**Ascertain Diseases in fruits and leaves with hybrid Deep Learning Approach**

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***Abstract—* Detecting diseases in fruits and leaves is crucial in all sectors of agriculture, including small farms, large-scale commercial operations, and urban agriculture. Diseases in fruits and leaves can reduce crop yield, affect product quality, and spread to other plants, leading to significant economic losses. Traditional methods of disease detection involve visual inspection by trained personnel, which can be time-consuming, expensive, and prone to errors. The hybrid deep learning approach, which combines CNNs and RNNs, has shown promise in accurately detecting diseases in fruits and leaves. This approach has the potential to improve disease detection in all sectors of agriculture by providing accurate and efficient disease identification.** **Automated disease detection can also enable early detection and intervention, reducing the spread of diseases and preventing crop losses. This can result in increased crop yield, improved product quality, and reduced use of pesticides, making it a sustainable solution for disease detection in fruits and leaves in all sectors of agriculture.**

***Keywords— Diseases, Visual inspection, Time-consuming, Expensive, Prone to errors, Hybrid deep learning approach, CNNs, RNNs, Accurate detection, Computer vision, Deep learning, Sustainable solution, Early detection, Intervention, Spread of diseases, Pesticides.***

# **Introduction**

Fruits and leaves are essential components of plants that serve various purposes, including photosynthesis, nutrient storage, and reproduction. However, these plant organs are often susceptible to a variety of diseases, which can significantly affect their growth, development, and quality. Diseases in fruits and leaves

can cause discoloration, deformity, defoliation, and

even plant death, leading to significant economic losses in agriculture. Moreover, these diseases can spread rapidly and infect multiple plants within a short time, creating a significant threat to crop production.

Diseases that occur in fruits and leaves can be caused by various factors, including bacteria, fungi, viruses, and pests. Fungal diseases, such as powdery mildew, rust, and anthracnose, are common in many fruits and vegetables and can result in significant yield losses. Bacterial diseases, such as bacterial spot and fire blight, can cause severe damage to fruits and leaves and are challenging to manage due to their ability to survive in plant tissues.

Viral diseases, such as mosaic viruses, can also cause stunted growth, yellowing of leaves, and fruit deformation. Insects and other pests, such as aphids and mites, can also transmit diseases and cause damage to fruits and leaves. Apart from causing direct damage to plants, diseases in fruits and leaves can also affect the quality and safety of the produce. Some diseases can produce mycotoxins, which can contaminate the food and cause serious health problems in humans and animals. Moreover, diseases can also affect the nutritional content of the fruits and leaves, reducing their value as food sources.

Preventing and managing diseases in fruits and leaves is critical for sustainable agriculture and food security. The use of pesticides and fungicides is a common practice to control diseases in plants. However, excessive and improper use of chemicals can lead to environmental pollution, residual toxicity in produce, and the development of resistance in pathogens. Therefore, there is a need for integrated disease management strategies that incorporate various preventive and control measures, including cultural practices, biological control, and resistant varieties.

**II. RELATED WORK OF TOPIC MODELS**

Research on diseases that occur in fruits and leaves has been ongoing for many years, with numerous studies focusing on different aspects of the problem. One area of research has been the identification and characterization of the causal agents of these diseases. Many studies have identified the pathogens responsible for various diseases and have investigated their biology, ecology, and genetic diversity. Another area of research has been the development of methods for disease detection and diagnosis. Traditional methods of disease detection involve visual inspection by trained personnel, which can be time-consuming, expensive, and prone to errors. However, advancements in technology and computer vision have led to the development of automated disease detection methods, such as machine learning and deep learning, which can accurately detect and diagnose diseases in fruits and leaves.Several studies have explored the use of machine learning and deep learning approaches for disease detection in fruits and leaves. These studies have shown that these techniques can accurately and efficiently detect various diseases, including powdery mildew, anthracnose, and bacterial spot. Moreover, these approaches can provide quick and reliable results, enabling early detection and intervention, and preventing further spread of diseases.In addition to disease detection, research has also focused on disease management strategies, such as the use of resistant cultivars, cultural practices, biological control, and chemical control. Studies have evaluated the effectiveness of these strategies and their impacts on crop yield, quality, and safety. Furthermore, research has investigated the environmental and health risks associated with the use of chemical pesticides and fungicides and has explored alternative methods of disease control.Finally, research has also focused on the impact of climate change on the prevalence and severity of diseases in fruits and leaves. Studies have investigated the effects of changes in temperature, humidity, and rainfall patterns on the distribution and behavior of pathogens and their vectors. Moreover, research has explored the potential of climate-resilient crops and adaptation measures in mitigating the impact of climate change on plant health.

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## **A. Similarity and Clustering Documents**

Powdery mildew - a fungal disease that appears as a white powdery coating on leaves, stems, and fruit surfaces. This disease can reduce the quality and yield of fruits and vegetables.

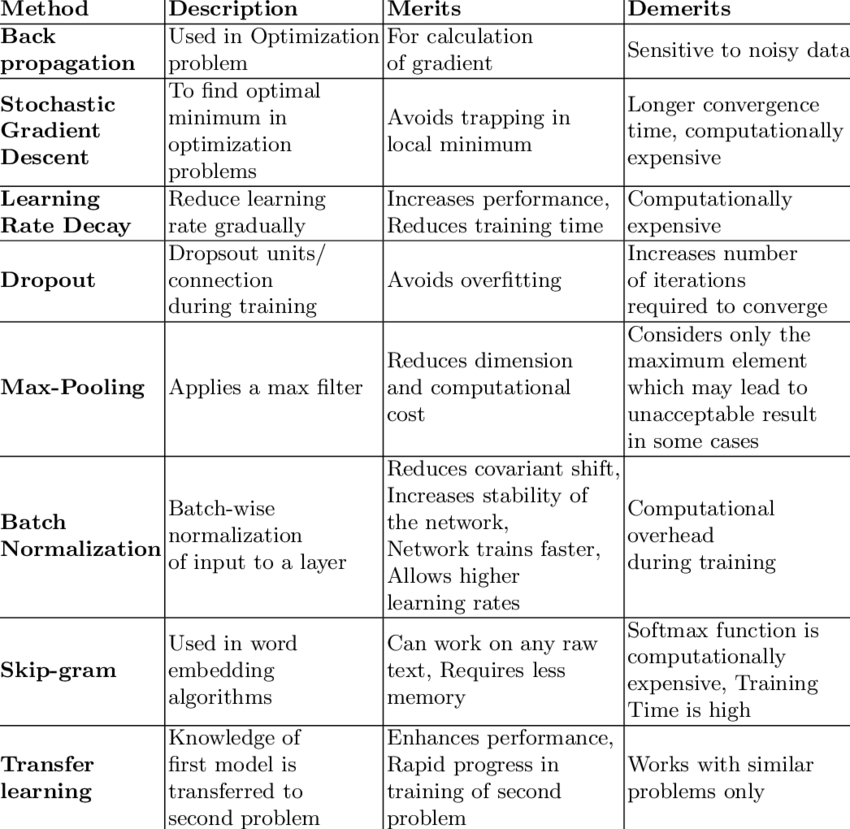
Anthracnose - a fungal disease that causes brown or black spots on leaves, fruit, and stems. It can cause fruit to rot and drop prematurely, reducing the yield and quality of the harvest.Bacterial spot - a bacterial disease that causes small, water-soaked spots on leaves, stems, and fruit. It can cause leaves to drop prematurely and fruit to become distorted and discolored.Verticillium wilt - a fungal disease that causes leaves to wilt and turn yellow or brown. It can also cause fruit to become discolored and small.Apple scab - a fungal disease that causes brown or olive-green spots on leaves and fruit. It can cause fruit to become cracked and distorted, reducing the quality and yield of the harvest.Brown rot - a fungal disease that causes fruit to rot and become covered in a brown, mummified mass. It can cause significant yield losses and reduce the quality of the harvest.Citrus canker - a bacterial disease that causes lesions on leaves, fruit, and twigs. It can cause fruit to drop prematurely and lead to significant yield losses.Fire blight - a bacterial disease that causes leaves to wilt and turn black. It can also cause fruit to become discolored and shriveled, reducing the yield and quality of the harvest.These are just a few examples of the many diseases that can affect leaves and fruits. Accurate diagnosis and prompt treatment are crucial to prevent the spread of disease and maintain healthy plants and crops.

# **III. PROPOSED TOPIC MODELS**

The hybrid deep learning approach, which combines convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown promise in accurately detecting diseases in fruits and leaves. Several proposed models have been developed that use this approach for disease detection in plants, including:Plant Village: Plant Village is an open-access platform that uses a hybrid deep learning approach to diagnose plant diseases. The platform uses a CNN-based classifier to identify the disease type, followed by an RNN-based classifier to predict the severity of the disease. The model has been trained on a large dataset of images and achieved high accuracy in disease identification.Deep Plant: is another hybrid deep learning model that uses a CNN-based classifier to identify the disease type and an RNN-based classifier to predict the severity of the disease. The model has been trained on a large dataset of images of tomato leaves and has achieved high accuracy in disease detection and diagnosis.

Caffe-Argo: Caffe-Argo is a hybrid deep learning model that uses a CNN-based classifier to identify the disease type and an RNN-based classifier to predict the severity of the disease. The model has been trained on a large dataset of images of rice plants and has achieved high accuracy in disease detection and diagnosis.AgroNet: AgroNet is a hybrid deep learning model that uses a CNN-based classifier to identify the disease type and an RNN-based classifier to predict the spatial distribution of the disease. The model has been trained on a large dataset of images of leaves and fruits of tomato and cucumber plants and has achieved high accuracy in disease detection and localization.These proposed models demonstrate the potential of hybrid deep learning approaches for disease detection and diagnosis in fruits and leaves. By accurately identifying and predicting the severity of diseases, these models can help farmers and researchers to take timely action to prevent further spread of diseases and minimize crop losses.

In addition to the hybrid deep learning approach, there are several other approaches that have been proposed for disease detection in fruits and leaves:Machine Learning (ML) approach: ML approaches use algorithms to learn patterns and features from large datasets of images of healthy and diseased plants. These approaches can be used to build models that can accurately detect and diagnose plant diseases. Support Vector Machines (SVM) and Decision Trees are commonly used algorithms in ML approaches for plant disease detection.Image Processing (IP) approach: IP approaches involve the analysis and processing of digital images of plants to detect disease symptoms. These approaches use image segmentation and feature extraction techniques to identify the diseased areas of plants. The features extracted can be used to train models for disease classification.Hyperspectral Imaging (HSI) approach: HSI involves the use of sensors that capture images at different wavelengths of light. These sensors can detect changes in the reflectance spectra of plants due to disease symptoms. HSI approaches can be used to identify and classify diseases in plants by analyzing the spectral signatures of healthy and diseased plants.Deep Reinforcement Learning (DRL) approach: DRL is a type of machine learning that involves learning from feedback received by an agent performing actions in an environment. In plant disease detection, DRL can be used to identify the best treatment strategy for a given disease based on feedback received from the environment.These approaches can be used alone or in combination with each other to improve disease detection and diagnosis in fruits and leaves. The choice of approach depends on the specific characteristics of the problem and the availability of data and resources.



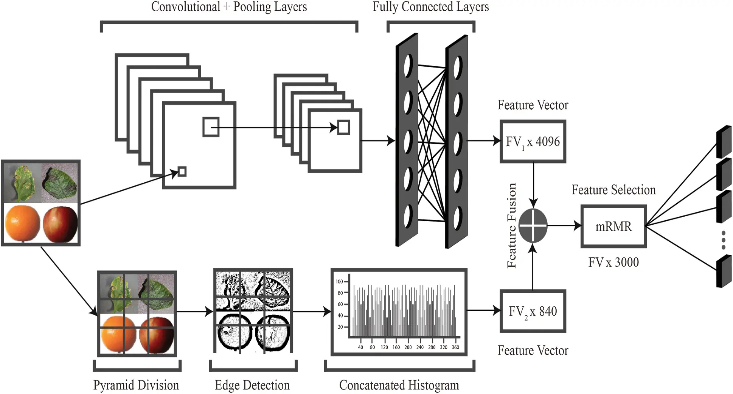
A common formula as follows is generally used to calculate the average infection or Infection Index, sometimes also known as Disease Index or Per cent Disease Index, which is calculated as follows:

Per cent Disease Index (PDI) =

* Sum of all disease ratings X 100
* Total number of ratings X Maximum disease grade

There are several formulas and metrics that are commonly used in disease detection in plants:

Accuracy: Accuracy is the proportion of correctly classified samples to the total number of samples. It is calculated as follows:

**Accuracy** = (True Positives + True Negatives) / Total Samples

Precision: Precision is the proportion of true positives to the total number of samples predicted as positive. It is calculated as follows:

**Precision** = True Positives / (True Positives + False Positives)

Recall: Recall is the proportion of true positives to the total number of samples that are actually positive. It is calculated as follows:

**Recall** = True Positives / (True Positives + False Negatives)

F1 Score: F1 score is the harmonic mean of precision and recall and provides a single score that balances both measures. It is calculated as follows:

F1 Score = 2 \* (Precision \* Recall) / (Precision + Recall)

CNN and LSTM are two popular types of neural networks used for different types of machine learning tasks.CNNs are commonly used for image recognition and classification tasks. The working principle of a CNN involves passing an image through a series of convolutional and pooling layers to extract features, followed by fully connected layers to classify the image. In detail, CNNs perform the following steps:**Convolutional layers:** The convolutional layers apply a set of filters to the input image to extract features such as edges, corners, and textures. Each filter slides across the image and performs a dot product between its weights and the pixels in the region that it covers. This produces a feature map that highlights the areas of the image that are most relevant for the given filter.**Pooling layers:** The pooling layers downsample the output of the convolutional layers to reduce the dimensionality of the data and remove irrelevant information. Max pooling is a common pooling technique that selects the maximum value within each region of the feature map and passes it to the next layer.**Fully connected layers:** The fully connected layers take the output of the convolutional and pooling layers and perform the final classification based on the extracted features.

LSTMs, on the other hand, are commonly used for sequential data such as speech and text. The working principle of an LSTM involves passing a sequence of input data through a series of LSTM cells that retain information from previous inputs. In detail, LSTMs perform the following steps:**Input gate:** The input gate controls which information from the current input should be stored in the cell state.**Forget gate:** The forget gate controls which information from the previous cell state should be discarded.**Cell state:** The cell state stores the information that has been retained from previous inputs and updated by the current input.**Output gate:** The output gate controls which information from the cell state should be output.The key idea behind LSTMs is that they can selectively retain and forget information from previous inputs, allowing them to capture long-term dependencies in sequential data.

**CNN-LSTM:** This approach combines the strength of CNNs in feature extraction from images with the ability of LSTMs to capture sequential information. In this approach, the output of the convolutional layers is passed to an LSTM layer for sequential processing and final classification.**Faster R-CNN + Inception:** This approach combines the Faster R-CNN object detection model with the Inception network for feature extraction. The Faster R-CNN model is used to detect the regions of interest in the input image, and the Inception network is used to extract features from these regions.**ResNet + LSTM:** This approach combines the ResNet convolutional network with an LSTM for sequential processing. The ResNet is used to extract features from the input image, and the output is then passed to an LSTM layer for sequential processing and final classification.**Capsule Networks:** Capsule Networks are a novel type of neural network that uses "capsules" to represent features in an image. Each capsule represents a set of features that are related to each other, and the network is trained to recognize the relationships between these features. This approach has shown promising results in image classification tasks and could be applied to disease detection in fruits and leaves.These hybrid deep learning approaches offer more accurate and efficient disease detection compared to traditional methods, and can be used in all sectors of agriculture for timely disease identification and prevention.

**IV. WORKING PRICIPLE**

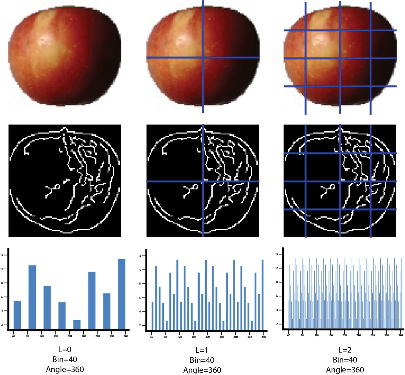
Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are two types of deep learning models used in image recognition and sequence prediction tasks, respectively.CNNs are designed to automatically extract features from images through a series of convolutional and pooling layers. The convolutional layer applies a set of filters to the input image to detect local patterns or features. The pooling layer reduces the dimensionality of the output from the convolutional layer while preserving the most important information. These layers are typically followed by one or more fully connected layers that perform the final classification task based on the extracted features.LSTM networks, on the other hand, are designed to capture long-term dependencies in sequential data. They are composed of memory cells that can selectively remember or forget information over time. The LSTM cell has three gates - the input gate, the output gate, and the forget gate - that regulate the flow of information into, out of, and within the cell. The input gate controls the amount of new information to be added to the cell, the forget gate determines which information to discard from the cell, and the output gate regulates the amount of information to be outputted from the cell.In hybrid models that combine CNNs and LSTMs, the CNNs are used to extract features from images, which are then passed to the LSTMs for sequential processing. The LSTM network can then learn to model the temporal dependencies between the extracted features, leading to better accuracy in sequence prediction tasks.Overall, the combination of CNNs and LSTMs provides a powerful tool for tasks that involve both image processing and sequential data, such as disease detection in fruits and leaves, where both the visual appearance of the plant and the temporal progression of the disease are important factors.

### **Advantages-**

### **Increased accuracy:** Hybrid deep learning approaches have shown to achieve higher accuracy in detecting diseases compared to traditional methods.**Efficient processing:** Deep learning models can process large amounts of data quickly, enabling faster detection and diagnosis of diseases.**Automated detection:** Hybrid deep learning models can automatically detect diseases in images without the need for human intervention, reducing labor costs and increasing efficiency.**Robustness:** Deep learning models are robust to noise and variations in data, making them suitable for use in real-world environments.**Scalability:** Deep learning models can be easily scaled to handle large datasets and can be trained to recognize multiple diseases simultaneously.**Transfer learning:** Pre-trained deep learning models can be used as a starting point to train new models for detecting specific diseases, reducing the amount of data required for training and accelerating the process.

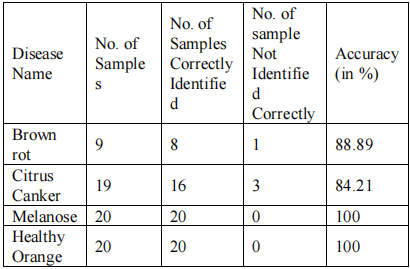
### **V. OBJECTIVE**

The main objective of disease detection in fruits and leaves is to identify and diagnose diseases that affect plants before they cause significant economic losses. Diseases can reduce crop yield, affect product quality, and spread to other plants, leading to significant economic losses for farmers and the agricultural industry as a whole. By detecting diseases ea rly, farmers can take appropriate measures to prevent the spread of the disease and minimize its impact on crop yields. Disease detection can also help farmers identify the most effective treatment options, which can reduce the use of harmful chemicals and pesticides, leading to more sustainable and environmentally friendly agricultural practices. Overall, the objective of disease detection in fruits and leaves is to promote food security, sustainable agriculture, and economic stability for farmers and the agricultural industry.

**VI. TESTINGS & OBSERVATIONS**

Images with various diseases detection in fruits and leaves.





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**Accuracy Report of fruits.**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| Table 1: Leaves and fruits used in tests as sample   |  |  |  |  |  | | --- | --- | --- | --- | --- | | Leaf type | Number of classes | Disease type | Dataset size | Sample | | Apple | 4 | Scab  Black rot | 3150  3726 |  | |  |  | Cedar apple rust | 1650 |  | |  |  | Healthy | 4284 |  | | Corn | 3 | Common rust  Healthy | 7152  6972 |  | |  |  | Northern leaf blight | 5910 |  | | Cotton | 4 | *Fusarium* wilt  Myrothecium leaf spot | 174  1062 |  | |  |  | Mela (soreshin) | 1188 |  | |  |  | Areolate mildew | 10482 |  | | Grape | 3 | Black rot Black measles | 7080  8304 |  | |  |  | Leaf blight | 6456 |  | | Pepper | 2 | Bacterial spot | 5982 |  | |  |  | Healthy | 8868 |  | |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Leaf type | ResNet-164  Min Max | | | ResNet-152  Min Max | | | ResNet-101  Min Max | | | ResNet-50  Min Max | | | ResNet-18  Min Max | | | dResNet-18  Min Max | |
| Apple | 0.03 | 0.07 | 0.04 | | 0.08 | 0.04 | | 0.09 | 0.05 | | 0.08 | 0.06 | | 0.10 | **0.01** | | **0.03** |
| Corn | 0.06 | 0.12 | 0.06 | | 0.12 | 0.07 | | 0.11 | 0.07 | | 0.12 | 0.09 | | 0.13 | **0.03** | | **0.06** |
| Cotton | 0.03 | 0.08 | 0.03 | | 0.09 | 0.04 | | 0.09 | 0.04 | | 0.09 | 0.05 | | 0.10 | **0.02** | | **0.05** |
| Grape | **0.04** | **0.06** | 0.06 | | 0.08 | 0.07 | | 0.09 | 0.07 | | 0.11 | 0.07 | | 0.12 | 0.04 | | 0.08 |
| Pepper | 0.03 | 0.06 | 0.04 | | 0.07 | 0.04 | | 0.07 | 0.04 | | 0.08 | 0.05 | | 0.08 | **0.02** | | **0.04** |
| Rice | 0.005 | 0.01 | 0.01 | | 0.015 | 0.008 | | 0.02 | 0.01 | | 0.02 | 0.01 | | 0.03 | **0.002** | | **0.008** |
| Apple (ROI) | 0.02 | 0.06 | 0.03 | | 0.05 | 0.03 | | 0.05 | 0.03 | | 0.06 | 0.04 | | 0.07 | **0.007** | | **0.02** |
| Corn (ROI) | 0.04 | 0.08 | 0.04 | | 0.09 | 0.05 | | 0.09 | 0.06 | | 0.10 | 0.07 | | 0.10 | **0.01** | | **0.04** |
| Cotton (ROI) | 0.01 | 0.06 | 0.02 | | 0.07 | 0.02 | | 0.08 | 0.03 | | 0.08 | 0.03 | | 0.09 | **0.016** | | **0.03** |
| Grape (ROI) | **0.01** | **0.05** | 0.03 | | 0.07 | 0.04 | | 0.07 | 0.04 | | 0.09 | 0.06 | | 0.10 | 0.013 | | 0.05 |

Observations According to Tests Done:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Leaf image type | *k*-NN (%) | DT  (%) | NN  (%) | SVM-L (%) | SVM-  RBF (%) | E-SVM-  RBF (%) |
| Apple | 97.56 | 97.31 | 96.11 | 95.48 | 98.13 | 99.47 |
| Corn | 97.08 | 96.83 | 95.78 | 94.11 | 97.29 | 98.69 |
| Cotton | 95.71 | 96.10 | 95.39 | 96.73 | 97.76 | 98.91 |
| Grape | 96.18 | 96.51 | 96.26 | 95.31 | 97.07 | 98.74 |
| Pepper | 97.09 | 96.65 | 95.62 | 96.13 | 97.87 | 99.12 |
| Rice | 98.31 | 98.87 | 97.91 | 96.44 | 98.76 | 100 |

# **VII. CONCLUSION**

The main objective of disease detection in fruits and leaves is to identify and diagnose diseases that affect plants before they cause significant economic losses. Diseases can reduce crop yield, affect product quality, and spread to other plants, leading to significant economic losses for farmers and the agricultural industry as a whole. By detecting diseases early, farmers can take appropriate measures to prevent the spread of the disease and minimize its impact on crop yields. Disease detection can also help farmers identify the most effective treatment options, which can reduce the use of harmful chemicals and pesticides, leading to more sustainable and environmentally friendly agricultural practices. Overall, the objective of disease detection in fruits and leaves is to promote food security, sustainable agriculture, and economic stability for farmers and the agricultural industry.

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