application of Decision Tree for Agriculture Data. IITSI :16-20.

[14] V. Leemans and M. F. Destain, “A real-time grading method of apples based on features extracted from defects,” *Journal of Food Engineering*, vol. 61, no. 1, pp. 83–89, 2004, doi:10.1016/S0260-8774(03)00192-2.

[15] J. R. Quinlan, “Decision trees and multi-valued attributes,” in *Machine Intelligence 11*, J. E. Hayes and D. Michie, Eds. Oxford, UK: Oxford University Press, 1986, pp. 305–318.

[16] Z. Zia, “An expert system based on spatial data mining using decision tree for agriculture land grading,” in *Proc. Second Int. Conf. Intelligent Computation Technology and Automation*, China, Oct. 10–11, 2009, pp. 142–145.