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REVIEW ARTICLE

Empowering early detection of plant diseases in agriculture using artificial intelligence

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Abstract

Artificial Intelligence (AI) is revolutionizing plant disease diagnosis by providing transformative solutions to the challenges posed by agricultural diseases. AI-driven algorithms significantly reduce the time required for disease identification, enabling timely and precise control measures. These interventions help prevent the widespread proliferation of pathogens, mitigate crop losses and minimize economic damage. The integration of machine learning and deep learning particularly convolutional neural networks (CNNs) with computer vision systems enhances the precision, scalability and efficiency of disease monitoring. AI-powered tools offer real-time surveillance by capturing images of diseased leaves and generating data-driven insights, thereby facilitating targeted treatment applications while reducing resource wastage and environmental impact. Furthermore, the application of AI-powered mobile apps provides farmers with instant, field-level support to take preventive actions during the early stages of disease development. These technologies enable farmers to make informed, evidence-based decisions, optimize their agricultural practices and enhance crop yield and quality. Ultimately, AI plays a pivotal role in boosting agricultural productivity, ensuring food security and promoting both economic resilience and environmental sustainability. This review highlights recent advancements in machine learning algorithms, deep learning models especially CNNs and the role of mobile applications in early disease detection in agriculture.

Keywords: AI apps; computer vision; convolution neural network; deep learning; machine learning

Introduction

Plant pests and diseases have been affecting crops for many centuries account for up to 40 % of crop losses posing a continuous threat to global food security and nutrition (1). The global crop production reached 9.9 billion tonnes in 2023 -2024 and with the world population projected to rise to 9.8 billion by 2050, as a result, the agricultural yields must increase by 25-70 % to meet future food demands, emphasizing the importance of advancing AI technologies for effective plant disease management (2, 3). Recent studies report that plant disease prevalence in crops can reach 70-80 %, causing yield losses of up to 98 %, primarily due to various pathogens such as bacteria, fungi, viruses and others (4). This highlights the urgent need for early and accurate disease detection to minimize crop losses. However, traditional methods like visual inspection which depends on human observation to detect symptoms such as leaf discoloration or wilting, are manual, time-consuming and prone to inaccuracies and biochemical assays like ELISA and PCR, though reliable for pathogen identification, are expensive, require laboratory facilities and are unsuitable for large-scale field surveillance. These approaches frequently discover diseases only after symptoms appear, limiting the efficacy of early management measures. Farmers without access to expert knowledge often struggle to accurately diagnose plant diseases, leading to delayed control and increased crop losses. Detecting diseases as early as possible minimizes and eliminates financial losses. For example, Convolutional Neural Networks (CNNs) have demonstrated high accuracy in detecting multiple plant diseases, achieving 86.21 % accuracy for 12 diseases in tomato, potato and bell pepper leaves(5). Over time, techniques for diagnosing plant diseases have evolved and now, serological and DNA-based approaches are crucial for precise diagnosis, which is time-consuming and requires skilled labour. Therefore, it is essential to develop AI technologies, such as machine learning algorithms and deep learning models, as well as Internet of Things (IoT) devices, for the early and accurate diagnosis of plant diseases through AI-powered sensors. These AI-driven systems utilize multisensory technologies and intelligent support for the development of immersive diagnostic tools and smart farming systems, enabling real-time assessment of plant health by analyzing vast datasets, including high-resolution images and environmental parameters, to detect disease patterns (6). Fundamentally, AI is the capability of a computer to carry out tasks that involve human attention, like reasoning, understanding skills, perception, prediction and deciding proper solutions (7). The use of AI technology not only enhances labour safety and reduces environmental impact through precise disease detection, but also enables the application of smart measures, such as biochar and optimized fertilizers, to minimize the overuse of agrochemicals (8). AI models can further optimize technologies like biochar-enhanced soil treatments by closely monitoring nutrient availability, pH levels and microbial activity, all of which are critical factors associated with disease resistance (9). Utilizing digital image processing techniques, researchers can uncover patterns in the behaviour of plants in response to disease by gathering a vast quantity of data on their response to affected plants. Some researchers have suggested the use of automated plant disease recognition to address issues related to the lack of facilities for disease diagnosis (10). This review discusses recent advancements in the early detection of crop diseases using integrated machine learning and deep learning approaches, emphasizing their role in enhancing precision agriculture. By combining these AI techniques, significantly improved diagnostic accuracy is enabled, allowing for timely interventions that reduce crop losses and minimise the overuse of pesticides and fertilisers. The review also explores real-world applications, challenges and future directions for implementing these technologies effectively under field conditions.

Artificial Intelligence for Early Detection of Plant Diseases

AI is becoming increasingly important in agriculture, particularly in the timely recognition and classification of plant diseases, which are crucial for crop health and productivity. The initial step in this process is classification, which involves grouping input data, such as leaf images, spectral signs and sensor readings, into predefined categories representing healthy or diseased conditions. Machine learning (ML) and deep learning (DL) approaches, notably CNNs, have shown great accuracy in detecting diseases of plants. The growing demand for efficient, accurate and timely disease detection in agriculture has highlighted the need for AI technologies. AI enables real-time monitoring of crop health, helping to prevent losses and promote sustainable, productive farming practices. The AI-driven disease detection process involves multiple techniques that analyse plant images to accurately diagnose diseases, enabling timely interventions and improved crop management (Fig. 1). Traditional approaches, such as visual inspection and laboratory testing, are being complemented by AI-driven methods, including computer vision, deep learning and spectral analysis. An overview of the key instruments and methodologies used in plant disease prediction and integration with AI for improved diagnostic accuracy (Table 1). AI classification networks used in plant disease detection, including their architecture, principles and effectiveness are highlighted in Table 2. These networks including CNNs, RNNs and hybrid models, enhance early disease detection through automated image analysis and pattern recognition.

Machine learning methods (ML) for plant disease detection

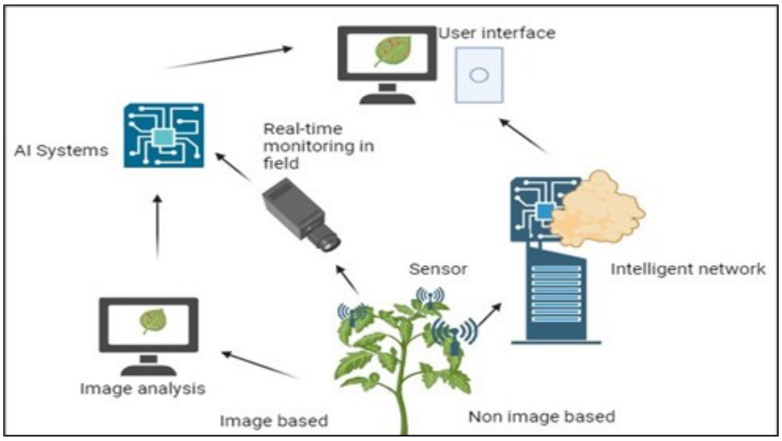

Fig. 1. Detection of diseases using artificial intelligence.

Table 1. Instruments and methodologies used in disease prediction

Instruments used in disease prediction	Methodologies used in disease prediction	References
Spectroradiometer, Infrared Thermometer, Chlorophyll Fluorescence	Random Forest (RF) model for detecting Septoria blotch disease on wheat.	(60)
Near-Infrared Spectroscopy (NIRS)	Artificial Neural Network (ANN) model for detecting *nutrient deficiencies* and disease stress in tea leaves.	(54)
Thermographic Camera, Two Linear Hyperspectral Scanners, Wavelengths 430 to 2376 nm	Neural Network (NN) model for classifying rape oil seeds infected with *Alternaria* in a greenhouse.	(61)
Ground-Based Digital Phenotyping System	Deep Learning-based model for early *yellow rust* detection in wheat.	(62)
Hyperspectral Photos of Soil and Canopies	Neural Network (NN) model for identifying *Phytophthora infestans* in tomatoes.	(63)
Thermal and Visible Light Imaging Cameras	Support Vector Machine (SVM) model for identifying plants infected with *Oidium neolycopersici*, focusing on temperature values and color channels.	(64)
Hyperspectral Scanners	Integrated Neural Network, Random Forest (RF) and Multiple Regression Networks were used to estimate the risk of *Stagonospora nodorum* blotch across 431 cases before planting.	(65)

Table 2. AI classification network for identifying plant diseases

Model used in classification network	Key features of the networks	Applications in plant disease detection	References
AlexNet	8-layer CNN, high accuracy and speed, ReLU activation, dropout for regularization	Used for plant disease detection with transfer learning, effective in early disease identification	(66)
VGG (VGG-16/VGG-19)	Deep architecture with 16 or 19 layers, uniform filter size (3×3), high accuracy	Extracts hidden features in plant leaves, useful for lesion detection and stress identification	(67)
ResNet (ResNet-50/ResNet-101)	Uses residual learning with skip connections, manages deep networks efficiently	Potentially useful for deep networks and used to identify plant diseases using pre-trained models	(68)
GoogLeNet (Inception-V1)	22-layer deep network, high accuracy, efficient computation resources usage	Pre-trained models fine-tuned for plant disease detection, used in resource-constrained environments	(69)
Inception-V3	48 layers, multi-scale feature extraction, factorized convolutions for reduced computation	Fine-tuned for plant disease classification, improves accuracy in complex backgrounds	(22)
YOLO (You Only Look Once)	Real-time object detection, high-speed processing	Detects plant diseases in real-time, useful for field-based applications	(70)
Xception	Depthwise separable convolutions, efficient feature extraction	High-accuracy plant disease classification with fewer computations	(71)
MobileNet (MobileNetV2/V3)	Lightweight architecture optimized for mobile and edge devices, depthwise separable convolutions	Used for real-time plant disease detection in mobile apps, IoT-based precision farming	(72)

Pre-existing data forms are the foundation of machine learning algorithms, which are used to customise search results based on search history (11). To identify excellent features and patterns, basic ML techniques like Random Forest (RF), Support Vector Machine (SVM), Linear Regression, K-Nearest Neighbor (KNN), Naive Bayes (NB) and Decision Trees are used. SVM aims to find an optimal hyperplane ($w_T x + b = 0$) that separates classes with the maximum margin. Decision Trees use the entropy formula ($H(X) = -\sum p(x) \log p(x)$) to split data based on information gain. K-NN classifies samples based on the majority, using distance measures like Euclidean distance. The frequently used techniques are Linear Regression, SVM, K-NN and Principal Component Analysis.

For classification tasks, SVM are employed. It identifies a separating hyperplane that maximizes the margin, or the distance between the nearest points of information of various classes (12). The performance of machine learning models, such as SVM, can be improved by adjusting variables like the kernel type (e.g., linear or radial basis function), the regularisation parameter (C) and the gamma value. SVM is categorized into linear and non-linear. In a linear SVM, data that is uniformly distributed allows for a linear hyperplane to separate the grades. Conversely, a non-linear SVM handles data that is distributed in various directions and higher dimensions (13). Most real-world applications are better addressed using non-linear SVMs. The use of kernel tricks is a key feature of SVMs, aiding in non-linear classification by transforming features through functions such as radial basis functions (RBF), polynomial functions and linear functions. Linear kernels are suitable for linearly separable data, polynomial kernels work well when interactions between features are important and RBF kernels are ideal for complex, non-linear relationships. This feature transformation increases the training time and the dimensions of the feature space.

Random Search samples search random parameter values within a certain range, whereas Grid Search checks combinations exhaustively. Bayesian Optimization is an efficient technique for hyperparameter tuning that models the performance function probabilistically and selects optimal parameters. It uses Gaussian Processes to construct a surrogate model, enabling efficient exploration of the search space. This approach reduces computational costs while enhancing the performance of models in plant disease classification.

Deep learning techniques (DL) for plant disease detection

Deep learning builds upon artificial neural networks (ANNs) by incorporating a deeper architecture with multiple layers. DL has more layers than ANN or ML, which allows it to recognise patterns that these algorithms are unable to recognise. The neurons in an ANN utilize transfer and activation functions, which rely on mathematical functions to introduce non-linearity. The activation function processes the weighted sum of inputs to determine the neuron's output. The neural network determines these weights during training. ANNs commonly employ the backpropagation algorithm to optimise model parameters by minimising errors through weight adjustments. Among deep learning approaches, Recurrent Neural Networks (RNNs) have shown remarkable success in identifying plant lesions from images with high accuracy. Their ability to capture temporal dependencies and contextual features makes them particularly effective in analyzing sequential patterns in plant disease progression. By leveraging RNN-based techniques, AI-driven plant disease detection systems can enhance precision and reliability, supporting early diagnosis and improved crop management (14). A key advantage of DL-based techniques is their ability to automatically extract features from input data, rather than depending on human feature engineering. DL is particularly suited for large-scale image datasets due to its capability to handle complex, high-dimensional data and learn abstract features automatically. DL is an extension of neural networks with a high layer count in neural network design. These networks can recognise features in the data and train themselves to predict the outcome. DL, particularly deep convolutional neural networks (DCNNs), has demonstrated superior performance in disease identification, outperforming traditional methods such as SVM and Naive Bayes. DCNN is able to detect various cucumber diseases with an accuracy of up to 93.41 %, highlighting its effectiveness in plant disease diagnosis (15).

Deep Belief Networks (DBNs) are a class of DL models that utilize multi-layers of Restricted Boltzmann Machines (RBMs) to learn hierarchical feature representations in an unsupervised manner (16). DBNs have been extensively applied in plant disease and pest detection, where they analyze plant images to identify affected regions, classify disease types and detect specific pest infestations. By leveraging deep feature extraction, DBNs can distinguish between various plant stress conditions, such as fungal infections, bacterial diseases and insect damage, based on lesion patterns, discoloration and texture variations in plant leaves. Studies have demonstrated that DBNs achieve high accuracy, ranging from 96 % to 97.5 %, in classifying plant diseases and pests, making them a reliable approach for precision agriculture (17). Compared to traditional machine learning (ML) techniques, deep belief networks (DBNs) excel in capturing complex patterns in image data without extensive feature engineering, thereby enhancing early detection and decision-making in crop protection. Their efficiency in processing large-scale agricultural datasets positions them as a promising tool for automated disease diagnosis and integrated pest management in modern farming systems.

The Deep Denoising Autoencoder (DDA) is an advanced neural network architecture that extends the functionality of traditional autoencoders by incorporating noise reduction capabilities, making it highly effective for detecting plant diseases and pest infestations (18). A DDA comprises two primary components: an encoder that compresses input data into a lower-dimensional representation and a decoder that reconstructs the original data while filtering out noise. This dual functionality allows DDA to serve 2 crucial objectives in plant health assessment removing noise from plant leaf images and developing a prediction framework for accurate disease recognition. In agricultural applications, image datasets frequently contain distortions resulting from environmental factors such as varying light conditions, occlusions or sensor imperfections. By denoising plant leaf images before classification, DDAs enhance the model's ability to extract meaningful features, improving overall prediction accuracy. Experimental results indicate that DDAs achieve an impressive accuracy rate of 98.3 % in categorising plant leaves affected by pests and diseases, outperforming conventional deep learning (DL) models in precision agriculture (19). This high level of accuracy underscores the potential of DDAs as a robust tool for automated plant disease diagnosis, precision farming and integrated pest management. Additionally, a comprehensive overview of open-source deep learning algorithms (Table 3) further highlights the accessibility and applicability of these techniques in real-world agricultural systems. The deep learning process for plant disease classification highlights key stages, including data preprocessing, feature extraction, model training, validation and disease prediction (Fig. 2).

Convolutional neural networks (CNNs)

Convolutional Neural Networks (CNNs) comprise many layers that extract hierarchical information from input images. CNNs have revolutionised plant disease identification by enhancing accuracy and diagnostic capabilities through advanced architectures, such as VGG-16, Inception-V3, ResNet-50 and AlexNet, as demonstrated in a study that reported high classification accuracy across multiple crop disease datasets (20). These architectures are specifically designed to enhance feature extraction, hierarchical pattern recognition and computational efficiency in deep learning-based plant disease detection. VGG-16, a deep convolutional neural network (CNN) with 16 layers, is known for its uniform filter size and sequential architecture, which enables the capture of fine-grained features in plant leaf images (21). In contrast, Inception-V3 employs parallel convolutional layers with different filter sizes to capture multi-scale patterns, making it highly effective for complex plant disease

Table 3. Open-source algorithms of deep learning technique

Algorithms of deep learning	Developers of the algorithms	Year of Release	Compatible devices of deep learning	Features used in deep learning	Coding language of deep learning	Applications of the algorithms	References
TensorFlow	Google	2015	CPUs, GPUs, TPUs	Dataflow graphs, ML/DL, Pre-built layers and functions, TensorFlow Lite for mobile/IoT	Python, C++	ML and DL applications, High-performance computing, Crop disease detection, Autonomous tractors	(30)
Keras	Open-source community, initially developed by François Chollet	2015	Uses TensorFlow, CNTK, Theano	High-level API, Simplified model creation, Pre-built layers and functions	Python	Rapid prototyping, DL model development, Disease classification in plants	(73)
PyTorch	Facebook AI Research	2016	CPUs, GPUs, Edge AI (PyTorch Mobile)	Dynamic computational graphs, Distributed training, Pre-built modules	Python, C++	Research, Prototyping, Image-based pest identification	(74)
Caffe	Berkeley Vision and Learning Center (BVLC)	2014	CPUs, GPUs	Efficient convolutional operations, Pre-built layers and functions	C++, Python	Object detection, Image and video classification, Weed detection	(75)
MXNet	Apache (Amazon)	2015	CPUs, GPUs, Cloud -based AI	Efficient distributed training, Scalable, Optimized for cloud computing	Python, Scala, Julia	Large-scale ML/DL, Satellite-based crop monitoring, Smart farming	(76)

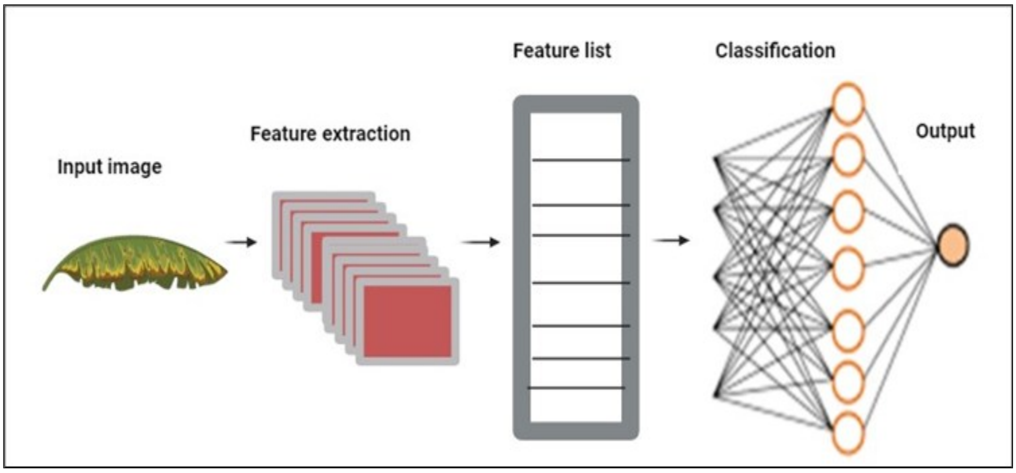

Fig. 2. Deep learning for plant disease classification.

identification (22). ResNet50, a residual network with 50 layers, introduces skip connections to mitigate vanishing gradient issues, thereby enabling deeper networks to converge efficiently and improving classification accuracy in large-scale plant disease datasets (23). Additionally, AlexNet, one of the earliest deep CNN architectures, utilises the Rectified Linear Unit (ReLU) activation and dropout layers to prevent overfitting, making it suitable for detecting plant diseases from images (24). Researchers have tested these CNN architectures to develop highly accurate plant disease detection models, achieving superior performance in visual recognition, feature extraction and semantic understanding of plant health conditions. These advancements demonstrate the efficacy of CNN-based deep learning models in precision agriculture, enabling early disease detection, automated diagnosis and informed decision-making for sustainable crop management. CNN is typically composed of several key layers, including convolutional layers, activation functions, pooling layers and fully connected layers, which work together to extract meaningful patterns from input images for classification tasks. The input layer serves as the first stage of a CNN, where raw image data is fed into the network. Following this, most CNN architectures incorporate convolutional layers as their second layer, responsible for extracting local features from input images through learnable filters (kernels) that detect edges, textures and patterns at various spatial hierarchies (25). Each convolutional operation produces an output known as a feature map, which highlights critical features relevant for plant disease detection. The ReLU is applied after each convolutional operation, ensuring that the network learns complex features effectively. This is followed by pooling layers, which down sample the feature maps to reduce computational complexity and enhance translational invariance, helping the model generalize better for unseen plant disease images (24). Finally, fully connected (dense) layers integrate extracted features for classification, where a softmax or sigmoid activation function generates probability scores for different plant diseases. These structured layers collectively enable CNNs to achieve high accuracy in plant disease identification, demonstrating superior performance over traditional machine learning models. Fig. 3 illustrates a standard CNN architecture, showcasing its hierarchical feature extraction and classification process. These layers use many types of 2-D filters to extract features from the image. As the number of images adds on, they can be used to reduce pooling, also known as down-sampling layers, which reduces dimension and produces a more compact representation of the image (26).

The models trained on large datasets, such as ImageNet, can be fine-tuned for domain-specific tasks, eliminating the need for a vast amount of training data. Once the model has been trained successfully, it can recognize different sorts of diseases. When a leaf image is input into a

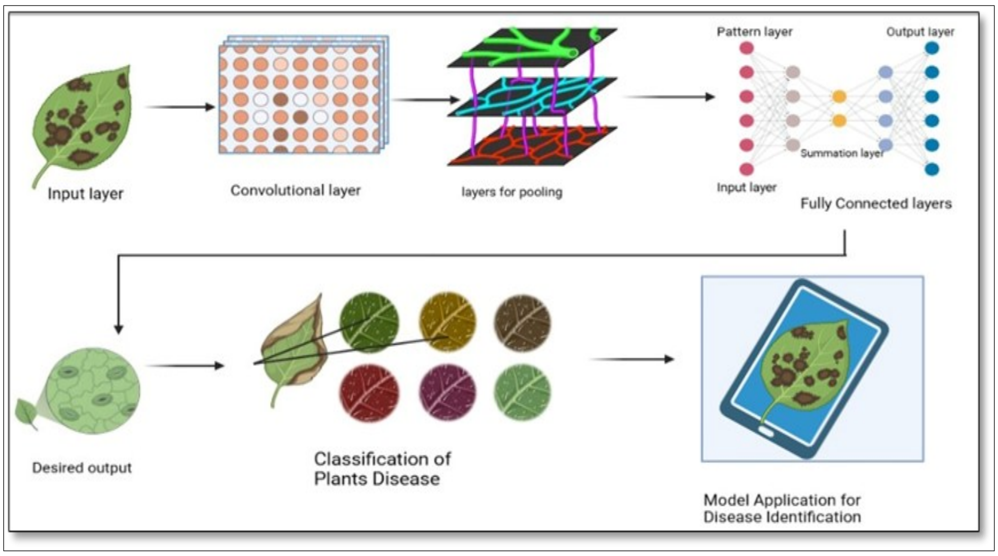

Fig. 3. Working of CNN in plant disease detection.

CNN for disease identification, the decision-making process begins with the image passing through convolutional layers that extract important features. These layers capture patterns such as edges, textures and shapes relevant to identifying diseases. The extracted feature vectors are then processed, with unnecessary dimensions being removed to streamline the data. Finally, the refined features pass through the fully connected layers, where the network analyzes the information and makes a conclusion regarding the presence of a disease or pest. Research indicates that CNNs can classify images of plant leaves affected by pests or diseases with a high accuracy rate range of 99-99.2 %. Efficient Net optimizes depth, width and resolution scaling, to achieve accuracy (27). Table 4 summarizes various CNN applications in crop disease identification. Small datasets can lead to overfitting and poor generalisation in CNNs. Data augmentation methods, including flipping, colour jittering, rotation and scaling, artificially increase the dataset size and model resilience (28). When actual data is limited, Generative Adversarial Networks (GANs) can produce synthetic samples that resemble real-world data, aiding in the training of deep learning (DL) models (29). However, synthetic data must be strictly evaluated to maintain realism minimize model bias. Deep CNN training demands a significant amount of processing power; hence, GPUs (Graphics Processing Units) are vital for speeding up matrix operations (30). Faster R-CNN, on the other hand, uses a Region Proposal Network (RPN) to produce potential object areas before classification, resulting in higher accuracy but greater processing complexity (31). Mask R-CNN builds on Faster R-CNN by incorporating a pixel-level segmentation mask, making it suitable for applications that require accurate disease area detection (32). The selection of these models relies on the trade-off between accuracy and real-time processing requirements.

Computer vision (CV) for plant disease identification

CV is crucial for the early and accurate detection of plant diseases through the analysis of visual symptoms, such as lesions, discolouration and deformities. CV techniques, such as object detection and semantic segmentation, are instrumental in identifying and locating plant disease symptoms by detecting lesion regions, discolouration and texture on leaves. Object detection highlights affected areas using bounding boxes, while semantic segmentation classifies each pixel to map diseased tissue precisely, enabling accurate diagnosis and quantification of disease severity. (33). This method can automatically transform plant images into attributes, such as colour histograms, texture features, lesion size and shape, which can be used for the classification and detection of plant diseases. However, CV algorithms require a substantial amount of annotated image data for model training and may not be suitable for diseases that have not been previously detected. Different applications of AI in plant pathology are given in Table 5. Object detection models are crucial in plant disease diagnosis, pest detection and yield estimation because they localise multiple objects in images. Semantic segmentation is crucial for disease localisation in leaves, fruits and crops because it labels each pixel in the image. Models such as U-Net and DeepLabV3+ offer fine-grained segmentation by collecting both global context and local data, therefore distinguishing between diseased and healthy areas. These models are especially beneficial for early disease

Table 4. CNN applications in crop disease identifications

Technologies used in CNN	Diseases identified	Data source obtained in identification	DL Model(s) used in applications	Accuracy	Additional features of applications	References
IoT, AI (RiceTalk platform)	Rice blast disease	Non-image IoT devices	CNN	89.4 %	Real-time analysis, soil cultivation sensing	(77)
IoT, AI (RiceTalk platform)	27 diseases related to 10 crops (e.g., tomatoes, potatoes,	Harsh mountainous environment	CNN	91.3 %	User-friendly interface for farmers	(78)
Mask R-CNN	Apple leaf diseases (5 classes)	2029 images of diseased apple leaves	CNN (Mask R-CNN)	78.8 %	Object instance segmentation, small dataset.	(79)
DL (various models)	Citrus disease severity	5406 images of infected citrus leaves	ResNet-34, DenseNet-169, AlexNet, VGG13, Inception-v3, SqueezeNet-1.1	92.60 %	Data augmentation, model comparison.	(80)
Federated Learning (FL) with CNN	Multi-crop disease classification	Distributed mobile devices dataset	Federated CNN (Fed-CNN)	93.7 %	Decentralized learning for privacy preservation	(81)
Transformer-based ViTs (Vision Transformers)	Maize rust classification	1306 samples for common rust	ViT-B/16	98.37 %	Outperforms CNNs in feature extraction	(82)
MobileNet, EfficientNet	Tomato and potato leaf diseases (10 classes)	PlantVillage dataset	MobileNetV2, EfficientNet-B3	95.3 %	Optimized for mobile and IoT applications	(83)

Table 5. Applications of AI in early detection of diseases in plants

Plant species	Diseases and conditions identified	Algorithm used in the detection	References
Cotton	Early scorch, Little whiteness	K-means Clustering	(84)
Rice	Nitrogen content deficiency	Artificial Neural Network	(85)
Citrus	Citrus greening, Anthracnose, Citrus canker	Support Vector Machine	(86)
Sugarcane	Red rot, Sugarcane mosaic virus, Leaf spot, Brown spot, Yellow spot	Support Vector Machine	(87)
Potato	Late blight, Leaf blight	Fuzzy C-means Clustering, Neural Networks	(88)
Apple	Apple Rust, Early Blight	Radial Basis Function Neural Network	(89)
Tomato	Late scorch, Yellow spot	Convolution Neural Network	(90)
Apple	Mosaic Rust, Brown spot, *Alternaria* leaf spot	Deep Convolution Neural Network	(91)
Pomegranate	Fruit spot, Bacterial blight	Support Vector Machine	(92)
Cotton	Tiny Whiteness, Cottony mould	K-means Clustering, Neural Network	(93)
Tulsi	Maturity evaluation	Back Propagation Multi-Layer Perceptron Neural Network	(94)

identification, as precise localisation may help farmers apply pesticides more effectively, thereby decreasing environmental impact. However, segmentation requires large annotated datasets, which can be mitigated by data augmentation using GANs to artificially expand limited datasets. Additionally, YOLO a real-time object detection system generates bounding boxes and class probabilities in a single pass, making it highly efficient and suitable for on-device inference (29). AI applications are crucial for early disease detection in plants, underscoring their importance in facilitating timely intervention and crop protection.

Challenges and Solutions in AI-Based Plant Disease Detection

AI-based plant disease detection faces multiple challenges that impact its efficiency, accuracy and practical applicability in the real world. One significant issue is the scarcity of labeled training data, as deep learning models require extensive datasets to achieve high accuracy in disease identification. Labelling agricultural data is particularly challenging due to the need for expert knowledge to accurately identify complex disease symptoms, variability in disease expression across crops and environments and the time-consuming nature of field data collection (34). Addressing this challenge involves leveraging unsupervised learning techniques, data augmentation strategies and advanced cost functions to handle noisy and incomplete data (35, 36). Another technical limitation is the vanishing and exploding gradient problem, which hampers effective model training by either diminishing or amplifying gradients across layers. This issue can be mitigated by using activation functions such as ReLU, proper weight initialisation and batch normalisation techniques (37).

Additionally, DL models often suffer from overfitting, where they learn noise instead of generalising patterns, thereby reducing their performance on unseen data. Strategies such as dropout regularisation, L2 regularisation and early stopping help prevent overfitting, ensuring robust model performance (38). Computational cost is another critical barrier, as training deep learning models demands substantial hardware resources. Model optimisation techniques, such as pruning, quantisation and distributed training, along with the use of hardware accelerators like GPUs and Field-Programmable Gate Arrays (FPGAs), can enhance computational efficiency (39, 40). Another challenge is data imbalance, where certain plant diseases are underrepresented in datasets. This imbalance can cause models to be biased toward more common diseases, reducing their ability to accurately detect rare but potentially severe diseases, which are critical for crop protection. Oversampling techniques, such as duplicating minority class samples, can improve class balance but may also risk overfitting.

Furthermore, privacy and security concerns arise when AI systems process sensitive farm data, making centralized data storage vulnerable to breaches. Federated Learning (FL) addresses this issue by enabling decentralised model training across multiple edge devices, such as IoT devices, sensors and drones, without transferring raw data to a central server. It also minimises bandwidth usage, enhances data security and enables models to adapt to the unique agricultural conditions of a given region (41, 42). Overcoming these challenges through innovative techniques will enhance the accuracy, efficiency and scalability of AI-driven plant disease detection systems, making them more practical for real-world agricultural applications.

Machine learning technique (ML) vs. deep learning techniques (DL)

The key differences between ML and DL techniques is summarized in Table 6. Machine learning (ML) and deep learning (DL) models have been widely utilised for plant disease diagnosis, each with its advantages and disadvantages. Traditional ML models, such as SVMs and RFs, rely on manually extracted features like texture, colour and form to achieve good accuracy (75-90 % for small-scale datasets). CNNs and Transformers, on the other hand, automatically learn hierarchical features, frequently achieving accuracies exceeding 95 % on large datasets such as Plant Village (43). However, DL models require a large amount of labelled data and processing resources, making ML more practical in low-data scenarios. ML models beat DL when datasets are small or when feature engineering is more efficient than automated feature extraction. For example, SVMs and RFs perform well on spectral and hyperspectral imaging datasets that include precomputed domain-specific characteristics (e.g., vegetation indices). CNNs over-fit on short datasets (<1000 pictures), while regularisation approaches stabilize ML models (44). Furthermore, in cases such as leaf disease classification with handmade morphological data, ML models attain comparable accuracy at a reduced computational cost, making them preferred in resource-constrained contexts. DL models excel at extracting high-level features, whereas classical ML models rely on handcrafted features, which limits their scalability. These findings underscore the significance of advanced deep learning (DL) architectures for large-scale image classification (43).

Automated Plant Disease Detection Systems

Image acquisition and pre-processing are the initial steps in identifying plant diseases, starting with the capture of images using a computerised vision or imaging device. Unprocessed images often appear raw and frequently contain noise, such as Gaussian noise, salt-and-pepper noise and blurring, along with distortions that necessitate pre-processing to remove unwanted elements and enhance contrast. The HSV (Hue, Saturation, Value) technique is commonly used in image processing for color segmentation because it isolates chromatic information from intensity, making it useful for distinguishing individual colours. Masking is widely used to isolate or emphasise specific portions of an image by filtering out undesired elements. Background removal employs various methods, including thresholding, edge detection and

Table 6. Machine learning technique (ML) vs. deep learning techniques (DL)

Criteria	Machine learning	Deep learning
Feature extraction	Manual	Performed by network
Volume of data	The large volume of data may not improve the accuracy.	Improved accuracy.
Type of function	Applies a single function or algorithm	Applies multiple mathematical functions at different layers.
Hardware	Normal processors	High power processors

colour-based segmentation, to isolate the primary subject from its surroundings and improve clarity. For more complex backgrounds, advanced techniques such as GrabCut and Deep Lab are employed to isolate disease-affected regions and improve focus accurately.

Furthermore, Gaussian blurring is used to remove noise and smooth images by averaging pixel values in a weighted manner, thereby improving visual quality and facilitating subsequent processing tasks, such as edge detection and object recognition. Agricultural researchers often employ masking and background removal strategies to enhance processing accuracy and efficiency (45). This step includes the removal of unwanted distortions and contrast intensifier to sharpen and highlight the image features.

Image segmentation follows, isolating the region of interest (ROI) from the background using methods such as global, variable, adaptive thresholding, edge detection and region-based segmentation (46). Area-based segmentation techniques are important in image processing, with region expansion and region splitting being 2 often-used methods. Region growth begins with a seed point and extends by adding neighboring pixels with comparable qualities, making it useful for segmenting homogenous regions. In contrast, area splitting is a top-down method that breaks a picture into smaller pieces based on predetermined criteria until homogeneity is achieved. These techniques are used in remote sensing and object recognition, where precise segmentation is required for analysis and interpretation. In plant disease diagnosis, region-based segmentation is a fundamental image processing approach that divides an image into relevant parts based on pixel similarities in shape, form and brightness value. This approach separates diseased regions from healthy areas, enhancing diagnostic accuracy. Clustering algorithms like K-means and fuzzy C-means are extensively used for this purpose because they successfully categorize pixels into clusters that share comparable attributes (47, 48). K-means works by minimizing variation within clusters, making it effective in distinguishing between affected and unaffected plant patches. In contrast, fuzzy C-means gives probability to pixels, allowing for more flexible segmentation, which is especially beneficial when disease symptoms change gradually. In plant pathology, precision segmentation is crucial because it separates diseased tissues and makes it easier to identify signs, including necrosis, chlorosis and leaf spots (49).

Following segmentation, feature extraction is used to determine important attributes of the segmented areas, such as colour, texture and shape. Understanding surface roughness and patterns which are essential for differentiating between various diseases, is possible through texture analysis, which is frequently carried out using the Grey Level Co-occurrence Matrix (GLCM). While shape analysis identifies pathogen-induced malformations, colour-based features help distinguish pigmentation differences caused by infections. To effectively categorize plant diseases and enable early diagnosis and efficient disease control techniques in agriculture, these collected features are subsequently fed into machine learning models. Mathematical models play a crucial role in image processing techniques used for plant disease detection, particularly in segmentation and feature extraction. Segmentation methods like Otsu's thresholding help separate diseased regions from healthy ones by maximizing inter-class variance. Edge detection techniques, such as the Sobel operator, identify boundaries of affected areas. Feature extraction methods, including GLCM, utilize statistical measures such as contrast to quantify disease patterns for AI model training. Morphological features work better than others when it comes to recognizing the damaged location on a leaf (50). Colour attributes play a crucial role in recognizing and classifying infected areas, as colour differences often signal disease symptoms such as chlorosis, necrosis, or fungal patches. Gabor texture and colour moments are 2 of the most frequently used colour properties for analysis. Gabor texture filtering is especially useful in capturing spatial frequency information, allowing it to detect texture patterns associated with diseased plant surfaces. Colour moments, such as mean, standard deviation and skewness, provide a statistical representation of the colour distribution in an image, making it easier to distinguish between healthy and diseased regions (51). According to studies, combining colour-based characteristics with machine learning models improves classification accuracy in plant disease detection (52). Several advanced techniques are used to extract these features, such as the hue histogram (53), which represents the distribution of colours in an image and the colour correlogram, which captures spatial colour relationships to improve disease identification accuracy. These collected features are combined into an input feature vector, which acts as the basis for the classification procedure (54). Finally, classification categorizes the images into predefined classes using an input feature vector derived from the extracted features. This step involves 2 stages: training and testing. During training, the model learns from a database setup to improve its accuracy. The selection of a suitable classifier relies on the particular issue at hand and effective classification requires a robust training dataset to achieve high accuracy (55). The automated plant disease detection process, which highlights AI-driven techniques (Fig. 4), enables efficient and accurate diagnosis. Data augmentation approaches improve training by artificially diversifying the images used in AI models. Rotation, flipping and scaling are common approaches for reducing over-fitting and improving model resilience. Advanced approaches, such as GANs, create synthetic images to expand datasets, while CutMix and MixUp combine images to enhance generalization. These strategies enable deep learning models to learn disease variances more efficiently, resulting in improved accuracy in real-world situations (28). For the diagnosis of diseases, several imaging modalities provide distinct benefits. RGB imaging is frequently used to address simple visual problems, however, it is not very effective at identifying infections in their early stages. By capturing a broad spectrum of wavelengths, hyperspectral imaging enables it possible to identify diseases early on by identifying minute spectral variations in plant tissues. Before the expression of symptoms, the temperature changes detected by thermal imaging can be a sign of plant stress. Edge computing reduces latency and allows for instantaneous disease detection in the field by processing image data

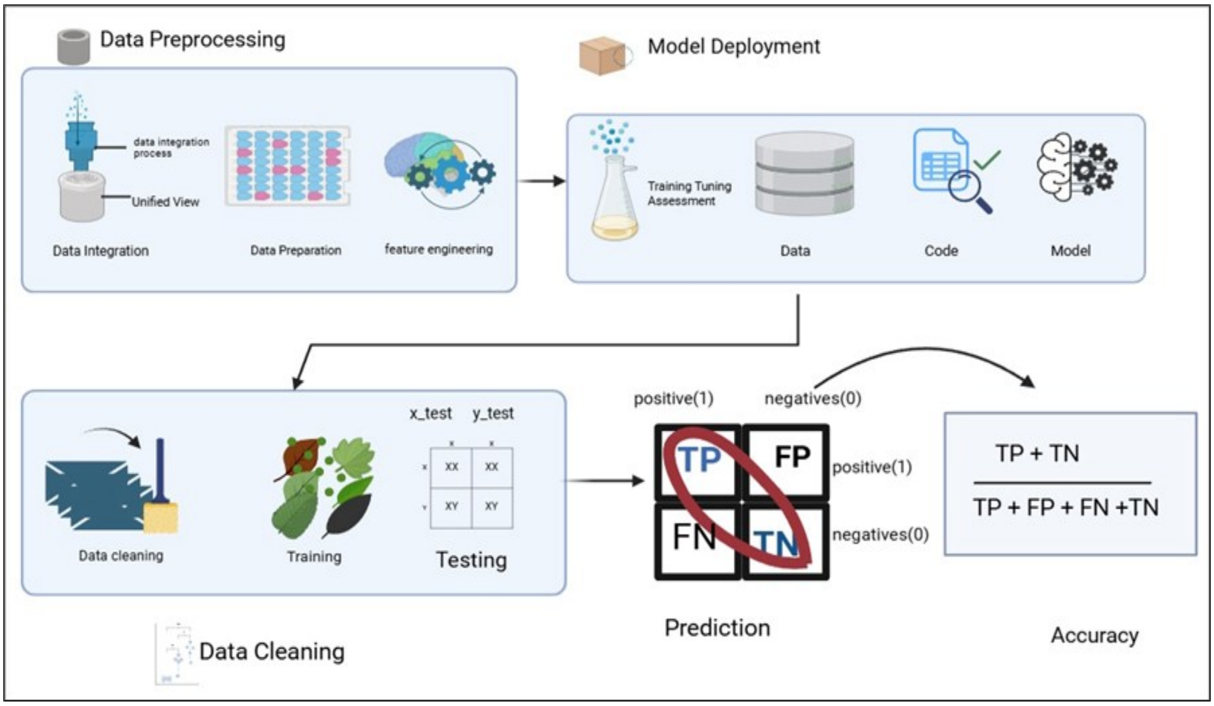

Fig. 4. Automated plant disease detection.

directly on edge devices, such as drones, Internet of Things and sensors, for real-time analysis. By reducing the need for cloud processing, this method increases the effectiveness of AI-driven precision agriculture (56).

Leveraging AI-Powered mobile applications for plant disease detection

Plant disease detection and management via mobile apps are becoming increasingly significant as they provide farmers with real-time solutions and enable early control of diseases. These apps utilize artificial intelligence to enhance their functionality, offering features such as image-based disease identification, personalized treatment suggestions and community support. However, their effectiveness and user satisfaction vary significantly, necessitating a thorough evaluation framework to ensure quality and usability. Mobile apps bring advanced plant disease detection tools directly to farmers' smartphones, enabling on-the-spot diagnosis without the need for expensive laboratory tests or expert consultations. This accessibility is particularly crucial for farmers in remote or underserved areas where traditional agricultural support services are limited. By enabling real-time analysis of plant diseases, these applications would allow farmers to minimize crop loss and control the spread of diseases.

The study identified Plantix as the most comprehensive app, successfully integrating AI for plant identification, disease detection and treatment recommendations. Plantix also includes community features that allow users to share experiences, ask questions and receive advice from other users and experts, fostering a collaborative environment for plant care and disease management (57). Analyzing user comments and feedback from app stores helps developers understand user expectations, enabling them to improve app functionalities and software quality. The apps generally scored well in terms of effectiveness, ease of use and design, but there is a need for significant improvements in AI-based technologies. However, to serve as complete solutions, these apps must improve their advanced functionalities and overall quality. Future app developments should consider user feedback and integrate robust AI features to meet the evolving needs of farmers and plant enthusiasts. This approach will ensure that mobile apps continue to be a valuable tool in modern agriculture, promoting sustainable practices and minimizing crop losses. Agrio combines AI with remote sensing to predict pest incidence, alerting farmers to treatment suggestions. Crop Doctor, developed by agricultural research organizations, detects plant diseases offline using machine learning (ML) algorithms, making it ideal for low-connectivity areas (58). These applications enable farmers to make informed decisions by providing real-time diagnostics and insights into their agricultural operations. In terms of mobile inference, on-device AI and cloud-based AI have distinct trade-offs. On-device AI employs edge computing to execute inference locally, resulting in low latency, offline capabilities and enhanced privacy. Lightweight models such as MobileNet and EfficientNet are designed for real-time processing on smartphones. However, on-device AI is constrained by hardware limitations such as memory and processing capacity. While cloud AI offers great accuracy and scalability, it requires continuous internet access and incurs data transmission costs, making it unsuitable for rural farmers. Mobile AI confronts several issues, including significant battery consumption, as running deep learning (DL) models constantly on mobile processors depletes power quickly. Internet reliance is another key concern, particularly for cloud-based inference, as inconsistent connections in rural locations impede real-time decision-making. Latency is crucial in applications that require quick input, such as pest alarms or diseases diagnostics, because delays might prevent timely intervention (59). Model quantization, pruning and edge TPU acceleration can help address these issues by reducing compute needs and increasing energy efficiency. Lists of AI-powered apps for plant disease detection and diagnosis, detailing their features, functionalities and agricultural applications (Table 7).

Table 7. AI apps for plant disease detection and diagnosis

AI Apps	Application of AI apps	References
Plant doctor	Assesses disease accuracy and reliability	(95)
Leaf doctor	Uses pixel-based image analysis to calculate disease percentage	(96)
Plantix	Provides plant protection guidance and extension activities for farmers	(57)
Crop doctor	Predicts diseases and suggests treatments using CNN and ML algorithms	(58)
Rice doctor	Identifies disease stage and recommends pesticides exclusively for rice crops	(97)
Ricexpert	Detects rice diseases, pests, nutrient deficiencies and provides e-rice advisory and marketing tools	(98)
Pestoz	Diagnoses plant diseases and pest infestations in the early stages	(99)
Plant health app	AI-based tool for real-time plant disease detection via smartphone cameras	(100)

Conclusion

The integration of artificial intelligence (AI) into plant disease diagnosis is proving to be a game-changer in agriculture, with significant potential for early detection and diagnosis of plant diseases. These models work on large datasets of plant images to identify patterns, extract features and classify diseases with high accuracy. ML algorithms such as SVM, decision trees and random forests offer interpretability and require less data, while DL models, especially CNNs, excel in handling complex image data and automating feature extraction without manual input. These AI models include high precision, scalability, rapid processing and real-time decision support for farmers. They enable early detection of diseases, reducing yield loss and input costs while promoting sustainable agriculture. Moreover, AI-enabled mobile applications extend these benefits directly to the field, empowering farmers with accessible, user-friendly tools for timely intervention and making real-time decisions before the outbreak of the disease. Despite their powerful performance, ML models often require structured data and feature engineering, while DL approaches demand large, labelled datasets and high computational resources. Integrating multimodal data such as hyperspectral imaging, environmental parameters and soil health indicators with AI models remains an underexplored area. Exploring the potential of AI not only for disease detection but also for recommending targeted chemical and pesticide treatments opens a valuable new avenue in agricultural research. In addition, autonomous field robots equipped with AI, such as the plant health robot, enable real-time disease detection and precision spraying, reducing labour requirements and minimizing pesticide use, further revolutionizing precision farming. Overall artificial intelligence is reshaping plant disease management by enabling faster, more accurate and sustainable disease detection.

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Authors' contributions

DP contributed to the conceptualization of the study and was responsible for refining the language aspects of the manuscript. IJ was involved in conceptualization, conducted formal analysis, provided supervision and validation and contributed to language editing. RK contributed to the formal analysis and supported data interpretation. SC was involved in conducting the formal analysis of the research data. AMX participated in formal analysis and helped structure the analytical framework. KM participated in the study's conceptualization, performed formal analysis and assisted with supervision and validation All authors read and approved the final version of the manuscript.

Compliance with ethical standards

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References

1. Savary S, Willocquet L, Pethybridge SJ, Esker P, McRoberts N, Nelson A. The global burden of pathogens and pests on major food crops. Nat Ecol Evol. 2019;3(3):430–39. https://doi.org/10.1038/s41559-018-0793-y
2. Food and Agriculture Organization of the United Nations (FAO). FAOSTAT Statistical Brief [Internet]. Rome: FAO; 2023 [cited 2025 Mar 25]. Available from: https://openknowledge.fao.org/bitstreams/df90e6cf-4178-4361-97d4-5154a9213877/download
3. Ray DK, Mueller ND, West PC, Foley JA. Yield trends are insufficient to double global crop production by 2050. PloS One. 2013;8(6):e66428. https://doi.org/10.1371/journal.pone.0066428
4. Nazarov PA, Baleev DN, Ivanova MI, Sokolova LM, Karakozova MV. Infectious plant diseases: etiology, current status, problems and prospects in plant protection. Acta Naturae. 2020;12(3):46–59. https://doi.org/10.32607/actanaturae.11026
5. Rastogi P, Dua S, Dagar V. Early disease detection in plants using CNN. Procedia Comput Sci. 2024;235:3468–78. https://doi.org/10.1016/j.procs.2024.04.328
6. Kliestik T, Kral P, Bugaj M, Durana P. Generative artificial intelligence of things systems, multisensory immersive extended reality technologies, and algorithmic big data simulation and modelling tools in digital twin industrial metaverse. Equilibrium Q J Econ Econ Policy. 2024;19(2):429–61. https://doi.org/10.24136/eq.2024.014
7. Russell SJ, Norvig P. Artificial intelligence: A modern approach. 4th ed. Boston: Pearson; 2016.
8. Minofar B, Milcic N, Marousek J, Gavurova B, Marouskova A. Understanding the molecular mechanisms of interactions between biochar and denitrifiers in N_2O emissions reduction: pathway to more economical and sustainable fertilizers. Soil Tillage Res. 2025;248:106405. https://doi.org/10.1016/j.still.2024.106405
9. Marousek J, Strunecky O, Vanickova R, Midelashvili E, Minofar B. Techno-economic considerations on latest trends in biowaste valuation. Syst Microbiol Biomanuf. 2024;4(2):598–606. https://doi.org/10.1007/s43393-023-00159-4
10. Kumar A, Kumar P, Suma K. Deep learning for automated

diagnosis of plant diseases: A technological approach. J Electr Syst. 2024;20(1). https://doi.org/10.52783/jes.1234

11. Yoganarasimhan H. Search personalization using machine learning. Manage Sci. 2020;66(3):1045–70. https://doi.org/10.1287/mnsc.2018.3255
12. Panigrahi KP, Das H, Sahoo AK, Moharana SC, editors. Maize leaf disease detection and classification using machine learning algorithms. In: Satapathy SC, Bhateja V, Das S, Udgata SK, editors. Progress in computing, analytics and networking: proceedings of ICCAN 2019; 2019 Mar 30–31; Bhubaneswar, India. Singapore: Springer; 2020. https://doi.org/10.1007/978-981-15-2414-1_66
13. Pukkela P, Borra S. Machine learning based plant leaf disease detection and severity assessment techniques: state-of-the-art. In: Liao B, editor. Classification in BioApps: automation of decision making. Cham (Switzerland): Springer International Publishing; 2017. p. 199–226. https://doi.org/10.1007/978-3-319-65981-7_8
14. Xu J, Chen J, You S, Xiao Z, Yang Y, Lu J. Robustness of deep learning models on graphs: A survey. AI Open. 2021;2:69–78. https://doi.org/10.1016/j.aiopen.2021.05.002
15. Ma J, Du K, Zheng F, Zhang L, Gong Z, Sun Z. A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Comput Electron Agric. 2018;154:18–24. https://doi.org/10.1016/j.compag.2018.08.048
16. Zhang N, Ding S, Zhang J, Xue Y. An overview on restricted Boltzmann machines. Neurocomputing. 2018;275:1186–99. https://doi.org/10.1016/j.neucom.2017.09.065
17. Madhuri J, Reddy BR, Kalnoor G, Indiramma M, Nagarathna N. Optimizing Crop Recommendations with Improved Deep Belief Networks: A Multimodal Approach. IEEE Access. 2025;13:1–1. https://doi.org/10.1109/ACCESS.2025.3542284
18. Zilvan V, Ramdan A, Suryawati E, Kusumo RBS, Krisnandi D, Pardede HF, editors. Denoising convolutional variational autoencoders-based feature learning for automatic detection of plant diseases. In: Proceedings of the 3rd International Conference on Informatics and Computational Sciences (ICICoS); 2019 Oct 29–30; Semarang, Indonesia. Piscataway (NJ): IEEE; 2019. p. 1–6. https://doi.org/10.1109/ICICoS48119.2019.8982494
19. Gupta L, Vyas V. Plant disease classification using AI–Spl deep learning and machine learning. 3C Tecnología: Glosas de innovación aplicadas a la pyme. 2023;12(2):65–76. https://doi.org/10.17993/3ctecno.2023.v12n2e44.65-76
20. Too EC, Yujian L, Njuki S, Yingchun L. A comparative study of fine-tuning deep learning models for plant disease identification. Comput Electron Agric. 2019;161:272–79. https://doi.org/10.1016/j.compag.2018.03.032
21. Mohameth F, Bingcai C, Sada KA. Plant disease detection with deep learning and feature extraction using plant village. J Comput Commun. 2020;8(6):10–22. https://doi.org/10.4236/jcc.2020.86002
22. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016 Jun 27–30; Las Vegas (NV): IEEE; 2016. p. 2818–26. . https://doi.org/10.1109/CVPR.2016.308
23. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2016 Jun 27–30; Las Vegas (NV): IEEE; 2016. p. 770–78. https://doi.org/10.1109/CVPR.2016.90
24. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems (NeurIPS 2012); 2012 Dec 3–8; Lake Tahoe (CA): NeurIPS Foundation; 2012. p. 1097–1105. https://doi.org/10.1145/3065386
25. Hijazi S, Kumar R, Rowen C. Using convolutional neural networks for image recognition. San Jose (CA): Cadence Design Systems Inc.; 2015.
26. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436–44. https://doi.org/10.1038/nature14539
27. Tan M, Le Q, editors. EfficientNet: Rethinking model scaling for convolutional neural networks. In: Proceedings of the 36th International Conference on Machine Learning (ICML); 2019 Jun 9–15; Long Beach (CA): PMLR; 2019. p. 6105–14. https://doi.org/10.48550/arXiv.1905.11946
28. Shorten C, Khoshgoftaar TM. A survey on image data augmentation for deep learning. J Big Data. 2019;6(1):1–48. https://doi.org/10.1186/s40537-019-0197-0
29. Goodfellow I, Bengio Y, Courville A. Deep learning. Healthc Inform Res. 2016;22(4):351–54. https://doi.org/10.4258/hir.2016.22.4.351
30. Abadi M. TensorFlow: learning functions at scale. In: Proceedings of the 21st ACM SIGPLAN International Conference on Functional Programming (ICFP); 2016 Sep 18–24; Nara, Japan. New York (NY): Association for Computing Machinery; 2016. p. 1–1. https://doi.org/10.1145/2951913.2976746
31. Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards real time object detection with region proposal networks. IEEE Trans Pattern Anal Mach Intell. 2016;39(6):1137–49. https://doi.org/10.1109/TPAMI.2016.2577031
32. He K, Gkioxari G, Dollar P, Girshick R. Mask R-CNN. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV); 2017 Oct 22–29; Venice (Italy). Piscataway (NJ): IEEE Computer Society; 2017. p. 2980–88. https://doi.org/10.1109/ICCV.2017.322
33. Kurmi Y, Gangwar S. A leaf image localization based algorithm for different crops disease classification. Information Process Agric. 2022;9(3):456–74 . https://doi.org/10.1016/j.inpa.2021.03.001
34. Ale L, Sheta A, Li L, Wang Y, Zhang N, editors. Deep learning based plant disease detection for smart agriculture. In: Proceedings of the 2019 IEEE Globecom Workshops (GC-Wkshps); 2019 Dec; Piscataway (NJ): IEEE; 2019. p. 1–6. https://doi.org/10.1109/GCWkshps45667.2019.9024439
35. Gregor K, LeCun Y. Learning fast approximations of sparse coding. In: Proceedings of the 27th International Conference on Machine Learning (ICML); 2010 Jun 21–24; Haifa (Israel). New York (NY): Omnipress; 2010. p. 399–406.
36. Ranzato MA, Mnih V, Susskind JM, Hinton GE. Modeling natural images using gated MRFs. IEEE Trans Pattern Anal Mach Intell. 2013;35(9):2206–22. https://doi.org/10.1109/TPAMI.2013.29
37. Krause J, Sapp B, Howard A, Zhou H, Toshev A, Duerig T, et al., editors. The unreasonable effectiveness of noisy data for fine-grained recognition. In: Computer Vision–ECCV 2016: Proceedings of the 14th European Conference on Computer Vision; 2016 Oct 11–14; Amsterdam, The Netherlands. Cham: Springer; 2016. p. 301–20. https://doi.org/10.1007/978-3-319-46487-9_19
38. Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R. Dropout: A simple way to prevent neural networks from overfitting. J Mach Learn. 2014;15(1):1929–58. https://doi.org/10.1007/978-981-15-0135-7_3
39. Islam M, Dinh A, Wahid K, Bhowmik P. Detection of potato diseases using image segmentation and multiclass support vector machine. In: Proceedings of the 30th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE); 2017 Apr 30–May 3; Windsor (ON), Canada. Piscataway (NJ): IEEE; 2017. p. 1–4. https://doi.org/10.1109/CCECE.2017.7946594
40. Micheli A. Neural network for graphs: A contextual constructive approach. IEEE Trans Neural Netw. 2009;20(3):498–511. https://doi.org/10.1109/TNN.2008.2010350
41. McMahan B, Moore E, Ramage D, Hampson S, Arcas BA. McMahan B, Moore E, Ramage D, Hampson S, Arcas BA. Communication-efficient learning of deep networks from decentralized data. In:

Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS); 2017 Apr 20–22; Fort Lauderdale (FL), USA. p. 1273–82. https://doi.org/10.5555/3305381.3305516

42. Yang Q, Liu Y, Chen T, Tong Y. Federated machine learning. ACM Trans Intell Syst Technol. 2019;10(2):1–19. https://doi.org/10.1145/3298981

43. Mohanty SP, Hughes DP, Salathe M. Using deep learning for image-based plant disease detection. Front Plant Sci. 2016;7:1419. https://doi.org/10.3389/fpls.2016.01419

44. Carranza-Rojas J, Goeau H, Bonnet P, Mata-Montero E, Joly A. Going deeper in the automated identification of Herbarium specimens. BMC Evol Biol. 2017;17:1–14. https://doi.org/10.1186/s12862-017-1014-z

45. Sannakki SS, Rajpurohit VS, Nargund VB, Kulkarni P. Diagnosis and classification of grape leaf diseases using neural networks. In: Proceedings of the 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT); 2013 Jul 4–6; Tirunelveli, India. Piscataway (NJ): IEEE; 2013. p. 1–5. https://doi.org/10.1109/ICCCNT.2013.6726616

46. Makandar A, Halalli B. Image enhancement techniques using highpass and lowpass filters. Int J Comput Appl. 2015;109(14):12–25. https://doi.org/10.5120/19273-1004

47. Ell TA, Sangwine SJ. Hypercomplex Fourier transforms of color images. IEEE Trans Image Process. 2006;16(1):22–35. https://doi.org/10.1109/TIP.2006.884955

48. Camargo A, Smith J. An image-processing based algorithm to automatically identify plant disease visual symptoms. Biosyst Eng. 2009;102(1):9–21. https://doi.org/10.1016/j.biosystemseng.2008.09.030

49. Iqbal MA, Talukder KH. Detection of potato disease using image segmentation and machine learning. In: Proceedings of the International Conference on Wireless Communications Signal Processing and Networking (WiSPNET); 2020 Aug 4–6; Chennai, India. Piscataway (NJ): IEEE; 2020. p. 43–47. https://doi.org/10.1109/WiSPNET48689.2020.9198563

50. Yao Q, Guan Z, Zhou Y, Tang J, Hu Y, Yang B. Application of support vector machine for detecting rice diseases using shape and color texture features. In: Proceedings of the International Conference on Engineering Computation; 2009 Mar 17–19; Hong Kong, China. Piscataway (NJ): IEEE; 2009. p. 79–83. https://doi.org/10.1109/ICEC.2009.73

51. Huang W, Guan Q, Luo J, Zhang J, Zhao J, Liang D. New optimized spectral indices for identifying and monitoring winter wheat diseases. IEEE J Sel Top Appl Earth Obs Remote Sens. 2014;7(6):2516–24. https://doi.org/10.1109/JSTARS.2013.2294961

52. Sibiya M, Sumbwanyambe M. A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. Agri Eng. 2019;1(1):119–31. https://doi.org/10.3390/agriengineering1010009

53. Sugimura D, Mikami T, Yamashita H, Hamamoto T. Enhancing color images of extremely low light scenes based on RGB/NIR images acquisition with different exposure times. IEEE Trans Image Process. 2015;24(11):3586–97. https://doi.org/10.1109/TIP.2015.2448356

54. Srivastava AR, Venkatesan M, editors. Tea leaf disease prediction using texture-based image processing. In: Emerging Research in Data Engineering Systems and Computer Communications: Proceedings of CCODE 2019; 2019 Dec 21-22; Chennai, India. Singapore: Springer; 2020.

55. Whitmire CD, Vance JM, Rasheed HK, Missaoui A, Rasheed KM, Maier FW. Using machine learning and feature selection for alfalfa yield prediction. AI. 2021;2(1):71–88. https://doi.org/10.3390/ai2010006

56. hao J, Kechasov D, Rewald B, Bodner G, Verheul M, Clarke N, et al. Deep learning in hyperspectral image reconstruction from single RGB images—A case study on tomato quality parameters. Remote Sens. 2020;12(19):3258. https://doi.org/10.3390/rs12193258

57. Samal I, Bhoi TK, Pradhan AK, Mahanta DK. Plantix app: A success story of artificial intelligence in plant protection. Van Sangyan. 2023;10:24–44.

58. Mandal R, Lohar P, Wakalkar P. Crop Doctor A prediction model using machine learning algorithm. In: Proceedings of the 4th International Conference on Communication & Information Processing (ICCIP); 2022.

59. Li T, Fan Y, Li Y, Tarkoma S, Hui P. Understanding the long-term evolution of mobile app usage. IEEE Trans Mob Comput. 2021;22(2):1213–30. https://doi.org/10.1109/TMC.2021.3098664

60. Odilbekov F, Armoniene R, Henriksson T, Chawade A. Proximal phenotyping and machine learning methods to identify *Septoria tritici* blotch disease symptoms in wheat. Front Plant Sci. 2018;9:685. https://doi.org/10.3389/fpls.2018.00685

61. Ramcharan A, Baranowski K, McCloskey P, Ahmed B, Legg J, Hughes DP. Deep learning for image-based cassava disease detection. Front Plant Sci. 2017;8:1852. https://doi.org/10.3389/fpls.2017.01852

62. Patel D, Patel NI, Patel M, editors. Advancements in wheat disease detection: a comprehensive survey of techniques, challenges. In: Proceedings of the International Conference on Information and Communication Technology for Intelligent Systems; 2024 Mar 22-23; Ahmedabad, India. Singapore: Springer; 2024 [cited 2025 Apr 16]. p. 1-10. https://doi.org/10.1007/978-981-97-6684-0_51

63. Tian Y, Yang G, Wang Z, Li E, Liang Z. Detection of apple lesions in orchards based on deep learning methods of CycleGAN and YOLOV3-dense. J Sens. 2019;2019(1):7630926. https://doi.org/10.1155/2019/7630926

64. Raza S-e-A, Prince G, Clarkson JP, Rajpoot NM. Automatic detection of diseased tomato plants using thermal and stereo visible light images. PloS one. 2015;10(4):e0123262. https://doi.org/10.1371/journal.pone.0123262

65. Das S, Pattanayak S, Behera PR. Application of machine learning: A recent advancement in plant diseases detection. J Plant Prot Res. 2022:122–35.

66. Antonellis G, Gavras AG, Panagiotou M, Kutter BL, Guerrini G, Sander AC, et al. Shake table test of large-scale bridge columns supported on rocking shallow foundations. J Geotech Geoenviron Eng. 2015;141(5):04015009. https://doi.org/10.1061/(ASCE)GT.1943-5606.0001284

67. Soliman MM, Kamal MH, Nashed MAE-M, Mostafa YM, Chawky BS, Khattab D, et al. Violence recognition from videos using deep learning techniques. In: Proceedings of the 2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS); 2019 Dec 9–11; Cairo, Egypt. New York: IEEE; 2019 [cited 2025 Apr 16]. p. 1–6. Available from: https://doi.org/10.1109/ICICIS46948.2019.9014714

68. Szymak P, Piskur P, Naus K. The effectiveness of using a pretrained deep learning neural networks for object classification in underwater video. Remote Sens. 2020;12(18):3020. https://doi.org/10.3390/rs12183020

69. Wang G, Sun Y, Wang J. Automatic image-based plant disease severity estimation using deep learning. Comput Intell Neurosci. 2017;2017(1):2917536. https://doi.org/10.1155/2017/2917536

70. Alhwaiti Y, Khan M, Asim M, Siddiqi MH, Ishaq M, Alruwaili M. Leveraging YOLO deep learning models to enhance plant disease identification. Sci Rep. 2025;15(1):7969. https://doi.org/10.1038/s41598-025-88432-4

71. Chollet F, editor. Xception: Deep learning with depthwise separable convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2017 Jul 21-26;

Honolulu, HI, USA. Piscataway (NJ): IEEE; 2017. https://doi.org/10.1109/CVPR.2017.195

72. Mishra S, Singh A, Singh V, editors. Application of MobileNet-v1 for potato plant disease detection using transfer learning. 2021 Workshop on Algorithm and Big Data; 2021; New York, NY, USA. New York: Association for Computing Machinery; 2021. https://doi.org/10.1145/3465735.3465745

73. Saleem MH, Potgieter J, Arif KM. Plant disease classification: A comparative evaluation of convolutional neural networks and deep learning optimizers. Plants. 2020;9(10):1319. https://doi.org/10.3390/plants9101319

74. Wang DaWei WD, Deng LiMiao DL, Ni JianGong NJ, Gao JiYue GJ, Zhu HongFei ZH, Han ZhongZhi HZ. Recognition pest by image-based transfer learning. J Phys Conf Ser. 2019;1187:042027. https://doi.org/10.1088/1742-6596/1187/4/042027

75. Jia Y, Shelhamer E, Donahue J, Karayev S, Long J, Girshick R, et al., editors. Caffe: convolutional architecture for fast feature embedding. In: Proceedings of the 22nd ACM International Conference on Multimedia; 2014 Nov 3-7; Orlando, FL, USA. New York: ACM; 2014. https://doi.org/10.1145/2647868.2654889

76. Chen T, Li M, Li Y, Lin M, Wang N, Wang M, et al. MXNet: A flexible and efficient machine learning library for heterogeneous distributed systems. arXiv preprint arXiv:1512.01274. 2015 Dec 3.

77. Chen W-L, Lin Y-B, Ng F-L, Liu C-Y, Lin Y-W. RiceTalk: Rice blast detection using Internet of Things and artificial intelligence technologies. IEEE Internet Things J. 2019;7(2):1001–10. https://doi.org/10.1109/JIOT.2019.2947624

78. Ai Y, Sun C, Tie J, Cai X. Research on recognition model of crop diseases and insect pests based on deep learning in harsh environments. IEEE Access. 2020;8:171686–93. https://doi.org/10.1109/ACCESS.2020.3025325

79. Jiang P, Chen Y, Liu B, He D, Liang C. Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks. IEEE Access. 2019;7:59069–80. https://doi.org/10.1109/ACCESS.2019.2914929

80. Zeng Q, Ma X, Cheng B, Zhou E, Pang W. Gans-based data augmentation for citrus disease severity detection using deep learning. IEEE Access. 2020;8:172882–91. https://doi.org/10.1109/ACCESS.2020.3025196

81. Li W, Shen Z, Liu X, Wang M, Ma C, Ding C, Cao J, et al. Representative kernels-based CNN for faster transmission in federated learning. IEEE Trans Mob Comput. 2024;23(12):13062–75. https://doi.org/10.1109/TMC.2024.3423448

82. Ramadan ST, Sakib T, Rahat MA, Mosharrof S. Cyclegan-based data augmentation with CNN and vision transformers (ViT) models for improved maize leaf disease classification. In: Proceedings of the 2023 IEEE 64th International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS); 2023. p. 1–6.

83. Nazir T, Iqbal MM, Jabbar S, Hussain A, Albathan M. EfficientPNet—an optimized and efficient deep learning approach for classifying disease of potato plant leaves. Agric. 2023;13(4):841. https://doi.org/10.3390/agriculture13040841

84. Jaware TH, Badgujar RD, Patil PG. Crop disease detection using image segmentation. World J Sci Technol. 2012;2(4):190–4.

85. Orillo JW, Cruz JD, Agapito L, Satimbre PJ, Valenzuela I. Identification of diseases in rice plant (Oryza sativa) using back propagation artificial neural network. In: Proceedings of the 2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM); 2014 Nov 12; Cebu City, Philippines. Piscataway (NJ): IEEE; 2014. p. 1–6. https://doi.org/10.1109/HNICEM.2014.7016248

86. Gavhale KR, Gawande U. An overview of the research on plant leaves disease detection using image processing techniques. IOSR J Comput Eng. 2014;16(1):10–16. https://doi.org/10.9790/0661-16111016

87. Renugambal K, Senthilraja B. Application of image processing techniques in plant disease recognition. Int J Eng Res Technol. 2015;4(3):919–23. https://doi.org/10.17577/IJERTV4IS030919

88. Biswas S, Jagyasi B, Singh BP, Lal M. Severity identification of potato late blight disease from crop images captured under uncontrolled environment. IEEE Canada International Humanitarian Technology Conference (IHTC). 2014;1–5. https://doi.org/10.1109/IHTC.2014.7147519

89. Chouhan SS, Kaul A, Singh UP, Jain S. Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology. IEEE Access. 2018;6:8852-63. https://doi.org/10.1109/ACCESS.2018.2800685

90. Arivazhagan S, Shebiah RN, Ananthi S, Varthini SV. Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features. Agri Eng Int: CIGR J. 2013;15(1):211–17.

91. Liu C, Han J, Chen B, Mao J, Xue Z, Li S. A novel identification method for apple (*Malus domestica* Borkh.) cultivars based on a deep convolutional neural network with leaf image input. Symmetry. 2020;12(2):217. https://doi.org/10.3390/sym12020217

92. Gaikwad D, Karande K, Deshpande H. Pomegranate fruit diseases identification and grading. In: Proceedings of the International Conference on Communication and Signal Processing 2016 (ICCASP); 2016 Dec; International Conference on Communication and Signal Processing (ICCASP 2016), Advances in Intelligent Systems Research; 2016 Dec; p. 672–79. https://doi.org/10.2991/iccasp-16.2017.96

93. Al-Hiary H, Bani-Ahmad S, Reyalat M, Braik M, Alrahamneh Z. Fast and accurate detection and classification of plant diseases. Int J Comput Appl. 2011;17(1):31–38. https://doi.org/10.5120/975-1373

94. Mukherjee S. t‑SNE based feature extraction technique for multi‑layer perceptron neural network classifier. In: Proceedings of the 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT); 2017; Kerala, India. Piscataway (NJ): IEEE; 2017. p. 1–5.

95. Hue Y, Kim JH, Lee G, Choi B, Sim H, Jeon J, et al. Artificial intelligence plant doctor: plant disease diagnosis using GPT4-vision. Res Plant Dis. 2024;30(1):99–102. https://doi.org/10.5423/RPD.2024.30.1.99

96. Pethybridge SJ, Nelson SC. Leaf Doctor: A new portable application for quantifying plant disease severity. Plant Dis. 2015;99(10):1310–16. https://doi.org/10.1094/PDIS-03-15-0319-RE

97. Jain S, Sahni R, Khargonkar T, Gupta H, Verma OP, Sharma TK, et al. Automatic rice disease detection and assistance framework using deep learning and a Chatbot. Electronics. 2022;11(14):2110. https://doi.org/10.3390/electronics11142110

98. Mohapatra S, Tripathi R, Acharya P, Shahid M, Raghu S, Guru P, et al. NRRI 'riceXpert' APP: taking rice technologies in the doorstep of farmers [Internet]. 2018 [cited 2025 Jun 12]. Available from: https://icar-crri.in/icar-nrri-developed-mobile-app-ricexpert/#:~:text=The %20ICAR %2DNRRI %20'ricexpert',field %20and %20post %20harvest %20operations

99. Silva G, Tomlinson J, Onkokesung N, Sommer S, Mrisho L, Legg J, et al. Plant pest surveillance: from satellites to molecules. Emerg Top Life Sci. 2021;5(2):275–87. https://doi.org/10.1042/ETLS20200309

100. Al-Hiary H, Bani-Ahmad S, Reyalat M, Braik M, Alrahamneh Z. Fast and accurate detection and classification of plant diseases. Int J Comput Appl. 2011;17(1):31–38. https://doi.org/10.5120/975-1373

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