Popular Article

Deep Learning Models for Early Detection of Diseases in Vegetable Crops

Shivanjali Sarswat

Ph.D. scholar, SKAUST, Jammu & Kashmir

ARTICLE HISTORY

Received: May 01, 2026
Accepted: May 01, 2026
Published: May 13, 2026

Abstract

Vegetable crops are extremely susceptible to a wide range of diseases brought on by bacteria, viruses, fungus, and environmental stresses. Reducing crop losses, guaranteeing food security, and advancing sustainable agriculture all depend on early disease identification. Conventional disease diagnosis techniques mostly rely on expert manual inspection, which is labour-intensive, time-consuming, and frequently imprecise in field settings. Plant disease identification may now be done effectively and automatically through recent developments in computer vision and deep learning technology. Common datasets, performance indicators, benefits, drawbacks, and prospects for further research are highlighted in the article. Results show that deep learning-based systems can enhance precision agriculture techniques for sustainable vegetable production and greatly increase the accuracy of disease identification.

DOI: https://doi.org/10.5281/zenodo.20152906

Corresponding author email: *Sarswatshivanjali@gmail.com*

Keywords: Deep Learning, Vegetable Crops, Plant Disease Detection, Artificial Intelligence, Precision Agriculture

Introduction

Global food production and economic growth depend heavily on agriculture. Vegetable crops like tomatoes, potatoes, chillies, cucumbers, brinjal, and onions are important for both agricultural revenue and human nourishment. However, plant diseases negatively impact agricultural quality and yield, resulting in significant global financial losses. Recent research indicates that plant diseases cause a 20–30% annual decline in agricultural productivity worldwide.

Traditional techniques of diagnosing diseases mostly rely on agricultural professionals' visual assessment. These techniques are costly, time-consuming, and frequently unsuccessful in identifying diseases in their early stages. Automated illness detection systems that can correctly diagnose symptoms from photos of plant leaves have been made possible by the quick development of artificial intelligence, machine learning, and computer vision.

Deep learning models can automatically extract complex features from diseased plant images without requiring manual feature engineering. These models have been successfully applied in identifying diseases such as tomato leaf blight, potato late blight, bacterial spot, powdery mildew, and mosaic virus in vegetable crops. Recent advancements in transfer learning, attention mechanisms, and lightweight CNN architectures have further improved disease detection efficiency in real-field agricultural conditions

Deep Learning Techniques Used in Vegetable Disease Detection

1. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have become one of the best deep learning methods for identifying plant diseases due to their exceptional capacity to extract features from images and recognise patterns. CNNs are specifically made to use convolutional, pooling, and fully connected layers to process multidimensional picture data. By automatically learning hierarchical characteristics from photos of plant leaves, these architectures do away with the requirement for human feature engineering (Abade *et al*., 2020).

Vegetable crop disease detection has made extensive use of a number of CNN designs, such as AlexNet, VGG16, ResNet, DenseNet, EfficientNet, and MobileNet. Large-scale picture datasets like

PlantVillage and PlantDoc, which include annotated photos of both healthy and damaged crop leaves, are typically used to train these algorithms. Due to their effective feature propagation techniques and deep residual learning capabilities, ResNet and DenseNet have shown the best classification performance among these architectures (Pacal *et al*., 2024).

According to recent research, in controlled laboratory settings, CNN-based disease classification systems can reach detection accuracies higher than 95%. Additionally, because of their reduced computational complexity and quicker inference speed, lightweight architectures like MobileNet and EfficientNet are being used more and more for smartphone-based disease diagnosis applications (Kumar *et al*., 2025).

2. Transfer Learning

Transfer learning has grown in importance as a method for analysing agricultural images, especially when there aren't enough labelled datasets available. Through fine-tuning, transfer learning applies pre-trained deep learning models created on huge benchmark datasets like ImageNet to tasks involving the categorisation of plant diseases. Training time, computing demands, and the requirement for large agricultural datasets are all greatly reduced via transfer learning. VGG16, ResNet50, InceptionV3, and EfficientNet are examples of pre-trained architectures that have been effectively used for disease detection in tomato, potato, cucumber, and chilli crops. Research has demonstrated that transfer learning techniques enhance model generalisation and classification accuracy, especially in real-world settings with fluctuating illumination, complicated backgrounds, and picture noise (Upadhyay *et al*., 2025).

3. Models for Detecting Objects

In order to accurately locate and identify disease-affected areas in vegetable crop leaves, stems, and fruits, object detection models are being used more and more. Object detection techniques simultaneously locate and classify unhealthy areas inside an image, in contrast to conventional image classification models that merely forecast disease categories.

In real-time illness diagnosis systems, sophisticated object identification frameworks like SSD (Single Shot Detector), Faster R-CNN, and YOLO (You Only Look Once) have shown impressive efficacy. While Faster R-CNN offers better localisation accuracy for complicated disease symptoms, YOLO-based models are especially beneficial due to their rapid processing speed and real-time field deployment capabilities (Shoaib *et al*., 2023).

In field settings with fluctuating sunlight, overlapping leaves, and diverse backdrops, these algorithms may identify several illnesses at once. By facilitating site-specific crop management techniques and focused pesticide administration, object detection systems also aid precision agricultural applications.

Applications in Vegetables

Vegetable Crop	**Common Diseases Detected**	**Deep Learning Models**
Tomato	Early blight, late blight, bacterial spot	CNN, ResNet, YOLO
Potato	Late blight, early blight	VGG16, DenseNet
Chilli	Leaf curl virus, anthracnose	CNN, MobileNet
Cucumber	Powdery mildew, downy mildew	Faster R-CNN
Onion	Purple blotch, stemphylium blight	Transfer Learning Models

The scalability and usefulness of AI-based disease monitoring systems in vegetable production systems have been further improved by recent developments that integrate object detection with drone imagery, IoT sensors, and mobile applications. As a result, object detection models are seen as a promising technology solution for intelligent and sustainable agriculture management.

Advantages of Deep Learning in Disease Detection

High Accuracy of Detection

By automatically extracting complex picture elements like lesions, discolouration, spots, and texture variations from plant leaf photos, deep learning models—in particular, Convolutional Neural Networks (CNNs)—offer extremely accurate disease classification. According to studies, under controlled circumstances, disease detection accuracy can surpass 95% (Pacal *et al.*, 2024).

Early Disease Recognition

In the early stages of infection, deep learning algorithms can identify minor illness symptoms, allowing for prompt intervention and slowing the development of infections in vegetable crops. According to Abade *et al.* (2020), early detection greatly reduces crop productivity losses and increases the effectiveness of disease control.

Automated Extraction of Features

Deep learning models automatically extract pertinent features from unprocessed picture datasets, in contrast to conventional machine learning techniques that necessitate laborious feature engineering. This increases the efficiency and dependability of the model while requiring less human labour (Nigam & Jain, 2020).

Monitoring Diseases in Real Time

Real-time illness diagnosis in the field is made possible by deep learning algorithms connected with drones, IoT devices, and smartphone apps. Rapid decision-making and ongoing crop monitoring are made possible by these technologies (Upadhyay *et al*., 2025).

Decreased Reliance on Professionals

Systems for diagnosing diseases automatically lessen the need for ongoing oversight by plant pathologists and agricultural specialists. Farmers in isolated and rural locations with little access to expert advising services may especially benefit from this (Shoaib *et al*., 2023).

Assistance with Precision Farming

Targeted pesticide application and efficient resource management are made possible by the ability of object detection and segmentation algorithms to precisely identify contaminated areas within plant leaves and fruits. This lowers environmental pollution and increases input-use efficiency (Upadhyay *et al*., 2025).

Decreased Use of Pesticides

In order to reduce excessive chemical use and promote environmentally sustainable agriculture, accurate disease localisation and early detection enable selective pesticide use rather than blanket spraying (Shoaib *et al*., 2023).

Scalability in a Variety of Crops and Illnesses

Deep learning architectures are particularly versatile for a variety of agricultural applications since they can be trained and optimised for a variety of vegetable crops, including tomato, potato, chilli, cucumber, and onion (Pacal *et al*., 2024).

Enhanced Computational Effectiveness

For mobile-based and edge-computing agricultural applications, lightweight architectures like MobileNet and EfficientNet offer quick inference speed and reduced computational requirements (Kumar *et al*., 2025).

Improved Systems for Decision Support

AI-based disease detection systems improve crop productivity, quality, and financial returns by helping farmers and other agricultural stakeholders make data-driven management decisions.

Challenges and Limitations

Variability in the Environment

The accuracy of illness detection can be adversely affected by variations in lighting, background noise, humidity, and image quality (Shafay et al., 2025).

Similar Symptoms of Diseases

Similar visual symptoms are present in many plant diseases, which might result in misdiagnosis and decreased model reliability (Nigam & Jain, 2020).

High Requirements for Computation

For training and deployment, sophisticated deep learning models need strong hardware and substantial processing resources (Kumar et al., 2025).

Insufficient Generalised Models

The majority of current models are crop-specific and are unable to accurately identify diseases in a variety of vegetable crops (Shoaib et al., 2023).

Restricted Use in Rural Areas

The adoption of AI technologies in rural farming areas is hampered by poor internet access, a lack of technical infrastructure, and expensive implementation costs (Upadhyay et al., 2025).

Restricted Field Datasets

The majority of models are less effective in real-world scenarios because they were trained on datasets from laboratories (Pacal et al., 2024).

Prospects for the Future

Future studies ought to concentrate on:

AI integration with drones and the Internet of Things

Mobile apps that operate in real time

Hyperspectral and multispectral imaging

AI models that can be explained

Cloud-based advice systems for agriculture creation of inexpensive, farmer-friendly equipment

Global food security and sustainable vegetable production can be greatly enhanced by combining smart farming technologies with AI-enabled disease detection systems.

Conclusion

A revolutionary tool for early disease detection in vegetable crops is deep learning. Plant diseases can be identified from digital photos with great accuracy and efficiency using CNNs, transfer learning models, and object identification frameworks. By lowering crop losses, increasing agricultural output, and offering quick diagnosis, these technologies can help farmers. Future developments in artificial intelligence and precision agriculture are anticipated to improve the dependability and accessibility of deep learning-based disease detection systems, despite persistent obstacles such dataset constraints and field deployment problems.

References

Pacal, I., Kunduracioglu, I., Alma, M.H., et al. (2024). *A systematic review of deep learning techniques for plant diseases*. Artificial Intelligence Review, 57, 304.

Shafay, M., Hassan, T., Owais, M., et al. (2025). *Recent advances in plant disease detection: challenges and opportunities*. Plant Methods, 21, 140.

Upadhyay, A., Chandel, N.S., Singh, K.P., et al. (2025). *Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture*. Artificial Intelligence Review, 58, 92.

Shoaib, M., Shah, B., EI-Sappagh, S., et al. (2023). *An advanced deep learning models-based plant disease detection: A review of recent research*. Frontiers in Plant Science, 14, 1158933.

Nigam, S., & Jain, R. (2020). *Plant disease identification using Deep Learning: A review*. Indian Journal of Agricultural Sciences, 90(2).

Jelali, M.J. (2024). *Deep learning networks-based tomato disease and pest detection: a first review of research studies using real field datasets*. Frontiers in Plant Science, 15.

Das, P.K., Rupa, S.S., Pumrin, S., et al. (2024). *Deep Learning for Plant Disease Detection and Classification: A Systematic Analysis and Review*. Current Applied Science and Technology.

Mustofa, S., Munna, M.M.H., Emon, Y.R., et al. (2023). *A comprehensive review on Plant Leaf Disease detection using Deep learning*.

Abade, A.S., Ferreira, P.A., & Vidal, F.B. (2020). *Plant Diseases Recognition on Images using Convolutional Neural Networks: A Systematic Review*.

Kumar, A., Monga, H.P., Brahma, T., et al. (2025). *Mobile-Friendly Deep Learning for Plant Disease Detection: A Lightweight CNN Benchmark Across 101 Classes of 33 Crops*.