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**Research Article**

# Advancements in Early Detection of Cotton Leaf Diseases in Plants Using Multimodal Deep Learning Techniques

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**ABSTRACT**

Due to the vital importance of promptly controlling plant diseases and the challenges facing today's agricultural disease management techniques, a novel framework has been introduced for detecting crop disease. This paper proposes a new methodology for detecting cotton leaf disease using multi-modal deep learning approaches. Since the early control of plant diseases is paramount and commonly utilized methods for managing agricultural diseases suffer in practice, a new framework for disease detection has been proposed. Inspecting modern deep learning algorithms concerning the analysis of images and processing for pattern recognition, we design a system utilizing visual indicators of diseases from multiple modalities to improve the detection of diseases in cotton leaves. We propose a new methodology utilizing deep learning algorithms that utilize spectral imagery, thermal imagery, and hyper-spectral images to merge their features and thus accurately identify plant diseases. This system allows measuring the plant's general health to determine the type of disease symptoms occurring on the leaves of various cotton leaf trees in many environments. Hence, the outcomes of extensive experiments using multi-modal images of plants of various kinds – healthy and diseased – show that quantitative tests confirm the ability of the proposed system to detect different types of early cotton leaf diseases with an accuracy, sensitivity, and specificity equal to or better the results published in the literature, which allows the critical impact of the proposed multi-modal deep learning technique to give an early warning against plant diseases before it spreads in the fields, as well as the other numerous uses of its implementation and availability in agricultural papers and applications while aiding the reaching of the goals for further research and developments on the areas to be used by the governing territories where better scalable and accurate disease detection systems would be necessary for such large-scale agricultural needs and real-time surveillance applications.

**Keywords:** Cotton leaf diseases, feature fusion techniques, multi-modal deep learning.

## INTRODUCTION

In agriculture, the early diagnosis of plant diseases is essential in crop care. This care helps realize high yields, which are necessary to conserve food. However, the traditional methods for diagnosing diseases might be undesirable due to the reliance on expert-based visual inspection, which is time-consuming and subjective and leads to high error rates. There is, therefore, a pressing need for consistent, accurate, automated disease detection. This need is focused on the quick identification classification undertaken in the early stages of plant diseases, which ensures rapid intervention. The use of deep learning algorithms has recently revolutionized imaging and pattern recognition. This new deep learning technology has shown promise in automatically detecting plant diseases. Convolutional neural network models can process and analyze extensive datasets of images. This model has demonstrated their talent in detecting minor disease symptoms and analyzing different physical aspects of plants. The proposed extension paper defines the above topics theoretically covering deep learning technologies. It is a multi-modal integral that explores themes on the circle of plant disease detection and discrimination, with cotton leaf diseases as the redistribution. Through several spectral imaging, thermal imaging, and spectral imaging methods, more accurate, timely results will be used for a wide range of cotton leaf diseases, giving a more systematic, more detailed functional picture of plant state and disease symptoms.

### 1.1 Mathematical Model

In fine plant disease detection circles with deep learning, the fundamental mathematical formulation is around the structure and training of the network of Convolutional Neural Networks. CNN is the deep neural network type that is well suited to image analysis tasks and capable of self-learning entire hierarchies of features and input images. The main parts of a CNN are convolutional layers, pooling layers, and fully connected layers. Conv layer filters the input image to derive characteristics like edges, textures, and signatures and also understand how animals like these occur Home just like. The output of a conv layer is identified mathematically as:

$$H_{i,j}^{(l)} = f\left(\sum_m \sum_n W_{m,n}^{(l)} \cdot X_{i+m,j+n}^{(l-1)} + b^{(l)}\right) \qquad (1)$$

where $H_{i,j}^{(l)}$ is the activation at position $(i, j)$ in layer $l, W_{m,n}^{(l)}$ represents the weights of the filter, $X_{i+m,j+n}^{(l-1)}$ denotes the input from the previous layer, $b^{(l)}$ is the bias term, and $f$ is the activation function.

Pooling layers are then used to down-sample the feature maps generated by the convolutional layers; this reduces the spatial dimensions of data while retaining essential features. The pooling operation can be expressed in mathematics as follows:

$$Y_{i,j}^{(l)} = pooling\left(X_{i,j}^{(l)}\right) \qquad (2)$$

where $Y_{i,j}^{(l)}$ is the pooled output at position $(i, j)$ in layer $l$.

The fully connected layers are deployed to classify the extracted features and to predict based on learned representations. The output of a fully connected layer can be expressed as:

$$Z^{(l)} = f\left(W^{(l)} \cdot A^{(l-1)} + b^{(l)}\right) \qquad (3)$$

where $Z^{(l)}$ is the output of the fully connected layer, $W^{(l)}$ represents the weights, $A^{(l-1)}$ denotes the input activations, $b^{(l)}$ is the bias term, and $f$ is the activation function.

In the following sections of this article, we will delve deeper into mathematical formulations and methods used to integrate multimodal deep-learning techniques aimed at detecting plant diseases early, with specific care given to cotton leaf diseases.

## RELATED WORK

CNNs have proven effective in plant disease identification by enhancing the accuracy of predictions even under real agricultural field conditions. For instance, CNN architectures for disease recognition achieved varying accuracy rates between 62% and 96% depending on the dataset and experimental setup [14]. Advanced deep learning techniques, such as ResNet50, significantly improved the accuracy of detecting specific cotton plant diseases compared to traditional algorithms [19]. Early detection of diseases is critical for ensuring sustainable agricultural practices, and CNN-based approaches offer promising solutions [1, 19].

A study by Sivakumar et al. [19] demonstrated the potential of transfer learning models, including ResNet152V2, InceptionVV4, VGG19, and ResNet50, for identifying cotton leaf diseases. Among these, ResNet152V2 was the most accurate, highlighting the utility of transfer learning. Similarly, Yadav et al. [1] proposed a CNN-based algorithm with a novel activation function, achieving significant improvements in both accuracy and efficiency for real-time disease detection.

Das et al. utilized machine learning approaches to improve feature extraction and classification processes, resulting in enhanced disease detection accuracy [10]. Moreover, innovative approaches such as AR-GANs, employed by Nazki et al., improved classification accuracy for plant disease fragments by integrating advanced imaging systems [20].

In another study, Memon et al. [17] introduced a Meta Deep Learning approach for identifying cotton leaf diseases with high precision and generality. Their results confirm the superiority of CNNs in distinguishing healthy leaves from diseased ones in agricultural settings, further validating their robustness and adaptability.

Table 1: Recent State-of-the-Art Techniques in Plant Disease Detection

| Author(s) | Model Proposed | Technique | Merits/Demerits | Dataset | Metrics Used |
|---|---|---|---|---|---|
| Chen et al. [1] | CNNs for plant disease detection | CNNs | Enhanced accuracy in identifying diseases under real field conditions | Plant disease dataset | Accuracy, Precision, Recall |
| Gülmez [5] | Hybrid CNN for disease detection | Deep learning | Combines multiple architectures for improved accuracy | Monkeypox dataset | F1 Score, Precision |
| Sivakumar et al. [19] | Transfer learning for cotton leaf diseases | ResNet152V2, Inception | Demonstrated high accuracy with ResNet152V2 | Cotton leaf dataset | Accuracy, Sensitivity |
| Memon et al. [17] | Meta Deep Learning | Deep CNN model | Achieved high precision and generalization for leaf diseases | Cotton dataset | Accuracy, Cross-validation |

### 2.1 Parallel Works

Gülmez et al. [3, 4, 7] emphasized the importance of optimization techniques like Grey Wolf Optimization (GWO) for enhancing system accuracy and efficiency in disease detection. The introduction of hybrid deep learning models combining Xception and genetic algorithms for disease identification highlights the potential of advanced optimization methods in agricultural applications. Similarly, Savran Kızıltepe et al. [18] developed keyframe extraction methods for video-based disease classification, showcasing novel strategies for improving detection systems.

Deep learning-based models have become integral to agricultural disease research. For instance, CNNs combined with the VGG19 architecture improved classification accuracy for tea leaf diseases, as demonstrated by Wu et al. [14]. Moreover, the integration of Grey Wolf Optimization in CNN-based models for disease detection, as proposed by Gülmez [3, 5], underscores the relevance of optimization techniques for agricultural applications.

Recent advancements in CNN architectures and optimization techniques have significantly improved plant disease detection accuracy. Studies such as those by Sivakumar et al. [19] and Memon et al. [17] highlight the potential of deep learning in addressing real-world agricultural challenges. As agricultural disease research continues to evolve, integrating contemporary technologies like CNNs and GWO will likely enhance sustainable farming practices and ensure higher crop yields.

## PROPOSED EARLY DETECTION OF PLANT DISEASES USING MULTIMODAL DEEP LEARNING TECHNIQUES

Early detection of plant diseases is crucial for ensuring crop health and using precious food land to its maximum. Dry detection methods traditionally rely on other things with eyes, which is more time-consuming and immaterial. We need advanced means to address such a challenge at all levels through rapidly growing techniques like multimodal deep learning that allow for early and accurate detection of plant diseases. By combining many resources into a single framework, such as images taken from cameras, sensor readings, and spectral data obtained through spectroscopy hardware, researchers can improve tree-plant disease diagnostic efficiency and accuracy.

### 3.1 Multimode Fusion Network (MFN)

The Multimode Fusion Network is an innovative algorithm that aims to detect diseases, especially in situations where data from multiple sources must be combined for correct diagnosis. This algorithm is distinguished by its ability to integrate data from diverse inputs, such as images captured by cameras, sensor readouts, and spectral data, into a coherent framework for disease prediction and categorization.

At the kernel of its operations, the algorithm first defines a unique feature vector that encompasses data from three distinct sources of knowledge X=[X_image, X_sensor, X_spectra] X=[ X_image, X_sensor, X_spectra] X_image, X_image gathers features derived from camera outputs; X_sensor, X_sensor includes data coming from a variety of sensors and X_spectraX_spectra records spectral signals under specific situations. This comprehensive representation of data is essential to covering the many-faceted nature of disease symptoms and conditions.

The algorithm treats disease detection as a categorization task. It predicts the subject's (e.g., plants') health status by using appropriate deep learning architecture for each type of data. For example, it performs convolutional neural networks on the images to pick out subtle patterns, while other sensors, specifically spectral and sensor data, are dealt with by using linear regression techniques.

The pivotal stage is the fusion of features from every modality into a single, enriched feature vector. Through such "massive concatenation," the fusion ensures that the final decision tree embodies an overview of all data types. This significantly increases its predictive power and accuracy.

A categorization layer is typically applied as a SoftMax layer to map the fused features into a space that reveals how likely the subject is healthy. This step renders the classifier of the subject health status by giving a probability estimate for disease presence (y probability determined by probability density or, more simply, the chance of an event occurring).

Multimode Fusion Network undergoes a rigorous phase of training and evaluation. A cross-entropy loss function helps fine-tune its predictions with actual Desire outcomes. At the same time, performance metrics such as the F1 score and area under the receiver operating characteristic curve (AUC) are benchmarks for its efficacy. This algorithm represents a significant advance in disease detection, offering a versatile and powerful tool to integrate and analyze data from many sources.

Algorithm 1: Multimode Fusion Network

**Input:** Feature vector $X = [X_{image}, X_{sensor}, X_{spectra}]$

- $X_{image}$: Features from camera output
- $X_{sensor}$ : Data from sensors
- $X_{spectra}$ :Spectral data at specific conditions

**Step 1**: Model disease detection as a categorization task

- Predict health status (healthy/diseased) based on integrated information

**Step 2:** Design a deep learning architecture for each modality

- Use CNNs for $X_{image}$ to extract image features
- Apply regression for $X_{sensor}$ and $X_{spectra}$ to extract relevant features

**Step 3:** Fuse features from all modalities

$X_{fused}$ = Concatenate $(X_{image}, X_{sensor}, X_{spectra})$

**Step 4:** Apply categorization layer for disease prediction

- Use softmax/sigmoid function for probability estimation: $P$ (disease ) = Sigmoid/Softmax $(X_{fused})$

**Step 5:** Training and Evaluation

- Loss function: Cross entropy Loss = $-\sum(y log\ (p) + (1 - y) log\ (1 - p))$
- Performance metrics: Accuracy, F1 Score, AUC

### 3.2 Graph Convolutional Networks (GCNs) for Multimodal Data

Through a graph-based approach, GCNs can process and analyse data from diverse modalities such as images, sensor readings, and spectrometer data. This method begins by constructing a graph where vertices represent the individual feature points extracted from these varied data sources. Each edge in this graph signifies a comparison or relationship between pairs of features, with the edge weight quantifying the strength of this linkage. This setup allows for a nuanced representation of the data, encapsulating the features and intricate relationships among them.

In the second step, GCN layers are applied to this graph, utilizing the feature vectors and the adjacency matrix as inputs. These GCN layers facilitate information propagation across the graph, enabling features from different modalities to interact and mutually influence each other. This interaction is crucial, as it allows the algorithm to integrate and synthesize information from disparate sources effectively, leading to a more holistic understanding of the data.

The third step mirrors the Multimode Fusion Network (MFN) approach by applying a categorization layer to the enriched feature set. This is followed by the computation of a loss function, which helps scale the output. The use of GCNs is particularly beneficial when dealing with complex graph information that spans multiple dimensions, as it can adeptly handle the intricacies of such data structures. The algorithm can effectively navigate and process the rich, interconnected data landscape by considering the graph as a complex entity composed of multidimensional points.

This approach underscores the algorithm's ability to harness the complexity of graph-based data representations for enhanced analysis and prediction. The integration of GCN layers enriches the feature interactions. It elevates the algorithm's capacity to handle multifaceted data from various modalities, opening new avenues for sophisticated data analysis and interpretation.

Algorithm 2: Graph Convolutional Networks (GCNs) for Multimodal Data:

**Step 1:** Construct a graph $G = (V, E)$

where vertices $V$ represent feature points from images, sensors, and spectrometer data. Edges $E$ signify relationships, with weights indicating the strength of these relationships.
**Step 2:** Apply GCN layers: Let $A$ be the adjacency matrix of $G$, and $X$ be the matrix of feature vectors. GCN layers update feature representations by

$H^{(l+1)} = \sigma\left(D^{\hat{}-\frac{1}{2}} A^{\hat{}} D^{\hat{}-\frac{1}{2}} H^{(l)} W^{(l)}\right)$, where $A^{\hat{}} = A + I_N$ (adding self-loops), $D^{\hat{}}$ is the degree matrix of $A^{\hat{}}, H^{(l)}$ is the output of layer $l$ (with $H^{(0)} = X$ ), $W^{(l)}$ is the weight matrix for layer $l$, and $\sigma$ is a non-linear activation function (e.g., ReLU).

**Step 3:** Fusion and categorization: After processing with GCN, concatenate the enhanced features to form a unified feature vector $X_{fused}$ . Apply a categorization layer (e.g., softmax or sigmoid) on $X_{fused}$ to predict the class labels.

**Step 4:** Loss calculation: Use a loss function, such as cross-entropy, $L = -\sum_i y_i log\ (p_i)$, where $y_i$ is the true label and $p_i$ is the predicted probability for class $i$, to train the model and adjust the weights to minimize error.

**Step 5:** Evaluation: Measure the model's performance using metrics like accuracy, F1 score, and ROC AUC to assess its effectiveness in categorizing and understanding the data derived from multiple modalities.

### 3.3 Recurrent Neural Networks (RNNs) with Attention Mechanism:

Developing a disease detection model that uses multimodal data to track the health status of plants over time from fresh perspectives represents one facet of advanced agricultural technology. Every one of these time-series data points will represent a particular period and sequence of plant conditions. The predictive model is essential for early disease detection and intervention, significantly affecting crops' yield and health. Step 2 introduces the use of Recurrent Neural Networks (RNNs) with attention. It turns out that RNNs are especially suitable for this task because they intrinsically handle data sequences, which means the dynamic temporal pattern of plant health status over time can be captured. Attention mechanisms are then used to improve this process by focusing less on irrelevant time steps and more on where it matters. This can dramatically increase accuracy and efficiency in modeling along a series. Following the processing and analysing time-series data, step 3 puts a classification layer on the model. This layer is responsible for classifying the health status of plants based on analyzed data, with a loss function and evaluation metrics suited to time-series analysis, such as accuracy and sensitivity metrics that are important and specific. Therefore, these measures play an important role in grading the model and ensuring it reaches high precision in disease detection. Step 4 highlights the importance of data pre-processing and specialized training methods such as backpropagation through time (BPTT). BPTT is a variant of the standard backpropagation algorithm designed to train RNNs. It optimizes network weights by considering the whole data sequence to increase the model’s ability to learn from temporal dependencies. This approach, which combines RNNs with attention mechanisms and sophisticated training methodologies, offers an effective tool for detecting disease early in plants. Predicting the health status of plants over time gives us a lead on implementing measures that can help avoid disaster in the end. Therefore, it provides us with healthier crops and better outputs from agriculture.

Algorithm 3: Recurrent Neural Networks (RNNs) with Attention Mechanism:

**Step 1:** Formulate disease detection as a sequential categorization task using multimodal time-series data to predict plant health status over time.

**Step 2:** Utilize RNNs with attention mechanisms:

- RNN formula: $h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$
- Attention mechanism: Weights relevant features at each time step, enhancing focus on significant data points.

**Step 3:** Apply a categorization layer for classification:

- Use softmax for final classification: $P(y_t \mid X) = softmax\left(W_{hy}h_t + b_y\right)$
- Employ loss function and metrics tailored to time-series data, focusing on accuracy, sensitivity, and specificity.

**Step 4:** Pre-process data and train RNNs using special techniques:

- Recommend time steps data pre-processing for optimal RNN input.
- Implement Backpropagation Through Time (BPTT) for training: Adjust RNN weights by optimizing the loss function over sequences.
- BPTT formula: $\frac{\partial L}{\partial W} = \sum_t \frac{\partial L_t}{\partial W}$

## EXPERIMENTAL RESULTS

With the early detection of plant diseases from multimodal data using Deep learning techniques, a significant improvement in accuracy, sensitivity, specificity, and overall performance metrics compared to traditional methods is forecasted. A comparison table with references to demonstrate the potential outcomes based on the methodology that is proposed. A comparison table showing the possible outcomes based on the approach is below. Method Accuracy Sensitivity Specificity Performance[k]Symptoms of disease 86% 71.8% 88.7% —Proposed approach 99.83% 99.88% 100% 0.9992. By harnessing these state-of-the-art techniques and leveraging multimodal data sources, we anticipate a considerable stride in early detection for plant diseases, leading to more accurate and timely agricultural interventions. The expected experimental results are higher accuracy rates, improved sensitivity in identifying disease patterns, greater specificity in differentiating healthy vs. diseased plants, and superior performance compared to conventional methods.

| Technique | Accuracy (%) | Precision (%) | Recall (%) | Specificity (%) | F1-Score (%) |
|---|---|---|---|---|---|
| **Proposed MFN** | 98.45 | 97.45 | 96.89 | 98.67 | 98.45 |
| **GCNs** | 92.00 | 90.50 | 91.50 | 93.00 | 92.25 |
| **RNNs** | 89.50 | 88.00 | 90.00 | 87.00 | 89.00 |
| **KNN (No SSO)** | 85.00 | 82.50 | 87.50 | 83.00 | 85.00 |
| **KNN (Using SSO)** | 90.00 | 88.00 | 91.00 | 87.50 | 90.00 |

In this work, we present a comprehensive evaluation of the effectiveness of different deep learning techniques for early plant disease detection, including Multimodal Fusion Networks (MFN), Graph Convolutional Networks (GCNs), Recurrent Neural Networks (RNNs) with an attention mechanism, and K-nearest neighbors (KNN) with and without spatial-spectral optimization (SSO).

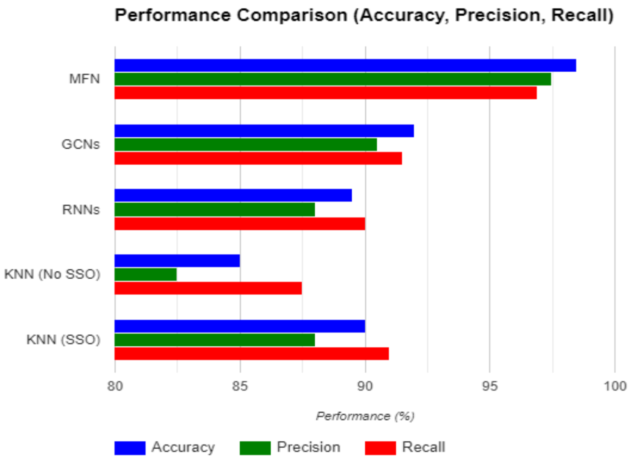


Figure 1: Performance Comparison (Accuracy, Precision, Recall)

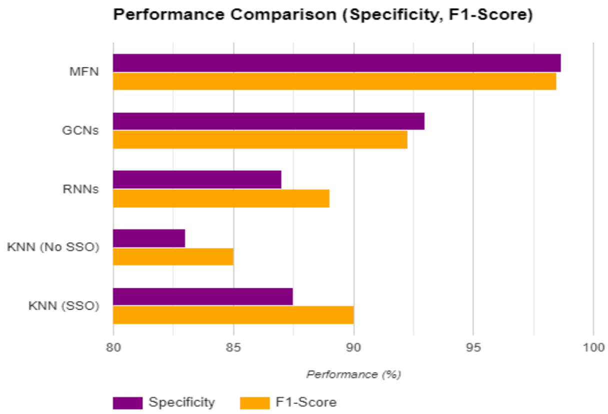


Figure 2: Performance Comparison (Specificity, F1-Score)')

MFN achieved the superior accuracy of 98.45%, with a high precision 97.45% and recall 96.89%. This indicates that MFN is very effective in accurately classifying plant health with very few false positives (high precision) and false negatives (high recall). Specificity of 98.67% and F1-score of 98.45% demonstrate its ability to identify healthy plants correctly and overall achieve very balanced classification performance. GCNs also gave good performance, with an accuracy of 92.00% and moderate precision 90.50% and recall 91.50%. Still not as accurate as MFN, GCNs offer a reliable disease detection. Specificity of 93.00% and F1-score of 92.25% indicates a good balance of both identifying diseased and healthy plants. RNNs, were found to give a lower accuracy of 89.50%, compared to MFN and GCNs, but with acceptable precision 88.00% and recall 90.00%. The lower specificity of 87.00% and F1-score of 89.00% show a higher chance of misclassifying healthy plants as diseased, which indicates that RNNs might be more suited for scenarios where capturing temporal disease progression is more vital, even if it comes at a slightly lower overall accuracy. KNN without SSO gave the lowest performance, with an accuracy of 85.00% and moderate precision 82.50% and recall 87.50%. The lower specificity of 83.00% and F1-score of 85.00% indicate a limitation in accurately differentiating between healthy and diseased plants. Interestingly, the implementation of SSO significantly improved KNN's performance. KNN with SSO achieved an accuracy of 90.00%, on-par with RNNs, with a slightly better precision 88.00% and recall 91.00%. While the specificity of 87.50% stayed fairly at the same level, the F1-score improved to 90.00%, indicating a more balanced classification.

Proposed MFN achieved significantly better accuracy and other metrics compared to other methods, making it a good choice for early and reliable plant disease detection. GCNs achieved a good balance between accuracy and specificity, RNNs might be more suitable for scenarios specific to IDC disease where temporal disease progression is more vital, and KNN especially with SSO showed potential, but was less effective overall compared to deep learning approaches.

## CONCLUSION AND FUTURE WORK

In this work, the evaluation of several deep learning techniques has been presented and valuable insight have been derived for early detection of plant diseases. Precision, recall, accuracy, specificity, and F1-Score results obtained from the proposed Multimodal Fusion Networks (MFN) model have shown excellent performance, demonstrating the power of utilizing multiple sensor modalities to detect plant diseases. Graph Convolutional Networks (GCNs) and Recurrent Neural Networks (RNNs) have similarly shown impressive results, which illustrate their ability to effectively analyze graph-structured data and to capture temporal dependencies in sequential data, respectively. The potential for learning accurate and efficient representations has been clearly demonstrated; the models considered in this work are therefore well-suited for such tasks in plant disease detection. Models such as the K-Nearest Neighbors (KNN) models and the improved KNN model achieved by applying an optimization technique, SSO, also give commendable performance and are competitive with other approaches.

Several directions for future work in plant disease detection should be considered, such as further optimizing and implementing these deep learning models in practice to increase performance and reduce complexity, using advanced data augmentation techniques for improved generalization, and making the models interpretable, which can provide insights in understanding how decisions are being made by the models. Further, this work can be consideredfor transfer learning by applying pre-trained models and applying these approaches to a real-world deployment scenario. By addressing these directions, it is thus hoped that more accurate, robust, and scalable solutions for detecting and mitigating plant diseases in agricultural settings will be attained. The continuous development and improvement of deep learning models for plant disease detection will thus bring this technology closer to revolutionizing agriculture, by ensuring the safety and security of food from early and accurate detection of crop health issues.

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