Review Article

**Artificial intelligence and machine learning applications in plant disease detection and management-A review**

**Abstract**

Artificial intelligence (AI) and machine learning (ML) have emerged as transformative technologies in plant disease detection and management, offering highly accurate, scalable, and real-time diagnostic solutions. Traditional disease detection methods, reliant on manual scouting and laboratory-based assays, are time-intensive, prone to human error, and often fail to detect early-stage infections. AI-driven approaches, particularly deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and vision transformers, have significantly improved disease classification accuracy, surpassing 95% in multiple studies. The integration of AI with the Internet of Things (IoT) enables real-time disease monitoring through smart sensors, drone-based imaging, and cloud computing, enhancing large-scale agricultural surveillance. Big data analytics play a crucial role in AI-driven disease management, utilizing satellite imagery, hyperspectral data, and field-based mobile applications to detect infections before symptoms become visible. Predictive analytics models, powered by AI, analyze environmental and pathogen-related data to forecast disease outbreaks, supporting proactive decision-making in precision agriculture. Despite significant advancements, challenges such as limited access to large, annotated datasets, computational resource constraints, and model generalization issues across diverse crops and climatic conditions persist. Ethical concerns related to data privacy and the adoption of AI technologies among farmers further hinder widespread implementation. Blockchain technology has been proposed for secure and transparent disease data sharing, while edge computing solutions aim to reduce latency in AI-driven disease detection systems. Autonomous AI-powered agricultural robots equipped with deep learning models and multispectral sensors are being developed for real-time disease monitoring and targeted treatment. Future research must focus on optimizing AI algorithms for large-scale agricultural deployment, integrating AI-driven genomic selection for disease-resistant crop breeding, and leveraging emerging technologies such as quantum computing and synthetic biology to enhance plant disease management and global food security.

**Keywords:** *Artificial Intelligence, Machine Learning, Plant Disease Detection, Deep Learning, Internet of Things, Big Data Analytics, Precision Agriculture*

**I. INTRODUCTION**

**A. Plant Diseases and Their Impact on Agriculture**

Plant diseases pose a major challenge to global food security, causing significant yield losses and economic damage. Estimates suggest that plant pathogens are responsible for approximately 10-16% of global crop losses annually, equating to economic losses exceeding $220 billion per year. The impact varies by region and crop type, with staple crops such as wheat, rice, maize, and potatoes being particularly vulnerable to fungal, bacterial, and viral infections (Vurro *et.al.,* 2010).

Fungal diseases such as rusts, mildews, and blights account for nearly 70% of all crop disease-related losses worldwide. For example, wheat rust diseases alone can cause up to 100% yield loss under severe conditions if not controlled in time. Viral diseases, such as the Tomato Yellow Leaf Curl Virus (TYLCV) and Rice Tungro Disease, can lead to complete crop failure in susceptible varieties. Bacterial infections, such as citrus greening (Huanglongbing), have devastated citrus orchards, reducing production by over 75% in severely affected regions (Ghosh *et.al.,* 2018).

Climate change has further exacerbated the spread and severity of plant diseases, as rising temperatures and altered precipitation patterns create favorable conditions for pathogens. The intensification of global trade and monoculture farming practices has also contributed to the rapid emergence and spread of plant diseases. Given these challenges, effective and timely disease detection is critical for minimizing crop losses and ensuring global food security.

**B. Traditional Methods of Plant Disease Detection and Management**

Traditional approaches to plant disease detection rely on manual scouting, visual inspection, and laboratory-based diagnostic techniques. Farmers and agronomists typically identify plant diseases based on visible symptoms such as leaf spots, discoloration, wilting, or fungal growth (Lucas *et.al.,* 1992). While experienced plant pathologists can diagnose many diseases accurately, this method is labor-intensive, time-consuming, and highly dependent on expertise. Studies indicate that visual assessments have an error rate of up to 30% due to variability in symptom expression and subjective interpretation.

Microscopy and biochemical assays are widely used for pathogen identification in research laboratories. Techniques such as enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction (PCR) allow for precise detection of specific pathogens. While highly accurate, these methods require specialized equipment, trained personnel, and significant time investment, making them impractical for large-scale field application (Chen *et.al.,* 2014).

Chemical control measures, including fungicides, bactericides, and pesticides, remain the dominant strategy for plant disease management. Over 2.5 million tons of pesticides are used annually worldwide, with fungicides accounting for approximately 25% of total pesticide use. The excessive use of chemical treatments has led to environmental contamination, human health risks, and the development of pesticide-resistant pathogens. Integrated disease management (IDM) strategies, which combine resistant crop varieties, cultural practices, and biological control agents, have been promoted as sustainable alternatives.

Despite these efforts, the limitations of traditional disease detection and management methods necessitate the adoption of advanced technologies for more efficient, accurate, and scalable solutions.

**C. Need for Advanced Technologies in Plant Disease Detection**

The increasing complexity and rapid spread of plant diseases demand technological interventions for early detection and precise management. Studies have shown that early disease detection can reduce crop losses by up to 40% and minimize unnecessary pesticide application. Current diagnostic methods often fail to detect infections in their early stages, when intervention is most effective.

Remote sensing technologies, including satellite imaging and unmanned aerial vehicles (UAVs), have shown promise in large-scale disease monitoring. Hyperspectral and multispectral imaging can detect physiological changes in plants before visible symptoms appear, enabling proactive disease control. These techniques, however, require advanced data processing capabilities and are often cost-prohibitive for smallholder farmers.

The adoption of precision agriculture and smart farming techniques, driven by the Internet of Things (IoT) and sensor networks, has improved disease detection efficiency (Saranya *et.al.,* 2023). IoT-based monitoring systems collect real-time environmental and crop health data, allowing for predictive modeling of disease outbreaks. Despite these advancements, the complexity of plant-pathogen interactions necessitates more robust, data-driven approaches to disease detection and management.

**D. Role of Artificial Intelligence (AI) and Machine Learning (ML) in Modern Agriculture**

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative tools for plant disease detection and management. AI enables automated analysis of complex datasets, while ML algorithms can identify patterns in plant health indicators that may be undetectable through traditional methods.

Machine learning techniques such as deep learning, convolutional neural networks (CNNs), and support vector machines (SVMs) have demonstrated high accuracy in plant disease classification based on image analysis . CNNs, in particular, have achieved classification accuracies exceeding 95% for various plant disease datasets. Transfer learning and data augmentation techniques have further improved model robustness, reducing the need for large, annotated datasets (Ding *et.al.,* 2022).

AI-powered decision support systems integrate real-time data from IoT sensors, drones, and weather stations to provide actionable insights for disease management. These systems utilize predictive analytics to forecast disease outbreaks, enabling farmers to take preventive measures before widespread infection occurs.

AI-driven robotic systems have also been deployed for automated disease monitoring and treatment. Autonomous drones and ground robots equipped with computer vision can identify diseased plants and apply targeted treatments, reducing chemical usage and labor costs. Blockchain technology is being explored for secure and transparent disease data sharing, facilitating collaborative disease management efforts.

**II. FUNDAMENTAL CONCEPTS OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING**

**A. Definition and Components of Artificial Intelligence**

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that can perform tasks such as learning, reasoning, problem-solving, perception, and decision-making. AI systems are designed to analyze large datasets, recognize patterns, and make autonomous or semi-autonomous decisions based on complex computations. The core components of AI include machine learning (ML), natural language processing (NLP), expert systems, robotics, and computer vision (Soori *et.al.,* 2023).

Machine learning is a subset of AI that enables computers to learn from data without explicit programming. Computer vision, another integral component, involves the interpretation of images and videos using AI algorithms. Expert systems use rule-based approaches to mimic human decision-making processes, while NLP allows machines to understand and process human language. Robotics in AI-driven agriculture includes automated disease detection, precision spraying, and robotic harvesting.

The increasing availability of high-dimensional agricultural data has accelerated the application of AI in plant disease detection. AI-powered models analyze multispectral and hyperspectral imaging data to identify plant stress and disease symptoms before visible signs appear (Ali *et.al.,* 2024). Advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved the accuracy of disease classification in crops such as wheat, maize, rice, and tomatoes.

**B. Introduction to Machine Learning and Its Types**

Machine learning enables computers to learn patterns from data and improve their performance without explicit programming. The primary goal of ML in agriculture is to enhance decision-making by analyzing large datasets, including images, sensor readings, and weather parameters. ML algorithms are broadly categorized into supervised learning, unsupervised learning, and reinforcement learning.

**1. Supervised Learning**

Supervised learning involves training a model on labeled datasets, where input-output pairs guide the learning process (Verma *et.al.,* 2021). This method is widely used in plant disease classification, where labeled images of healthy and diseased plants train models to recognize symptoms. CNN-based models, such as AlexNet and ResNet, have achieved over 95% accuracy in detecting plant diseases using large datasets like PlantVillage.

Support Vector Machines (SVMs) and Random Forest classifiers are commonly used for feature-based plant disease detection. These algorithms analyze spectral, texture, and morphological features from leaf images to distinguish between healthy and diseased plants. Transfer learning techniques further enhance supervised models by leveraging pre-trained networks for improved classification performance with limited data.

**2. Unsupervised Learning**

Unsupervised learning algorithms identify patterns in unlabeled data without predefined categories. Clustering techniques, such as k-means and hierarchical clustering, group plant disease symptoms based on similarities in spectral or textural features.

Principal Component Analysis (PCA) and Independent Component Analysis (ICA) reduce the dimensionality of hyperspectral plant images, improving computational efficiency while preserving essential disease-related information (Nguyen *et.al.,* 2015). These methods are useful for early disease detection, as they highlight subtle changes in plant physiology that may not be apparent through visual inspection.

**3. Reinforcement Learning**

Reinforcement learning (RL) enables AI models to optimize decision-making through trial and error. In plant disease management, RL is used in precision agriculture systems to optimize pesticide application and irrigation schedules based on real-time environmental data.

Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) algorithms help autonomous agricultural robots adapt to varying field conditions, improving disease detection accuracy and treatment efficiency. RL-based approaches are particularly effective in dynamic agricultural environments where real-time adaptation is necessary.

**C. Deep Learning and Its Role in Image-Based Disease Detection**

Deep learning (DL) has revolutionized plant disease detection by enabling automatic feature extraction from images, surpassing traditional feature engineering techniques. CNNs, a class of deep neural networks, are particularly effective for analyzing leaf images, identifying disease symptoms with high accuracy (Tugrul *et.al.,* 2022).

Pretrained deep learning models, such as VGG16, InceptionV3, and MobileNet, have been successfully applied to plant disease classification tasks, achieving accuracy levels above 97% in some cases. These models learn hierarchical feature representations, identifying color variations, lesions, and texture anomalies associated with plant diseases.

The integration of hyperspectral imaging and deep learning has further enhanced disease detection capabilities. Hyperspectral data captures information beyond the visible spectrum, revealing stress indicators linked to pathogen infections. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks process time-series data from remote sensing platforms, predicting disease progression over time (Moskolai *et.al.,* 2021).

Generative Adversarial Networks (GANs) have also been utilized to augment plant disease datasets, addressing the issue of limited labeled training images. By generating synthetic diseased plant images, GANs improve the robustness of deep learning models, reducing overfitting and enhancing generalization across diverse field conditions.

**D. Evolution of AI and ML in Agricultural Research**

The application of AI in agriculture has evolved significantly over the past few decades, driven by advances in computational power, data availability, and algorithmic improvements. Early AI-driven plant disease detection systems relied on rule-based expert systems, where predefined knowledge bases guided decision-making. These systems lacked adaptability and struggled with complex, unstructured data.

The shift toward ML-based approaches in the early 2000s allowed for more flexible and data-driven disease detection models (Pasrija *et.al.,* 2022). The advent of high-resolution imaging, UAV-based surveillance, and IoT-enabled smart farming systems provided vast datasets for training AI models. The development of DL architectures, such as CNNs and RNNs, in the 2010s significantly improved disease classification accuracy and scalability.

Recent advancements in AI-powered robotics, edge computing, and blockchain technology have further expanded the potential of AI in agriculture. Autonomous drones equipped with AI-driven image analysis capabilities can survey large agricultural fields, identifying disease outbreaks in real-time. AI-integrated IoT systems continuously monitor plant health metrics, enabling precision disease management strategies.

The integration of AI with big data analytics has facilitated predictive modeling of disease outbreaks, enhancing early warning systems and minimizing crop losses. AI-driven breeding programs are also accelerating the development of disease-resistant crop varieties through genomic selection techniques (Farooq *et.al.,* 2024).

Ongoing research continues to refine AI applications in plant pathology, addressing challenges related to model interpretability, data bias, and computational efficiency. The convergence of AI with emerging technologies such as quantum computing and synthetic biology holds promise for the future of AI-driven agriculture.

**III. IMAGE PROCESSING AND COMPUTER VISION FOR PLANT DISEASE DIAGNOSIS**

**A. Fundamentals of Image Processing in Agriculture**

Image processing has become an essential component of precision agriculture, providing accurate and efficient plant disease detection by analyzing visual and spectral data. Traditional plant disease detection methods rely on manual inspection, requiring expert knowledge and significant labor. These conventional approaches often fail to detect infections in their early stages, leading to delayed treatment and increased crop losses. Image processing techniques automate disease diagnosis by extracting relevant features from digital images, enabling large-scale, non-invasive monitoring of crop health (Abdullah *et.al.,* 2023).

Advanced imaging technologies such as digital RGB imaging, multispectral imaging, and hyperspectral imaging have revolutionized plant disease identification. Digital RGB cameras are widely used due to their affordability and integration with mobile devices and drones. Multispectral imaging, which captures reflectance data in a limited number of specific wavelengths, has proven effective in distinguishing healthy and diseased plants. Hyperspectral imaging, capturing hundreds of narrow spectral bands, provides even more detailed insights into plant physiology, allowing for the early detection of stress caused by pathogens before visible symptoms appear.

Thermal imaging is another technique that has been employed to detect plant diseases by measuring variations in temperature. Diseased plants often exhibit abnormal transpiration rates, which can be identified through differences in thermal emissions. These temperature variations provide early warning signs of infection, enabling timely disease intervention (Oerke *et.al.,* 2011). The integration of various image processing techniques has significantly improved plant disease detection accuracy, making them indispensable tools in modern agricultural research and practice.

**B. Role of Computer Vision in Disease Identification**

Computer vision, a field of artificial intelligence that enables machines to interpret visual information, has transformed plant disease identification by automating image analysis. Traditional plant disease detection relies on subjective assessments, which are prone to human error and inconsistency. Computer vision systems eliminate these challenges by analyzing plant images with high precision, ensuring rapid and objective disease diagnosis.

Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in plant disease classification. These models learn hierarchical patterns of disease symptoms directly from image datasets, removing the need for manual feature engineering. CNN-based models such as AlexNet, VGG16, and ResNet have achieved classification accuracies exceeding 95% in distinguishing between healthy and diseased plant leaves. The application of computer vision in plant pathology has significantly improved the efficiency and scalability of disease diagnosis, allowing for real-time monitoring of crop health.

Drones equipped with high-resolution cameras and AI-driven image analysis tools have further enhanced plant disease surveillance. These autonomous systems capture aerial images of large agricultural fields, detecting disease hotspots and providing actionable insights for precision farming (Xu *et.al.,* 2024). The integration of computer vision with the Internet of Things (IoT) has enabled continuous disease monitoring, ensuring timely intervention and minimizing economic losses.

**C. Common Image Processing Techniques Used**

Image processing techniques play a crucial role in enhancing plant disease detection accuracy. Before a model can classify a disease, the raw images must undergo several preprocessing steps to remove noise and enhance relevant features. One of the most common preprocessing techniques is filtering, where median and Gaussian filters are applied to reduce image noise while preserving important features such as lesion edges.

Normalization is another important step, adjusting image brightness and contrast to standardize datasets, which is particularly useful when images are captured under varying lighting conditions. Image enhancement techniques, including histogram equalization and adaptive thresholding, improve the visibility of disease symptoms by increasing the contrast between infected and healthy regions of plant leaves (Dhingra *et.al.,* 2018).

Feature extraction is a fundamental aspect of image processing that enables AI models to identify key characteristics associated with plant diseases. Color-based analysis is widely used since infected plants often exhibit discoloration patterns, such as yellowing, browning, or chlorosis, which serve as early indicators of stress. Texture analysis methods, including Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), extract information about the roughness and uniformity of disease lesions, which helps differentiate between fungal, bacterial, and viral infections.

Another critical technique is image segmentation, which divides an image into distinct regions to isolate diseased areas for precise analysis. Thresholding-based segmentation separates diseased tissues from healthy parts using pixel intensity differences, while edge detection methods such as Canny and Sobel filters identify lesion boundaries. More advanced deep learning-based segmentation techniques, such as U-Net and Mask R-CNN, provide pixel-wise disease localization, improving diagnostic accuracy.

**D. Application of Convolutional Neural Networks (CNNs) in Disease Identification**

Convolutional neural networks (CNNs) have revolutionized plant disease detection by enabling automated and highly accurate image classification. Unlike traditional machine learning models, which require manual feature selection, CNNs learn patterns directly from image data, improving their ability to generalize across different plant species and disease conditions (Abade *et.al.,* 2021).

Several pretrained CNN architectures, including AlexNet, VGG16, ResNet, and InceptionV3, have been widely used in plant disease classification. These models have achieved high classification accuracies, often exceeding 97%, on datasets such as PlantVillage, which contains over 50,000 images of diseased and healthy plant leaves. Transfer learning has further improved CNN performance by allowing models to leverage knowledge from large-scale image datasets, reducing the amount of labeled agricultural data needed for training.

Smartphone applications utilizing CNN-based plant disease diagnosis systems have also emerged, allowing farmers to capture images of diseased crops and receive instant treatment recommendations. These mobile applications enhance accessibility and empower farmers with real-time disease detection capabilities, reducing reliance on expert consultation and laboratory testing.

**E. Use of Spectral and Hyperspectral Imaging for Early Disease Detection**

Spectral and hyperspectral imaging technologies have enabled early plant disease detection by capturing reflectance patterns beyond the visible spectrum. Unlike RGB imaging, which is limited to three color channels, hyperspectral imaging captures hundreds of narrow spectral bands, providing detailed information on plant physiology and stress responses (Zhang *et.al.,* 2024).

Hyperspectral imaging is particularly effective in detecting diseases before visible symptoms appear. Many plant diseases alter the reflectance properties of leaves, especially in the near-infrared (NIR) and shortwave-infrared (SWIR) regions, where healthy plants typically show strong reflectance due to chlorophyll absorption. Deep learning models trained on hyperspectral data have achieved high classification accuracy by analyzing spectral signatures unique to different plant diseases.

Multispectral imaging, used in drone and satellite-based disease surveillance, has been instrumental in large-scale crop monitoring. These systems capture images at selected spectral bands, detecting changes in chlorophyll content, water stress, and disease-induced metabolic alterations. The integration of hyperspectral and multispectral imaging with machine learning models has significantly improved disease prediction capabilities, enabling proactive disease management and reducing crop losses (Ali *et.al.,* 2024).

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**IV. AI-BASED DISEASE DETECTION MODELS IN PLANTS**

**A. Classification and Prediction Models for Disease Diagnosis**

Artificial Intelligence (AI)-based models have significantly enhanced the accuracy and efficiency of plant disease diagnosis by automating classification and prediction tasks. These models leverage machine learning (ML) and deep learning (DL) algorithms to analyze large volumes of image and sensor data, identifying disease symptoms with high precision. Traditional disease detection methods rely on manual visual inspection, which is prone to errors and requires expert knowledge. AI-driven models address these limitations by learning complex patterns in plant health indicators and detecting infections at early stages.

Machine learning classifiers such as Support Vector Machines (SVMs) and Random Forest (RF) have been widely used in disease diagnosis, demonstrating robust performance in distinguishing between healthy and diseased plants based on extracted image features. Deep learning architectures, particularly convolutional neural networks (CNNs), have outperformed traditional ML approaches by automatically learning hierarchical disease features from large datasets. Advanced architectures, including recurrent neural networks (RNNs) and transformers, have further improved predictive accuracy by integrating temporal disease progression data (Mienye *et.al.,* 2024).

**1. Support Vector Machines (SVMs)**

Support Vector Machines (SVMs) are widely used for plant disease classification due to their ability to handle high-dimensional datasets and distinguish between complex patterns. These models operate by mapping input features into a higher-dimensional space, where a hyperplane separates different disease classes. SVMs have been applied in plant disease detection using spectral and textural features extracted from leaf images, achieving classification accuracies exceeding 90% in some cases.

Kernel functions, such as radial basis function (RBF) and polynomial kernels, enhance the ability of SVMs to classify non-linearly separable disease patterns. Studies have demonstrated that SVM-based models combined with hyperspectral imaging data effectively differentiate between early-stage and advanced-stage plant diseases, enabling proactive disease management strategies. Despite their high accuracy, SVMs require extensive parameter tuning and may struggle with large-scale image datasets compared to deep learning methods.

**2. Random Forest (RF) and Decision Tree Algorithms**

Random Forest (RF) and Decision Tree (DT) algorithms are frequently used in plant disease detection due to their ability to process structured and unstructured data efficiently (Goel *et.al.,* 2023). RF operates as an ensemble learning method, constructing multiple decision trees and averaging their outputs to improve classification stability. This model is particularly useful for analyzing spectral and morphological features extracted from plant images, providing high accuracy in disease classification tasks.

Decision trees, although effective in handling categorical and numerical data, tend to overfit training datasets when used independently. RF mitigates this issue by aggregating predictions from multiple trees, enhancing model robustness and generalization across different environmental conditions. Studies have shown that RF classifiers combined with feature selection techniques improve disease classification accuracy while reducing computational complexity (Azar *et.al.,* 2014).

**3. Deep Learning Architectures (CNNs, RNNs, and Transformers)**

Deep learning models, particularly CNNs, have revolutionized plant disease diagnosis by learning hierarchical features directly from image data. CNNs consist of convolutional layers that extract low-level and high-level disease features, enabling automated and accurate classification of plant diseases. These models have demonstrated exceptional performance in identifying multiple plant diseases from diverse datasets, achieving classification accuracies exceeding 97% on benchmark datasets such as PlantVillage.

Recurrent Neural Networks (RNNs) have been applied in disease prediction by analyzing sequential disease progression data. Long Short-Term Memory (LSTM) networks, a variant of RNNs, effectively capture long-range dependencies in plant disease trends, enabling predictive modeling of disease outbreaks based on historical climate and disease incidence data.

Transformers, initially developed for natural language processing, have recently been adopted in plant disease detection due to their ability to process high-dimensional image data efficiently. Vision Transformers (ViTs) have demonstrated superior performance in plant disease classification by leveraging self-attention mechanisms, achieving state-of-the-art accuracy levels in agricultural image analysis (Yadav *et.al.,* 2023).

**B. Feature Engineering and Data Augmentation in AI Models**

Feature engineering is a crucial step in AI-based plant disease detection, as it involves selecting and transforming relevant attributes to improve model performance. Traditional feature extraction methods include color-based, texture-based, and shape-based descriptors, which help differentiate between diseased and healthy plant tissues. In deep learning-based approaches, feature extraction is performed automatically by convolutional layers, reducing the need for manual intervention.

Data augmentation techniques, such as image rotation, scaling, flipping, and contrast adjustment, enhance model generalization by artificially expanding training datasets. Augmenting plant disease datasets helps mitigate the issue of limited labeled data and improves deep learning model robustness in real-world agricultural settings. Studies have shown that applying data augmentation increases CNN accuracy by 5-10%, significantly improving disease classification performance.

**C. Model Training, Validation, and Performance Evaluation**

The effectiveness of AI-based disease detection models depends on rigorous training, validation, and performance evaluation procedures. Training deep learning models requires large-scale labeled datasets, which are often collected through image repositories such as PlantVillage and field-based UAV surveys (Qadri *et.al.,* 2024). Transfer learning techniques allow pre-trained models to adapt to new datasets, reducing computational costs and training time while maintaining high accuracy.

Validation strategies, such as k-fold cross-validation, ensure that models generalize well across different datasets. Performance metrics commonly used for evaluation include accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve. Studies have demonstrated that CNN-based models achieve precision levels above 95% in distinguishing between various plant diseases, outperforming traditional machine learning classifiers (Ahad *et.al.,* 2023).

**D. Case Studies on AI-Based Disease Classification**

Several real-world case studies highlight the success of AI-based plant disease classification models. A study demonstrated that CNNs trained on 58 different plant disease classes achieved an overall accuracy of 99.35%, outperforming traditional classifiers. Another study using hyperspectral imaging and SVM classifiers detected early-stage fungal infections in wheat with an accuracy of 92%, enabling proactive disease management.

An AI-powered mobile application allowed farmers to diagnose plant diseases using smartphone images, achieving an accuracy of 93.6% across 14 different crops. The integration of deep learning with drone-based disease surveillance systems has further enhanced large-scale disease monitoring, reducing pesticide use by 30% and improving crop yield predictions (Shahi *et.al.,* 2023).

The continuous advancement of AI-based plant disease detection models promises to revolutionize agricultural disease management by improving diagnosis accuracy, reducing reliance on chemical treatments, and enabling early intervention strategies.

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**V. ROLE OF INTERNET OF THINGS (IoT) AND EDGE COMPUTING IN DISEASE DETECTION**

**A. IoT-Enabled Disease Monitoring Systems**

The Internet of Things (IoT) has revolutionized plant disease monitoring by enabling real-time data collection, analysis, and decision-making. IoT-based systems consist of interconnected devices such as sensors, drones, and cameras that continuously gather environmental and plant health data, providing a comprehensive view of disease progression. These systems offer real-time monitoring capabilities, allowing for early detection and timely intervention, reducing disease-related yield losses.

IoT networks integrate wireless sensor nodes deployed across agricultural fields, collecting data on temperature, humidity, soil moisture, and plant physiological parameters. Wireless communication technologies such as Zigbee, LoRa, and NB-IoT facilitate seamless data transmission between sensors and cloud-based platforms, where advanced algorithms analyze patterns associated with disease outbreaks. Studies have shown that IoT-based disease monitoring systems improve detection accuracy by up to 90% compared to manual scouting methods, leading to more efficient disease management strategies.

IoT-driven disease detection has been successfully implemented in large-scale agricultural production, where automated sensors detect fungal infections in wheat and rust diseases in coffee plantations. Real-time alerts sent to farmers through mobile applications enhance responsiveness, minimizing disease spread and optimizing pesticide application schedules (Sharma *et.al.,* 2024). The integration of IoT with artificial intelligence further enhances disease diagnosis accuracy, providing predictive insights based on historical data and current environmental conditions.

**B. Smart Sensors for Disease Identification in the Field**

Smart sensors play a crucial role in IoT-based plant disease detection by collecting high-resolution data on plant health indicators. These sensors, embedded in the field or mounted on drones, detect variations in plant color, temperature, chlorophyll content, and moisture levels, which serve as early warning signs of infections. Advanced sensors equipped with near-infrared (NIR) and thermal imaging capabilities have been used to detect stress symptoms caused by fungal, bacterial, and viral pathogens before visible signs appear.

Hyperspectral and multispectral sensors provide valuable insights by capturing plant reflectance patterns across multiple wavelengths. Studies have demonstrated that hyperspectral imaging sensors integrated with AI algorithms can classify plant diseases with over 95% accuracy, enabling early and precise disease management (Zhang *et.al.,* 2020). IoT-enabled electrochemical biosensors, which detect pathogen-specific biomarkers, have also been developed for real-time disease diagnosis, significantly reducing the time required for laboratory-based testing.

**C. Integration of AI with IoT for Real-Time Disease Detection**

The convergence of artificial intelligence with IoT has transformed plant disease detection by enabling real-time image analysis and predictive modeling. AI-powered IoT systems process vast amounts of data collected by field sensors, identifying subtle disease symptoms through deep learning models such as convolutional neural networks (CNNs). These AI-driven models analyze plant images, classify diseases, and provide automated treatment recommendations, minimizing the need for manual assessments.

Predictive analytics models integrated with IoT networks analyze past disease patterns and environmental conditions to forecast potential outbreaks, allowing farmers to take preventive measures. AI-based disease monitoring systems have been successfully implemented in large-scale crop production, where automated drones and ground-based robots equipped with vision-based sensors detect infections and optimize pesticide application, reducing chemical usage by 30%.

**D. Edge Computing for On-Site Decision Making**

Edge computing enhances IoT-driven plant disease detection by enabling real-time data processing at the source, reducing dependency on cloud-based computation. Traditional cloud-based AI models require continuous data transmission, leading to latency issues and increased network bandwidth consumption. Edge computing addresses these challenges by processing disease detection algorithms locally on IoT devices, such as edge servers and embedded AI chips (Chang *et.al.,* 2021).

In agricultural settings, edge AI devices installed in greenhouses and open fields analyze sensor data in real time, detecting disease symptoms within seconds and triggering automated responses. Studies have shown that edge computing reduces disease diagnosis latency by up to 80%, enabling faster decision-making and more efficient disease management. AI-enabled edge computing platforms, such as NVIDIA Jetson and Intel Movidius, have been deployed for real-time disease classification in crops such as tomatoes, wheat, and rice, achieving high processing speeds with minimal computational overhead.

**E. Cloud-Based AI for Large-Scale Disease Surveillance**

Cloud computing facilitates large-scale disease surveillance by storing and processing agricultural data collected from multiple farms, enabling collaborative disease management. AI-powered cloud platforms analyze satellite, UAV, and IoT sensor data to generate regional disease maps, providing real-time insights on disease outbreaks and their spread patterns (Rana *et.al.,* 2025). Cloud-based AI models trained on extensive datasets continuously improve their predictive capabilities, ensuring accurate disease forecasting and risk assessment.

AI-driven cloud platforms such as Google Earth Engine and Microsoft Azure FarmBeats integrate multispectral imaging data with AI algorithms to monitor plant health across thousands of hectares. These systems facilitate precision disease management by providing farmers with actionable recommendations through web and mobile applications, optimizing resource allocation and reducing economic losses.

**VI. AI AND ML APPLICATIONS IN DISEASE MANAGEMENT STRATEGIES**

**A. AI-Assisted Disease Forecasting Models**

AI-assisted disease forecasting models predict disease outbreaks by analyzing historical climate data, soil conditions, and pathogen behavior. Machine learning algorithms such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks process time-series data to identify patterns that precede disease onset (Men *et.al.,* 2021). Predictive models have been successfully used to forecast late blight outbreaks in potatoes and wheat rust epidemics, improving disease control efficiency.

**B. Decision Support Systems for Precision Disease Management**

Decision Support Systems (DSS) powered by AI assist farmers in making informed disease management decisions based on real-time data. These systems integrate AI-driven recommendations with agronomic knowledge, optimizing pesticide application, irrigation schedules, and crop rotation strategies. AI-based DSS platforms have improved disease management efficiency by 40%, reducing unnecessary chemical applications and enhancing sustainable farming practices.

**C. Role of AI in Smart Pesticide and Fungicide Application**

AI-driven precision agriculture techniques optimize pesticide and fungicide applications by targeting infected areas while minimizing chemical usage. UAV-mounted sprayers integrated with AI-based disease detection models apply fungicides only to diseased plants, reducing pesticide waste and environmental impact. Variable rate technology (VRT) guided by AI algorithms has demonstrated a 30% reduction in pesticide application costs while maintaining disease suppression effectiveness (Kebe *et.al.,* 2023).

**D. Autonomous Disease-Resistant Crop Breeding Using AI**

AI accelerates crop breeding programs by identifying disease-resistant traits in plants through genomic data analysis. Deep learning models analyze genetic markers associated with disease resistance, enabling plant breeders to develop more resilient crop varieties. AI-driven genomic selection techniques have shortened breeding cycles by 50%, facilitating the development of climate-resilient and disease-resistant crops.

**E. AI-Based Disease Monitoring Systems in Greenhouses and Open Fields**

AI-based disease monitoring systems deployed in greenhouses and open fields continuously track plant health using IoT sensors and computer vision. These systems analyze leaf images and environmental conditions to detect disease symptoms, providing automated alerts to farmers. AI-integrated smart greenhouses have increased disease detection efficiency by 90%, optimizing climate control and pest management strategies.

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**VII. INTEGRATION OF BIG DATA ANALYTICS IN AI-DRIVEN PLANT DISEASE MANAGEMENT**

**A. Data Sources for AI-Based Disease Detection**

Artificial intelligence-driven plant disease detection relies on vast datasets collected from diverse sources, including satellite imagery, drone-based imaging, mobile applications, and public databases. The availability of high-resolution datasets is essential for training deep learning models, improving classification accuracy, and enabling real-time disease surveillance. The integration of big data analytics enhances decision-making by providing comprehensive insights into disease patterns, environmental factors, and crop health indicators (Sabeeh *et.al.,* 2024).

**1. Satellite and Drone-Based Imaging**

Satellite and drone-based imaging play a crucial role in large-scale plant disease monitoring by capturing high-resolution images of agricultural fields. Multispectral and hyperspectral imaging sensors mounted on satellites provide valuable insights into plant stress, detecting disease symptoms before they become visible to the human eye. Hyperspectral imaging enables early detection of fungal, bacterial, and viral infections by analyzing plant reflectance patterns across hundreds of spectral bands.

Drones equipped with advanced imaging technologies, such as RGB, thermal, and multispectral cameras, offer real-time disease detection capabilities. Studies have shown that drone-based disease surveillance improves early detection accuracy by 85%, reducing crop losses and optimizing pesticide application. AI-powered image processing models analyze drone-captured data, classifying disease severity and identifying hotspots for targeted intervention.

**2. Mobile and Handheld Devices for Field-Level Detection**

Smartphone-based disease detection systems have gained popularity due to their accessibility and cost-effectiveness. AI-driven mobile applications utilize convolutional neural networks (CNNs) to classify plant diseases based on images captured by farmers. These applications provide instant disease diagnosis, reducing dependency on expert assessments and laboratory tests.

Portable spectrometers and handheld hyperspectral sensors further enhance field-level disease detection by analyzing leaf spectral signatures. Studies have demonstrated that handheld spectral devices achieve classification accuracies above 90%, making them valuable tools for real-time disease diagnosis (Fang *et.al.,* 2023). The integration of mobile and IoT-based disease detection technologies has improved precision agriculture practices, enhancing disease control strategies.

**3. Public Databases and Open-Source AI Models**

Open-source plant disease datasets facilitate the development of AI models by providing annotated images and sensor data for training deep learning algorithms. Large-scale datasets, such as PlantVillage, contain thousands of labeled images of diseased and healthy plants, enabling researchers to build robust CNN-based classifiers.

Publicly available hyperspectral and multispectral imaging datasets further contribute to AI-based disease research. AI-driven models trained on these datasets achieve high classification accuracy, improving the scalability of disease detection systems. The availability of open-source AI frameworks, such as TensorFlow and PyTorch, accelerates model development, facilitating the implementation of deep learning-based disease monitoring solutions (Hosny *et.al.,* 2019).

**B. Data Processing Techniques for Disease Analysis**

The processing of large agricultural datasets requires advanced techniques such as image preprocessing, feature extraction, and machine learning-based classification. Image preprocessing enhances the quality of plant images by applying noise reduction, contrast enhancement, and segmentation algorithms. Feature extraction methods, including texture analysis and color-based classification, improve the identification of disease symptoms.

Big data analytics tools, such as Apache Hadoop and Spark, enable large-scale data processing, facilitating real-time disease prediction and risk assessment. AI-based classification models, including CNNs and support vector machines (SVMs), analyze plant images to detect infections with high accuracy. The integration of big data processing with cloud computing platforms allows for scalable disease management solutions (Aceto *et.al.,* 2020).

**C. Role of AI in Predictive Analytics for Disease Outbreaks**

Predictive analytics powered by AI enables the forecasting of disease outbreaks by analyzing environmental conditions, historical disease patterns, and pathogen behavior. Machine learning algorithms, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) models, process time-series data to predict disease incidence.

AI-driven predictive models have been successfully applied to forecast late blight in potatoes, rust diseases in wheat, and fungal infections in vineyards. Studies indicate that AI-assisted disease prediction reduces crop losses by 30-40%, allowing for proactive disease management. The combination of climate data, satellite imagery, and AI analytics enhances the accuracy of disease forecasting models, supporting precision agriculture practices.

**D. Challenges in Big Data Utilization for Disease Management**

Despite the advancements in AI-driven plant disease detection, challenges remain in big data utilization. The lack of standardized agricultural datasets limits the scalability of AI models, affecting classification accuracy across different crop varieties and geographical regions (Wang *et.al.,* 2022).

The computational complexity of deep learning models poses a challenge in real-time disease analysis, requiring significant processing power and memory resources. The integration of edge computing and AI optimization techniques addresses these issues by enabling on-site disease classification. Ethical concerns related to data privacy and farmer adoption barriers also impact the widespread deployment of AI-based disease detection systems.

**VIII. RECENT ADVANCES AND INNOVATIONS IN AI FOR PLANT PATHOLOGY**

**A. Emerging AI Technologies in Plant Disease Detection**

Advancements in AI technologies have transformed plant disease detection, incorporating deep learning, IoT, and edge computing solutions. Vision transformers (ViTs) have demonstrated superior accuracy in plant disease classification by leveraging self-attention mechanisms, outperforming conventional CNNs.

**B. AI-Powered Robotics for Disease Monitoring and Treatment**

AI-powered agricultural robots equipped with multispectral sensors and deep learning models autonomously monitor crop health, detecting diseases with high precision (Padhiary *et.al.,* 2024). Autonomous drones and robotic sprayers apply fungicides selectively, reducing chemical usage by 30% while maintaining disease suppression effectiveness.

**C. Deep Learning Advancements for Early Disease Prediction**

Deep learning architectures, including generative adversarial networks (GANs) and reinforcement learning, have improved disease detection and prediction accuracy. GANs generate synthetic plant disease images, augmenting training datasets and enhancing model robustness.

**D. Blockchain for Secure and Transparent Disease Data Sharing**

Blockchain technology ensures secure data sharing among farmers, researchers, and policymakers, improving disease surveillance. AI-integrated blockchain platforms track disease outbreaks, facilitating collaborative decision-making in agricultural disease management (Obeidat *et.al.,* 2024).

**E. AI-Driven Automated Greenhouse Disease Control Systems**

AI-powered smart greenhouses utilize IoT sensors and computer vision to monitor plant health, automatically adjusting temperature, humidity, and light conditions. AI-integrated disease detection systems deployed in greenhouses have increased disease detection accuracy by 90%, optimizing crop production efficiency.

**IX. CHALLENGES AND LIMITATIONS IN AI-BASED PLANT DISEASE MANAGEMENT**

**A. Data Availability and Quality Constraints**

The accuracy of AI-driven disease detection models depends on high-quality labeled datasets. Limited access to large-scale agricultural datasets affects model generalization, reducing classification accuracy across different crops.

**B. Computational Challenges and Model Generalization Issues**

Deep learning models require significant computational resources for training and deployment. High-performance GPUs and cloud-based AI platforms address these challenges, but their cost remains a limitation for small-scale farmers (Shaikh *et.al.,* 2022).

**C. Need for Large-Scale Validation in Different Crops and Climates**

AI-based disease detection models require validation across diverse climatic conditions and crop varieties. Multispectral and hyperspectral imaging datasets improve model robustness, enhancing disease classification performance.

**D. Ethical Considerations and Farmer Adoption Barriers**

The adoption of AI-based disease management systems is hindered by data privacy concerns, cost barriers, and the need for digital literacy among farmers.

**E. Future Prospects and Research Directions**

Advancements in quantum computing, AI-driven synthetic biology, and automated disease-resistant crop breeding will shape the future of plant disease management, improving sustainability and global food security (Redhu *et.al.,* 2022).

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**X. Conclusion**  
Artificial intelligence and machine learning have revolutionized plant disease detection and management by enabling early, accurate, and large-scale disease diagnosis through advanced image processing, IoT integration, and predictive analytics. AI-powered models, including deep learning architectures, support vector machines, and vision transformers, have demonstrated high classification accuracy, reducing reliance on manual inspections and traditional laboratory tests. The integration of IoT and edge computing has facilitated real-time disease monitoring, while cloud-based AI platforms have enhanced large-scale disease surveillance. Despite significant advancements, challenges such as data availability, computational constraints, model generalization issues, and farmer adoption barriers remain. Addressing these limitations through improved AI model validation, blockchain-based secure data sharing, and AI-driven automated disease control systems will further enhance agricultural disease management. Future research in AI-driven genomic selection, quantum computing, and automated robotics will play a pivotal role in ensuring sustainable and resilient crop production.

**References**

1. Vurro, M., Bonciani, B., & Vannacci, G. (2010). Emerging infectious diseases of crop plants in developing countries: impact on agriculture and socio-economic consequences. *Food security*, *2*, 113-132.
2. Ghosh, D. K., Motghare, M., & Gowda, S. (2018). Citrus greening: overview of the most severe disease of citrus. *Adv Agric Res Technol J*, *2*(1), 83-100.
3. Lucas, G. B., Campbell, C. L., & Lucas, L. T. (1992). *Introduction to plant diseases: identification and management*. Springer Science & Business Media.
4. Chen, C. P., & Zhang, C. Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Information sciences*, *275*, 314-347.
5. Saranya, T., Deisy, C., Sridevi, S., & Anbananthen, K. S. M. (2023). A comparative study of deep learning and Internet of Things for precision agriculture. *Engineering Applications of Artificial Intelligence*, *122*, 106034.
6. Ding, K., Xu, Z., Tong, H., & Liu, H. (2022). Data augmentation for deep graph learning: A survey. *ACM SIGKDD Explorations Newsletter*, *24*(2), 61-77.
7. Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, *3*, 54-70.
8. Ali, F., Razzaq, A., Tariq, W., Hameed, A., Rehman, A., Razzaq, K., ... & Ondrasek, G. (2024). Spectral Intelligence: AI-Driven Hyperspectral Imaging for Agricultural and Ecosystem Applications. *Agronomy*, *14*(10), 2260.
9. Verma, R., Nagar, V., & Mahapatra, S. (2021). Introduction to supervised learning. *Data Analytics in Bioinformatics: A Machine Learning Perspective*, 1-34.
10. Nguyen, T. A., Veetil, J. V., Sarkar, P., & Vogel, S. S. (2015, February). Conference 9329: Multiphoton Microscopy in the Biomedical Sciences XV. In *The Moscone Center San Francisco, California, USA Conferences & Courses 7–12 February 2015* (Vol. 7, p. 395).
11. Tugrul, B., Elfatimi, E., & Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. *Agriculture*, *12*(8), 1192.
12. Moskolaï, W. R., Abdou, W., Dipanda, A., & Kolyang. (2021). Application of deep learning architectures for satellite image time series prediction: A review. *Remote Sensing*, *13*(23), 4822.
13. Pasrija, P., Jha, P., Upadhyaya, P., Khan, M. S., & Chopra, M. (2022). Machine learning and artificial intelligence: a paradigm shift in big data-driven drug design and discovery. *Current Topics in Medicinal Chemistry*, *22*(20), 1692-1727.
14. Farooq, M. A., Gao, S., Hassan, M. A., Huang, Z., Rasheed, A., Hearne, S., ... & Li, H. (2024). Artificial intelligence in plant breeding. *Trends in Genetics*.
15. Abdullah, H. M., Mohana, N. T., Khan, B. M., Ahmed, S. M., Hossain, M., Islam, K. S., ... & Ahamed, T. (2023). Present and future scopes and challenges of plant pest and disease (P&D) monitoring: Remote sensing, image processing, and artificial intelligence perspectives. *Remote Sensing Applications: Society and Environment*, *32*, 100996.
16. Oerke, E. C., Fröhling, P., & Steiner, U. (2011). Thermographic assessment of scab disease on apple leaves. *Precision agriculture*, *12*, 699-715.
17. Xu, J., Cui, Y., Zhang, S., & Zhang, M. (2024). The evolution of precision agriculture and food safety: a bibliometric study. *Frontiers in Sustainable Food Systems*, *8*, 1475602.
18. Dhingra, G., Kumar, V., & Joshi, H. D. (2018). Study of digital image processing techniques for leaf disease detection and classification. *Multimedia Tools and Applications*, *77*, 19951-20000.
19. Abade, A., Ferreira, P. A., & de Barros Vidal, F. (2021). Plant diseases recognition on images using convolutional neural networks: A systematic review. *Computers and Electronics in Agriculture*, *185*, 106125.
20. Zhang, Q., Luan, R., Wang, M., Zhang, J., Yu, F., Ping, Y., & Qiu, L. (2024). Research Progress of Spectral Imaging Techniques in Plant Phenotype Studies. *Plants*, *13*(21), 3088.
21. Ali, F., Razzaq, A., Tariq, W., Hameed, A., Rehman, A., Razzaq, K., ... & Ondrasek, G. (2024). Spectral Intelligence: AI-Driven Hyperspectral Imaging for Agricultural and Ecosystem Applications. *Agronomy*, *14*(10), 2260.
22. Mienye, I. D., Swart, T. G., & Obaido, G. (2024). Recurrent neural networks: A comprehensive review of architectures, variants, and applications. *Information*, *15*(9), 517.
23. Goel, L., & Nagpal, J. (2023). A systematic review of recent machine learning techniques for plant disease identification and classification. *IETE Technical Review*, *40*(3), 423-439.
24. Azar, A. T., Elshazly, H. I., Hassanien, A. E., & Elkorany, A. M. (2014). A random forest classifier for lymph diseases. *Computer methods and programs in biomedicine*, *113*(2), 465-473.
25. Yadav, P., Sharma, S. C., Mahadeva, R., & Patole, S. P. (2023). Exploring hyper-parameters and feature selection for predicting non-communicable chronic disease using stacking classifier. *IEEE Access*, *11*, 80030-80055.
26. Qadri, S. A. A., Huang, N. F., Wani, T. M., & Bhat, S. A. (2024). Advances and challenges in Computer Vision for Image-based plant disease detection: a Comprehensive Survey of Machine and Deep Learning approaches. *IEEE Transactions on Automation Science and Engineering*.
27. Ahad, M. T., Li, Y., Song, B., & Bhuiyan, T. (2023). Comparison of CNN-based deep learning architectures for rice diseases classification. *Artificial Intelligence in Agriculture*, *9*, 22-35.
28. Shahi, T. B., Xu, C. Y., Neupane, A., & Guo, W. (2023). Recent advances in crop disease detection using UAV and deep learning techniques. *Remote Sensing*, *15*(9), 2450.
29. Sharma, K., & Shivandu, S. K. (2024). Integrating artificial intelligence and internet of things (IoT) for enhanced crop monitoring and management in precision agriculture. *Sensors International*, 100292.
30. Zhang, N., Yang, G., Pan, Y., Yang, X., Chen, L., & Zhao, C. (2020). A review of advanced technologies and development for hyperspectral-based plant disease detection in the past three decades. *Remote Sensing*, *12*(19), 3188.
31. Chang, Z., Liu, S., Xiong, X., Cai, Z., & Tu, G. (2021). A survey of recent advances in edge-computing-powered artificial intelligence of things. *IEEE Internet of Things Journal*, *8*(18), 13849-13875.
32. Rana, R., & Bhambri, P. (2025). The Role of IoT in Shaping the Future of Geospatial AI. In *Recent Trends in Geospatial AI* (pp. 177-216). IGI Global Scientific Publishing.
33. Men, L., Ilk, N., Tang, X., & Liu, Y. (2021). Multi-disease prediction using LSTM recurrent neural networks. *Expert Systems with Applications*, *177*, 114905.
34. Kebe, A. A., Hameed, S., Farooq, M. S., Sufyan, A., Malook, M. B., Awais, S., ... & Abbas, N. (2023). Enhancing crop protection and yield through precision agriculture and integrated pest management: a comprehensive review. *Asian Journal of Research in Crop Science*, *8*(4), 443-453.
35. Sabeeh, E., & Zuhair Al-Taie, M. (2024). Enhancing Agricultural Decision-Making through Data Analysis: Predicting Crop Health Outcomes. In *BIO Web of Conferences* (Vol. 97, p. 00013). EDP Sciences.
36. Fang, S., Cui, R., Wang, Y., Zhao, Y., Yu, K., & Jiang, A. (2023). Application of multiple spectral systems for the tree disease detection: A review. *Applied Spectroscopy Reviews*, *58*(2), 83-109.
37. Hosny, A., Schwier, M., Berger, C., Örnek, E. P., Turan, M., Tran, P. V., ... & Aerts, H. J. (2019). Modelhub. ai: Dissemination platform for deep learning models. *arXiv preprint arXiv:1911.13218*.
38. Aceto, G., Persico, V., & Pescapé, A. (2020). Industry 4.0 and health: Internet of things, big data, and cloud computing for healthcare 4.0. *Journal of Industrial Information Integration*, *18*, 100129.
39. Wang, D., Cao, W., Zhang, F., Li, Z., Xu, S., & Wu, X. (2022). A review of deep learning in multiscale agricultural sensing. *Remote Sensing*, *14*(3), 559.
40. Padhiary, M., Saha, D., Kumar, R., Sethi, L. N., & Kumar, A. (2024). Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agricultural Technology*, 100483.
41. Obeidat, M. A., Abdallah, J., Hamadneh, T., Qawaqneh, H., & Mansour, A. M. (2024). Enhancing Agricultural Operations Through AI-Driven Agent Communication in Smart Farming Systems. *Ingenierie des Systemes d'Information*, *29*(3), 917.
42. Shaikh, T. A., Rasool, T., & Lone, F. R. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*, *198*, 107119.
43. Redhu, N. S., Thakur, Z., Yashveer, S., & Mor, P. (2022). Artificial intelligence: a way forward for agricultural sciences. In *Bioinformatics in agriculture* (pp. 641-668). Academic Press.

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