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A Review on Plant Leaf Disease Detection Using CNN Deep Learning Models

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Abstract—This paper aims to review the advancements in early-stage plant disease detection using neural network-based approaches, with a particular focus on improving agricultural practices and disease management. The objective is to provide a comprehensive overview of the various neural network architectures applied in plant disease detection, their methodologies, and the results achieved in real-world applications. The review encompasses the use of deep learning models, particularly convolutional neural networks (CNNs), for classifying and detecting plant diseases from images. It also discusses the preprocessing techniques, feature extraction methods, and dataset variations employed in these systems. Various evaluation metrics such as accuracy, precision, recall, and F1-score are analyzed to compare the performance of different models. The results presented in the review highlight the potential of neural networks in providing accurate, automated disease detection solutions that can assist farmers in early intervention. These systems contribute to enhancing crop yield, reducing pesticide use, and promoting sustainable farming practices. However, challenges such as dataset diversity, the need for extensive training data, and real-time application remain. The paper concludes by emphasizing the importance of developing robust, scalable, and easy-to-deploy models for real-time disease detection, with the potential to revolutionize precision agriculture and improve food security across diverse farming environments. Future research directions include enhancing model generalization, integrating multi-modal data, and improving the interpretability of deep learning models for practical agricultural use.

Keyword- Plant Disease Detection, Leaf Disease Identification, Convolutional Neural Networks (CNN), Deep Learning Models, Agricultural Image Classification.

Introduction

Plant diseases, particularly those affecting leaves, represent a major challenge to agricultural productivity and food security across the globe. These diseases can cause significant reductions in crop yield and quality, leading to financial losses for farmers and threats to national economies, especially in countries that rely heavily on agriculture. Early and accurate identification of plant diseases is essential to managing outbreaks and implementing effective control strategies. Traditional methods of disease detection—such as visual inspection by experts or lab-based diagnostics—are often time-consuming, labor-intensive, and subject to human error, making them inadequate for large-scale agricultural operations[1]–[3]. The fast development of artificial intelligence (AI), especially in the shape of deep learning, has created new possibilities for automating the detection and categorisation of plant leaf diseases in recent years. Designed for image recognition jobs, Convolutional Neural Networks (CNNs), a category of deep learning models, have demonstrated remarkable ability in detecting intricate patterns in leaf images, hence suited for this use. By automatically extracting relevant characteristics from raw image data without need of feature selection, CNNs enable more accurate and efficient

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classification of plant diseases depending on visual symptoms including spots, discolouration, and texture changes. Many studies have concentrated on creating and fine-tuning CNN architectures to identify diseases in crops including tomatoes, potatoes, corn, grapes, and rice. Popular CNN architectures such as AlexNet, VGGNet, ResNet, and Inception have been used either as basis models or with bespoke tweaks to fit the particular requirements of agricultural datasets. Apart from these conventional models, lightweight CNNs like MobileNet and EfficientNet are being looked at more and more for real-time field applications where computational resources could be constrained. The availability of labelled datasets like the Plant Village dataset, which includes thousands of photos of healthy and diseased plant leaves under controlled circumstances, is a major enabler of CNN-based research in plant pathology. These datasets let researchers test, validate, and train CNN models with a great degree of uniformity. Common preprocessing strategies to increase CNN model performance and expand their capacity to generalise across various plant kinds and disease situations include image scaling, normalisation, and augmentation methods like rotation, flipping, and zooming[4]–[6]. In this field, transfer learning has gained popularity as a method to allow pre-trained CNN models to be fine-tuned for particular plant disease datasets, hence greatly lowering training time and computing overhead. Notwithstanding these developments, the practical use of CNN-based plant disease detection systems still presents several issues. One significant problem is the variation in environmental variables, including lighting, background clutter, and leaf orientation, which can negatively impact model performance in real-world situations relative to laboratory settings.

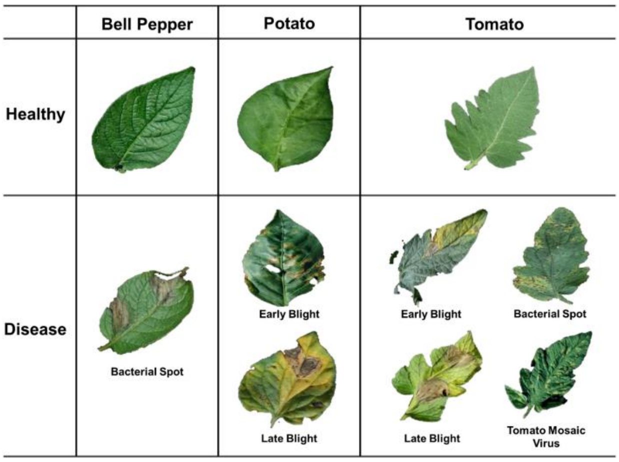

Fig. 1 Plant Leaf Disease Detection [7]

Class imbalance in datasets—where some diseases are over-represented while others are underrepresented—can result in biassed model results. Techniques include data augmentation, class weighting, synthetic data generation using Generative Adversarial Networks (GANs), and ensemble learning have been suggested to help to solve these problems. CNN models' interpretability is another cause for worry; while they provide great accuracy, the decision-making process is usually perceived as a "black box," which reduces user confidence and broad application in agricultural communities. Recent work in explainable artificial intelligence (XAI) tries to solve this by offering visual insights into which aspects or areas of the leaf most influence the predictions of the algorithm[8]–[11]. Integration with mobile platforms, unmanned aerial vehicles (UAVs), and Internet of Things (IoT) devices is broadening the range of CNN-based plant disease detection, hence providing real-time, on-site diagnostics and decision support for farmers. These developments could help sustainable agriculture by lowering costs, cutting pesticide overuse, and supporting it. Focusing on current methodology, CNN architectures, datasets, preprocessing approaches, performance evaluation measures, and real-world applications, this review paper offers a thorough overview of the use of CNN deep learning models in plant leaf disease detection. It also emphasizes recent trends and new technology in the sector and critically examines the difficulties experienced by scholars and practitioners[12]–[14]. By examining the strengths and limitations of existing approaches, this review aims to guide future research toward more robust, accurate, and accessible solutions for plant disease detection, ultimately contributing to the global effort to secure food production through technology-driven agriculture.

Literature Review

Wang 2025 et.al initially, limited and varied training data made diagnosing plant diseases and pests challenging. To address this, we compiled a large, diverse database covering various plant and insect species. By developing a modern architecture that combines Masked Image Modelling (MIM) with Contrastive Learning, we significantly improved detection accuracy. This approach helps to reduce production costs for agriculture by offering fast, practical, and economical identification of diseases and pests. Our approach tackles significant challenges in early-stage plant disease identification. By putting our dataset and code on GitHub, we want to help more study and development in plant pest and disease identification systems[15].

Wei 2024 et.al Though present plant disease classifiers shine in laboratory environments, their performance with real images suffers due to significant intra-class variation and modest inter-class distinctions. To address this issue, we developed a multimodal dataset for in-the-wild plant disease detection comprising visual data and comprehensive written descriptions for every sickness across the most classes. Our baseline method increases classification utilising multimodal prototypes by properly managing intra-class variation and inter-class similarity. It allows traditional education as well as few-shot. Although exhibiting significant possibilities for enhancing real-world plant disease identification, benchmark results highlight the complexity of the dataset and the baseline's promise[16].

Nigar 2024 et.al Plant diseases threaten world food security by reducing agricultural output and quality. Though deep learning methods offer excellent accuracy in detecting particular diseases, their black-box nature raises issues about interpretability. To address this, we developed a plant disease categorising tool using explainable artificial intelligence (XAI). Our algorithm accurately identifies 38 plant diseases with 99.69% accuracy, 98.27% accuracy, and 98.26% recall. In keeping with professional expertise, we provided graphic, clear explanations using the LIME framework. This approach increases confidence in AI predictions, guides better decisions, and is a major step towards consistent, open plant disease diagnostics for sustainable agriculture all around the world[17].

Shwetha 2024 et.al Yellowish-brown spots on jasmine leaves caused by bacteria and fungus pose grave threat to commercial plants and farm production. To address this, we trained a DCGAN model to identify jasmine plant diseases using a dataset of 10,000 images. The model employs a UNet architecture on a MobileNetV4 backbone for precise leaf disease segmentation. The proposed segmentation model had an average pixel accuracy of 0.91 and a mean intersection over union (mIoU) of 0.95. Using UNet for segmentation and DCGAN for dataset generation allows us to increase the efficacy of diagnosing and segmenting jasmine plant leaf diseases[18].

Mane 2024 et.al Diseases endangering traditional medicinal herbs could lead to their extinction. To address this, researchers proposed an early sickness detection hybrid model for basil leaves using Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and K-Nearest Neighbour (KNN). The model improves standard CNN by means of SVM and KNN for classification, hence supporting data augmentation to balance the dataset. Using a dataset of 803 basil leaf pictures, the

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CNN+SVM hybrid model recognised five distinct basil leaf diseases with a 95.02% accuracy, hence surpassing previous methods[19].

TABLE 1 LITERATURE SUMMARY

Author/year	Methodology	Research gap	Findings
Lin 2020 [20]	Use of Faster R-CNN & Mask R-CNN for early detection of plant pests.	Prompt, accurate, and automated disease detection in potato leaves is essential.	The detection of potato diseases was 97.8 percent accurate using logistic regression.
Rathore 2020 [21]	The accuracy rate of the CNN-based model in detecting diseases in rice was 99.61%.	Automatic disease diagnosis in rice using a CNN-based deep learning model.	The CNN model was able to classify rice diseases with an accuracy of 99.61%.
Nazki 2020 [22]	The accuracy of plant disease categorisation was enhanced by 5.2% by the use of GAN-based augmentation.	Class imbalance in GAN-based plant disease classification must be addressed.	When trained on synthetic samples, AR-GAN increased the accuracy of plant disease classification by 5.2%.
Singh 2020 [23]	Up to 31% improvement in plant disease identification precision is achieved using the PlantDoc dataset.	Accurate plant disease identification requires large-scale datasets that are not generated in laboratories.	The accuracy of plant disease categorisation was enhanced by as much as 31% using the PlantDoc dataset.
Abdu 2020 [24]	Image processing, division, feature extraction, classification, and approaches for detecting rice diseases.	Problems with accuracy, lack of real-time detection, dataset limitations, and feature optimisation; limited automation.	Recent developments in medical image processing, division, feature extraction, grouping, and condition identification.

Significance of Early Plant Disease Detection

Early plant disease diagnosis helps to prevent large-scale crop loss and ensure agricultural output. Early disease detection enables farmers to act swiftly, hence minimizing the impact on crop quality and production. This proactive approach not only safeguards crops but also reduces the reliance on expensive control measures. Early detection technology have evolved in recent years, providing farmers

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the ability to act before illnesses spread significantly. This significantly improves the overall efficiency of disease management strategies and supports food security.

A. *Economic Benefits of Early Detection*

Early detection of plant diseases helps to avoid notable economic losses brought on by extensive crop destruction. Treating an existing disease outbreak costs much more than avoiding one since, in certain situations, the harm to crops can be considerable and irreversible. Early diagnosis allows farmers to cut costs on pesticides, fertilisers, and other management measures[25]. Additionally, early intervention reduces the need for large-scale pesticide applications, which not only reduces costs but also minimizes the environmental and health risks associated with excessive chemical use. This results in more sustainable farming practices and a more profitable agricultural operation.

B. *Improved Crop Yields through Timely Intervention*

The improvement of agricultural output is among the most direct and powerful advantages of early plant disease identification. Early detection of diseases lets one take quick corrective actions like exact pesticide use or removal of diseased plants before the disease has a chance to spread widely.

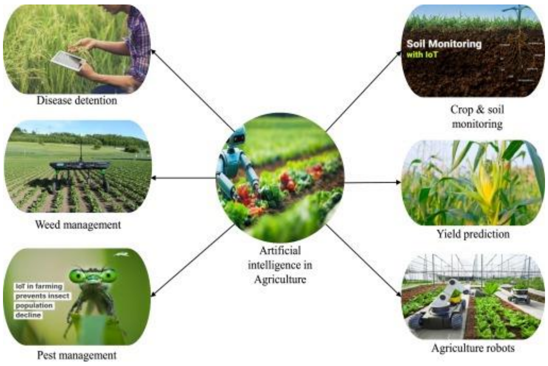

Fig. 2 Crop Yields through Timely Intervention [26]

This preventive strategy guarantees that crops can develop to their full potential without disruption as it stops the illness from harming healthy plants[27]. Dealing with the problem early helps the plants to keep maximum health all through their growth cycle, thereby producing stronger and higher-quality crops. For high-value crops, where even little yield losses can greatly impact the whole farm profitability, this is especially crucial. Early diagnosis not only stops crop loss but also optimises the output potential, therefore improving the economic feasibility of the farming enterprise and guaranteeing a greater return on investment.

C. *Environmental Impact and Sustainability*

Reducing the environmental effect of plant disease treatment depends on early identification. Often, traditional techniques control illnesses by use of pesticides and fungicides, which can greatly harm the environment. Excessive use of these herbicides harms non-target species including necessary pollinators and other useful insects, taints water sources, and causes soil deterioration. Early disease detection helps to ensure that only the impacted plants are treated; so, treatments can be more exact and focused. This strategy lowers the total demand for chemical applications, therefore reducing their harmful environmental effects[28]. When combined with precision agriculture tools, early detection technologies improve this process by guaranteeing that pesticides are used in the correct amounts and at the appropriate time, lowering needless waste. This in turn encourages more sustainable farming methods, therefore preserving biodiversity, safeguarding ecosystems, and enhancing the long-term health of agricultural landscapes.

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D. *Minimizing the Spread of Plant Diseases*

Once a plant disease is established, especially in monoculture agricultural systems, where crops are cultivated in large, uniform blocks, it can quickly spread across broad territories. As diseases travel fast from one plant to another, overwhelming fields in a short period, this extensive transmission can result in significant crop losses. Stopping this chain reaction depends on early detection being very important.

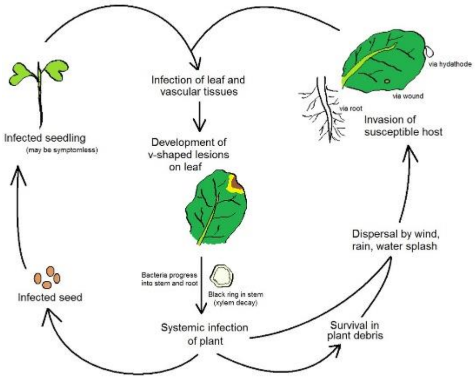

Fig. 3 Spread of Plant Diseases [29]

Identifying sick plants early helps farmers isolate them from healthy crops before the disease spreads more. This is especially true for highly infectious diseases, which can wipe out entire fields if left unchecked. Early detection tools enable farmers to act promptly and strategically to prevent the disease from spreading to neighbouring farms or harming close by crops.[30]. By significantly reducing the likelihood of large-scale outbreaks, this proactive approach ensures that agricultural businesses remain healthy, efficient, and economically viable in the long run.

E. ***Integration with Precision Agriculture***

Precision agriculture, which uses cutting-edge technology to track and control crop health in real-time, is being more and more integrated with early disease detection. Remote sensing, drones, and automated technologies let farmers find early indications of sickness that could not be obvious to the naked eye. For example, remote sensors can identify minute changes in plant colour or temperature suggesting the start of disease by use of spectral imaging, therefore monitoring plant health. Drones using cameras and sensors can swiftly survey vast areas, spotting problem areas throughout the field. Automated systems can process this data in real-time, giving farmer's instant analysis of possible problems. Whether it's changing irrigation, providing fertilisers, or using pesticides only where required, this seamless connectivity enables exact, focused actions[31]. This strategy reduces resource waste and improves disease management efficacy by guaranteeing that interventions are both precise and efficient, hence increasing agricultural output and sustainability.

Overview of Common Plant Leaf Diseases

Plant leaf diseases are one of the most prevalent and damaging challenges in agriculture. These diseases can significantly affect crop yield, quality, and even plant survival. They are caused by a variety of factors, including fungal, bacterial, viral, and environmental stressors, and often present visible symptoms like spots, wilting, and discoloration on the leaves.

A. ***Fungal Diseases***

Among the most common causes of plant leaf diseases are fungal infections, which greatly compromise crop health and farm output. Various fungal species typically cause diseases such as Powdery Mildew, Downy Mildew, and Leaf Rust. Often causing leaf deformation and early leaf drop, powdery mildew shows as a white, powdery coating on the upper side of leaves[32]. downy mildew creates yellowish or pale patches on the upper leaf surface and a greyish mold-like growth on the underside, hence compromising the general health of the plant. Leaf rust results in orange, yellow, or reddish patches on leaves, hence causing early leaf loss and lower photosynthesis. Warm, humid settings help these fungal infections to flourish and they can spread fast, especially in dense, moist conditions, hence greatly harming agricultural output. Uncontrolled early management could cause significant declines in crop quality and quantity, therefore endangering agricultural output all over the world.

B. Bacterial Leaf Diseases

Common in many crops, including tomatoes, peppers, and beans, bacterial illnesses like Bacterial Leaf Spot and Bacterial Blight are major obstacles for crop management. Usually, these illnesses show as water-soaked lesions on leaves that turn yellow or brown, therefore causing early leaf drop. These symptoms can greatly lower photosynthesis, therefore stressing the plant and lowering general production. Once an infection has started, controlling bacteria can be difficult since they can spread by several routes including water, wind, and tainted agricultural instruments. Some bacterial pathogens also survive in soil or plant waste, which causes repeated infections[33]. Unlike fungal illnesses, bacterial infections are frequently more difficult to control since there are fewer successful treatments available, particularly once the plant is sick. Although antibiotics and copper-based therapies might occasionally be beneficial, the most efficient approach to control bacterial infections is usually prevention by means of appropriate sanitation, crop rotation, and resistant plant types.

C. Viral Diseases

A variety of unique leaf abnormalities that greatly affect plant health are caused by viruses like Tobacco Mosaic Virus (TMV) and Tomato Yellow Leaf Curl Virus (TYLCV). While TYLCV causes yellowing, leaf curling, and stunted growth, TMV usually produces mosaic patterns on leaves with lighter and darker green patches. Insect vectors usually spread these viruses; aphids are the most prevalent carriers. Especially in high-density crop systems, the infection can spread quickly and cause poor plant development[34], lower production, and sometimes total loss of infected plants. Since there is no treatment for viruses, their transmission must be controlled by means of prevention and early identification. Reducing transmission depends on controlling the insect vectors by means of insecticide treatment or the use of resistant plant cultivars. Removing sick plants and maintaining proper field cleanliness also serve to control the spread of viral illnesses, which are usually catastrophic because of their lack of efficient treatment choices.

D. Nutrient Deficiencies

Nutrient deficiencies in plants, though not caused by pathogens, can lead to various symptoms that closely resemble those of leaf diseases. Common deficiencies include a lack of nitrogen, potassium, and magnesium, all of which are essential for plant growth and health. For example, nitrogen deficiency often causes general yellowing or chlorosis of the older leaves, while potassium deficiency can lead to yellowing along the edges of the leaves and reduced plant vigor[35]. Magnesium deficiency typically results in interveinal chlorosis, where the spaces between the veins turn yellow, leaving the veins green. These nutrient-related issues can often be mistaken for fungal or bacterial infections, complicating the diagnosis and treatment of plant problems. Proper soil management, including regular soil testing and appropriate fertilization, is critical to prevent these deficiencies. By maintaining the right balance of nutrients, plants can thrive, reducing the likelihood of symptoms that might otherwise mimic more serious diseases.

E. Environmental Stress and Leaf Diseases

Environmental factors such as drought, excessive moisture, temperature fluctuations, and pollution can place significant stress on plants, making them more vulnerable to a range of issues, including diseases.

When plants are stressed, their natural defenses weaken, allowing pathogens to take hold more easily. Stress-induced symptoms often mimic those of plant diseases, such as wilting, yellowing, or necrosis of the leaves, but these are not caused by pathogens. For instance, drought stress can lead to leaf curling and browning of leaf edges, while excessive moisture may cause root rot or fungal growth on the leaves[36]. Temperature fluctuations, especially extreme heat or cold, can cause cell damage and chlorosis. Pollution, such as exposure to toxic gases or chemicals, can also lead to leaf discoloration and spotting. These stress-related symptoms are often non-pathogenic and arise from the plant's inability to cope with unfavorable environmental conditions, highlighting the importance of proper environmental management and stress mitigation strategies.

Importance of Early Plant Disease Detection

By enabling prompt actions like focused pesticide sprays, early plant disease detection greatly improves agricultural output and quality by preserving plant health. By allowing the isolation or removal of sick plants, it minimises the spread of diseases in monoculture systems, hence safeguarding whole fields and adjacent farms. It also lessens the need for too many chemicals, hence reducing environmental effect and supporting sustainability. Early detection maximises resource efficiency and minimises waste by integrating well with precision agriculture technologies including drones and sensors[37]. This mix guarantees efficient, environmentally friendly farming operations and protects long-term agricultural production.

A. *Improved Crop Yield and Quality*

A key instrument for maintaining crop health and guaranteeing best production is early identification of plant diseases. Farmers may carry out quick and focused interventions by spotting diseases in their early stages, hence preventing the spread of the disease over the land. These interventions could involve adopting particular cultural practices like crop rotation, trimming, or enhancing irrigation techniques or precision pesticide treatments, which reduce the usage of chemicals[27]. These measures preserve plant viability and stop more harm. Consequently, crops can keep growing strongly, which will increase yields and enhance the quality of the produce. For high-value products, such as fruits and vegetables, this is particularly crucial since quality greatly affects market prices and consumer demand. Early disease diagnosis therefore not only protects the crops but also helps to preserve profitability and consumer confidence, hence guaranteeing the success of agricultural enterprises.

B. *Prevention of Disease Spread*

Once a plant disease is established, especially in densely planted fields or monoculture systems where plants of the same species are grown together, it can spread quickly. Diseases can travel fast from one plant to another in this close contact, hence possibly infecting significant percentages of the harvest. Preventing this quick spread depends on early identification of plant diseases. Early identification of the illness allows farmers to segregate or remove affected plants, therefore reducing the exposure to healthy crops[38], [39]. Early action keeps the disease in a small, controllable area, therefore prevents it from spreading to other farms or crops. The early detection and containment not only safeguard the impacted field but also stop the spread of the disease into a regional outbreak. A localised problem might rapidly become a widespread epidemic without early diagnosis, therefore causing major regional agricultural output interruptions and terrible economic losses.

C. *Reduced Use of Chemicals*

In agricultural management, early disease diagnosis is absolutely essential since it helps to lower the requirement for extensive chemical use. Early detection of diseases calls for only lower, more exact quantities of chemicals—such as insecticides and fungicides—to treat the impacted areas. When the disease is more advanced, this focused strategy differs significantly from the common application of broad-spectrum chemicals usually in larger quantities. Reducing the amount of pesticides used helps farmers not only save treatment expenses but also help to prevent harmful environmental effects linked with too high chemical use. Excessive use of fungicides and pesticides can cause environmental damage, water pollution, and harm to helpful species in the ecosystem[40]. Early disease diagnosis thus serves to encourage more sustainable agricultural practices, guarantees that measures of crop protection are efficient and environmentally friendly, hence supporting the economy as well as the environment.

D. *Environmental Sustainability*

Reducing the overuse of pesticides and fungicides, which is vital for fostering sustainable agriculture, depends much on early identification. Farmers who spot plant illnesses in their early stages can use chemicals in a controlled, focused way instead of broad-spectrum treatments. This not only lowers the quantity of pesticides required but also helps to stop needless runoff into surrounding ecosystems, therefore safeguarding water quality and maintaining local biodiversity. The prudent application of fungicides and pesticides helps to safeguard beneficial insects like pollinators, which are absolutely essential for the ecosystem and crop pollination[41]. Regulated chemical treatments help to preserve good soils, therefore preventing the deterioration brought on by chemical misuse. Early actions, then, encourage a better balanced agricultural system that supports environmental sustainability as well as high output. This strategy guarantees that, over the long run, agricultural methods stay feasible without endangering the health of the planet[42].

E. *Integration with Precision Agriculture*

A little early disease detection as a key component, modern precision agricultural methods rely on cutting-edge technologies to improve farm management practices. Enabling constant surveillance of large agricultural areas, tools like drones, sensors, and satellite photos offer real-time, thorough data on crop health. These tools let farmers find issues before they spread or get serious by spotting early indicators of disease, stress, or pest infestations. Farmers can use precise, focused treatments like insecticides or fertilisers just where required by identifying the damaged areas[43]. This targeted strategy not only lowers running expenses but also lessens the environmental effect of broad-spectrum treatments by greatly lowering the number of chemicals needed. This efficient use of resources results in improved crop yields, healthier soil, and less waste. In the end, including these contemporary methods into farm management encourages sustainability, resource optimization, and financial gains for farmers.

Conclusion

In conclusion, early detection of plant diseases plays a crucial role in enhancing agricultural productivity, sustainability, and food security. Timely identification allows farmers to implement effective preventive measures, minimizing the spread of diseases, reducing the reliance on pesticides, and preserving crop health. This approach not only cuts production costs but also improves yield and quality, benefiting both farmers and consumers. The advent of advanced technologies, including machine learning models, remote sensing, and sensor-based systems, has revolutionized plant disease detection by offering accurate, real-time insights into crop health, enabling more precise interventions. The integration of such technologies into precision agriculture facilitates targeted management, optimizing resource usage and reducing waste, which ultimately contributes to environmental sustainability. By focusing on specific areas with visible symptoms, farmers can reduce pesticide usage and its harmful impact on the environment, promoting healthier ecosystems and soils. Moreover, early disease detection plays a vital role in addressing global challenges, such as climate change and rising population demands, by ensuring stable and healthy food production. As these innovative technologies become more accessible and cost-effective, they offer the potential to transform farming practices globally, making agriculture more resilient and sustainable. Early detection of plant diseases is a key factor in safeguarding global food security, ensuring long-term agricultural productivity, and fostering a balance between increased production and environmental conservation. This integrated approach is essential for the future of sustainable agriculture and addressing the growing needs of a changing world.

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