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Leaf by Leaf: AI-Powered Plant Disease Prediction

Graduate Name: Group 3

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Concept note and Implementation Plan

Background

"*According to the Food and Agriculture Organization of the United Nations (FAO) the global economy loses over $220 billion annually to plant diseases, yet the first crucial warnings are often hidden on the crops' own leaves.*"

The Silent Threat

Diseases are a major challenge to global food security & the livelihood of farmers.

Economic Impact

Global economy loss every year to plant diseases.

Traditional Methods

Manual inspection is time-consuming, prone to human error

Objectives

Primary Goal

To develop an accurate and efficient AI model that can automatically detect plant diseases from images of leaves.

Transforming Detection

We aimed to leverage machine learning to provide an automated, image-based solution to a long-standing agricultural problem.

User-Focused Solution

Our objective was to create a user-friendly interface where anyone, from farmers to researchers without needing to write or run code.

SDG Relation

Our project directly supports the UN's Sustainable Development Goals (SDGs):

SDG 2 (Zero Hunger):

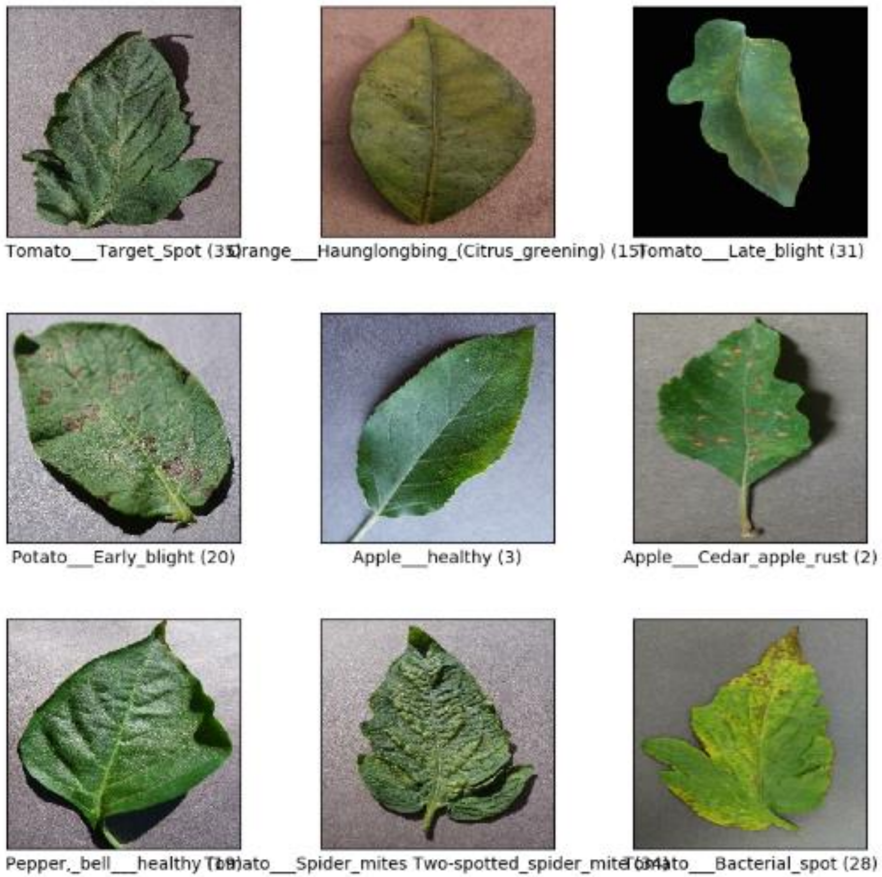
By enabling earlier disease detection we're helping protect crop yields, reduce losses, and boost overall food production efficiency.

SDG 12 (Responsible Consumption and Production)

Minimizing crop loss through timely intervention contributes to reducing food waste at the production stage.

Data

Data Collection



Data Source

We utilized the **PlantVillage** dataset, a public and well-regarded collection of plant imagery.

Dataset Size

Our subset contains approximately **87,000 JPEG/PNG** images of both healthy and diseased plant leaves.

Target Variable

The images are categorized into 38 distinct classes, which represent our target variable for classification. This includes various plants and their health statuses *(e.g., "Tomato_healthy", "Potato_Early_blight")*.

Train/Test Split

The dataset was pre-organized into training and validation sets. This split is crucial to train the model and then test its performance on unseen data, ensuring it can generalize well and isn't just "memorizing" the training images.

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Exploratory Data Analysis and Feature Engineering

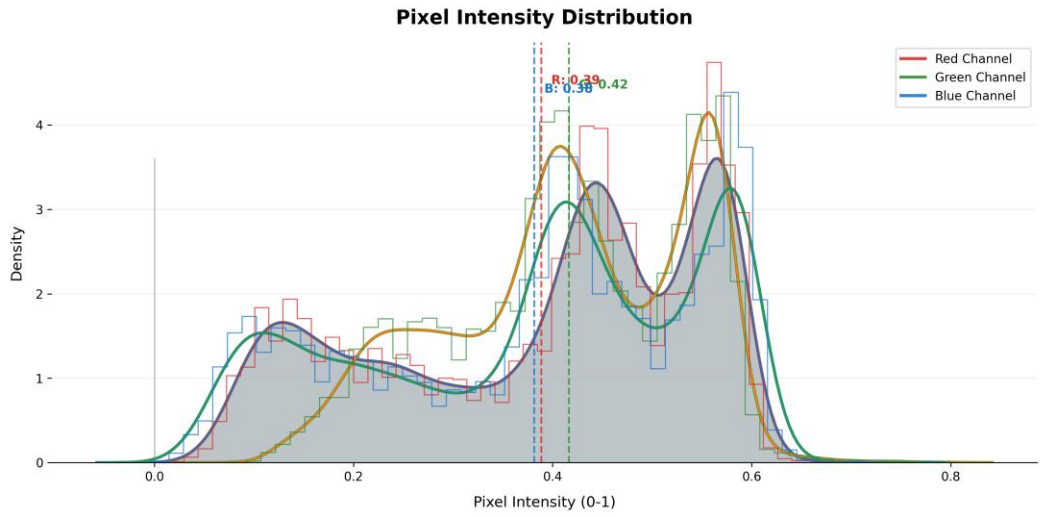
We have delved deep in to our data to understand and analyze the images and prepare them for our mode, some of which steps you can see below, but for more detail please visit the link to our repository.[Link]

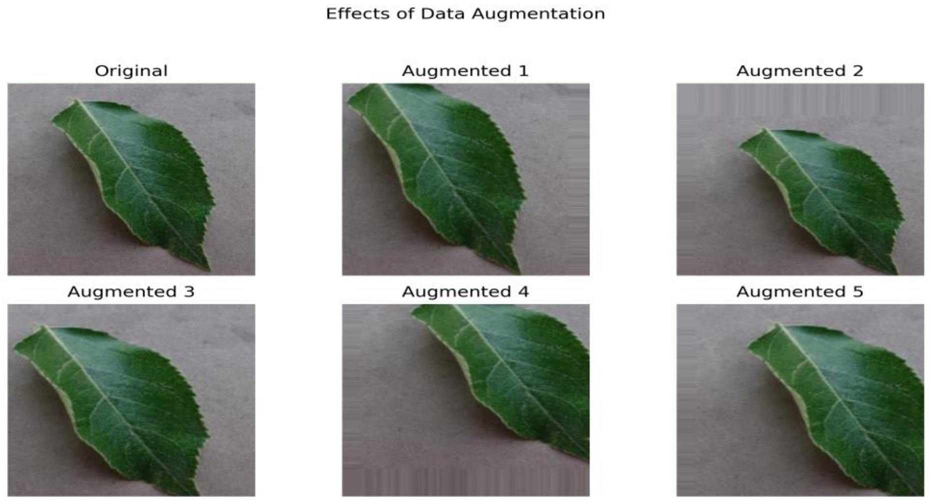
Image Processing

All images were standardized to a 224x224 pixel format for model compatibility. Pixel values were normalized from a 0–255 scale to a 0–1 scale, which helps the model train more efficiently.

Data Augmentation

To build a robust model, we artificially expanded our dataset by applying random transformations like zooming, shearing, and shifting to the training images. This helps the model learn to identify diseases under various conditions and prevents overfitting.





Model

Model Selection and Training

Model Choice:

Used **CNN** – standard for image classification due to strong pattern recognition.

Why MobileNet?

Chosen for its **balance of accuracy and efficiency**, ideal for mobile deployment.

Transfer Learning

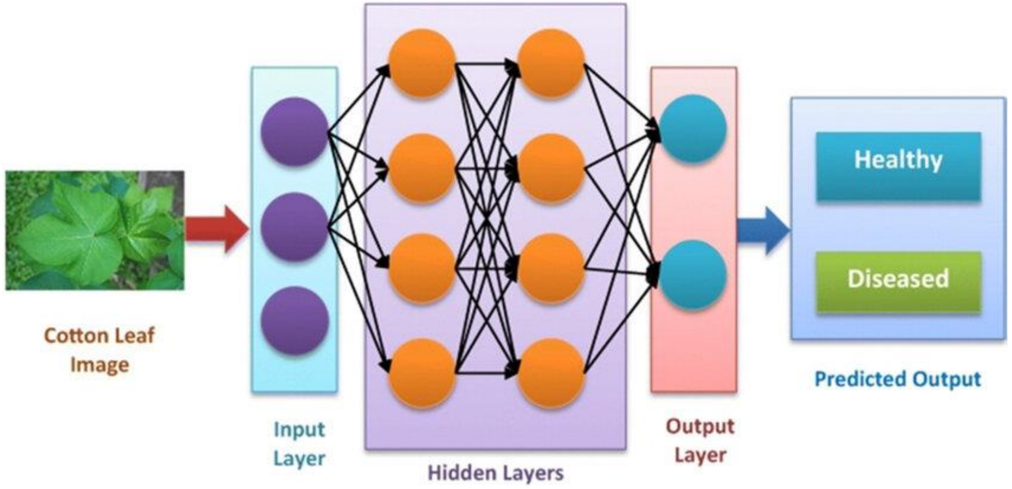
Initialized with **ImageNet pre-trained weights** to leverage learned features.

Customization

Replaced final layers with a **custom head for 38 disease classes**, using **softmax** for multi-class output.

Training Setup

Trained for **10 epochs** with **Adam optimizer** and **Categorical Crossentropy loss**.



A neural network is a type of machine learning model designed to mimic how the human brain learns. It's made up of layers of connected units called neurons that process data and learn patterns.

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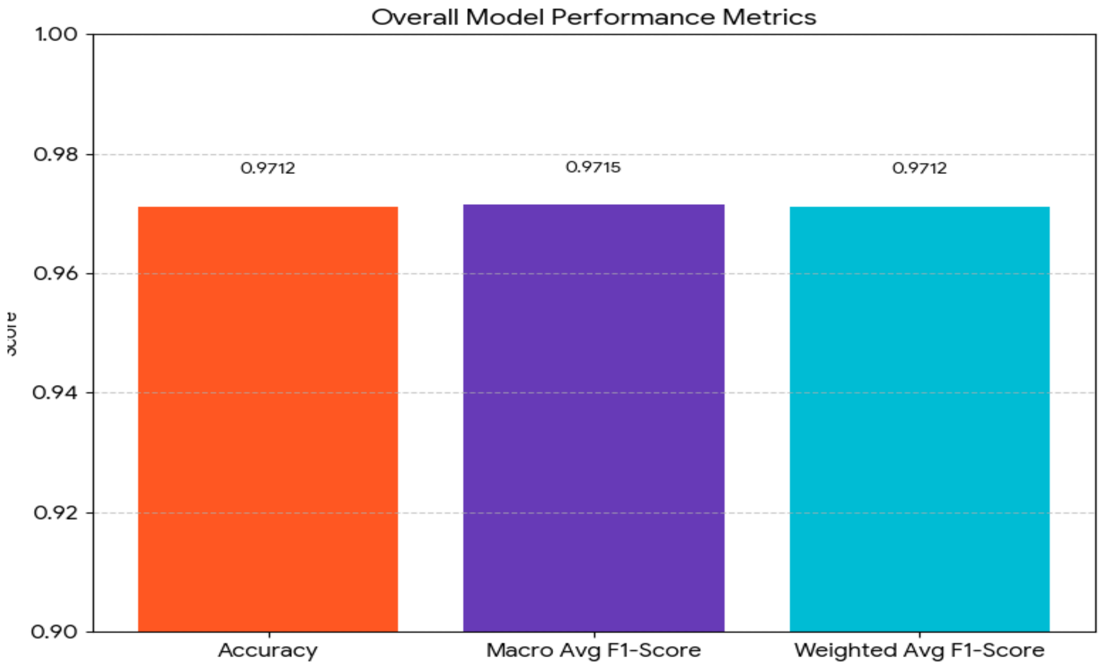
Model Evaluation and Hyperparameter Tuning



- **Accuracy**: 97.12%
- **Weighted Avg F1 Score**: 97.15%
- **Macro Avg F1 Score**: 97.12

Hyperparameters:

- **Optimizer**: We used the Adam optimizer with its default parameters for efficient learning.
- **Epochs**: The model was trained using different **10, 20, 30 & 40** epochs and found that 10 .
- **Regularization**: To prevent overfitting, we included a Dropout layer that randomly deactivates **10%** & **20%** of neurons during training.

Evaluation Metrics:

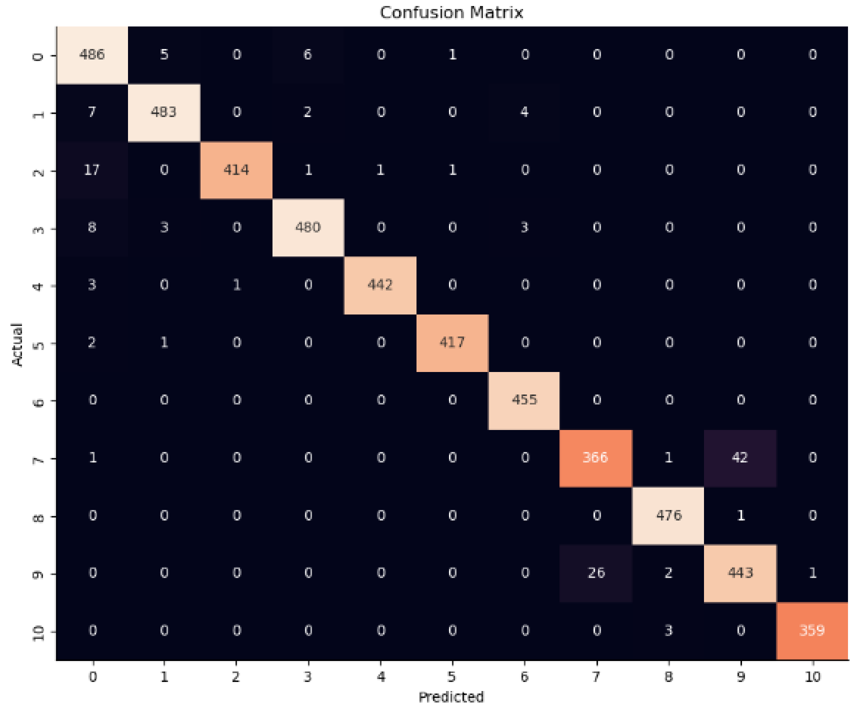
- **Accuracy**: We used CategoricalAccuracy to measure the percentage of correctly identified images.
- **Loss**: *CategoricalCrossentropy* was used to quantify the model's error during training, aiming to minimize this value.

Model Refinement and Testing

Confusion Matrix

This matrix gives us a good understanding of the model's performance on the **test data**. The strong diagonal line shows a high number of correct predictions for each class.

For instance*, out of hundreds of images for a class, the vast majority are correctly identified, with very few errors.*



Testing & Hyperparameter Tuning

The model was trained with an **Adam optimizer**, a dropout rate of 0.2 for regularization, and ran for 10 epochs. These parameters were chosen to balance learning speed and performance.

Results

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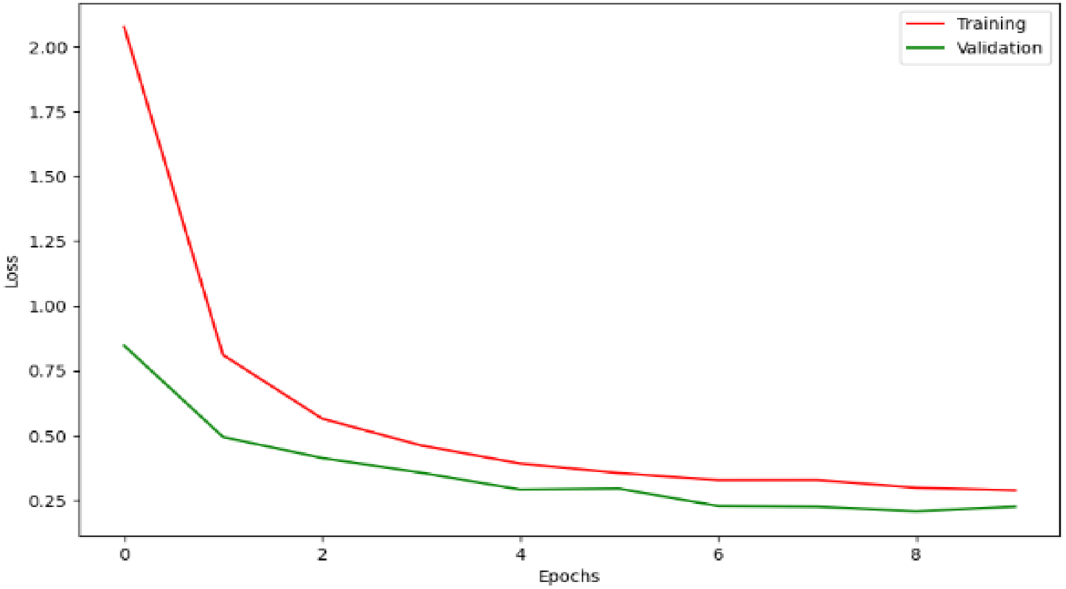
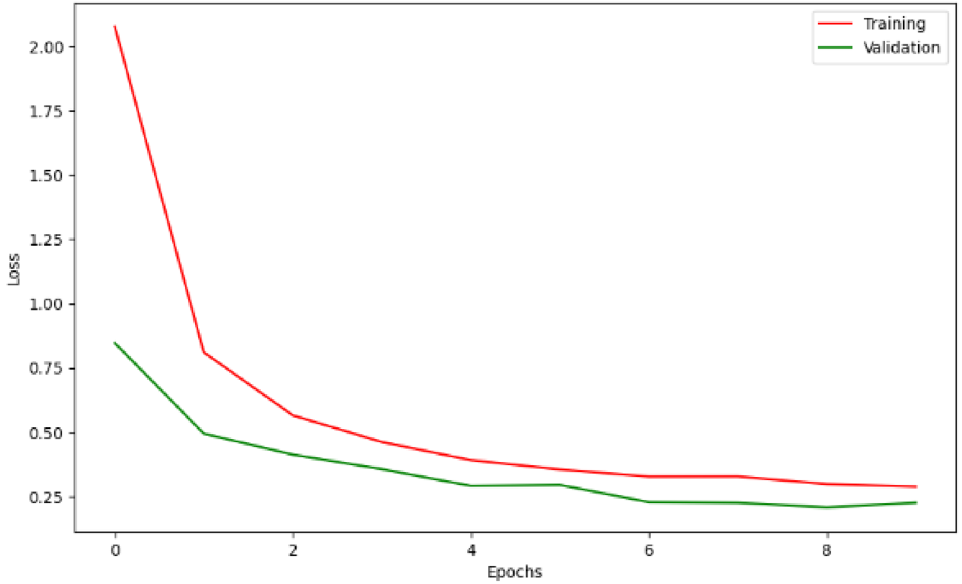
Evaluation Results

Training & Validation Accuracy

Both accuracy curves increase steadily and converge at approximately 90–93%. Their close alignment indicates that the model is not overfitting and performs reliably





Training & Validation Loss:

The loss, or error, for both sets decreased consistently and stabilized, showing the model learned effectively and reached a point of good convergence.

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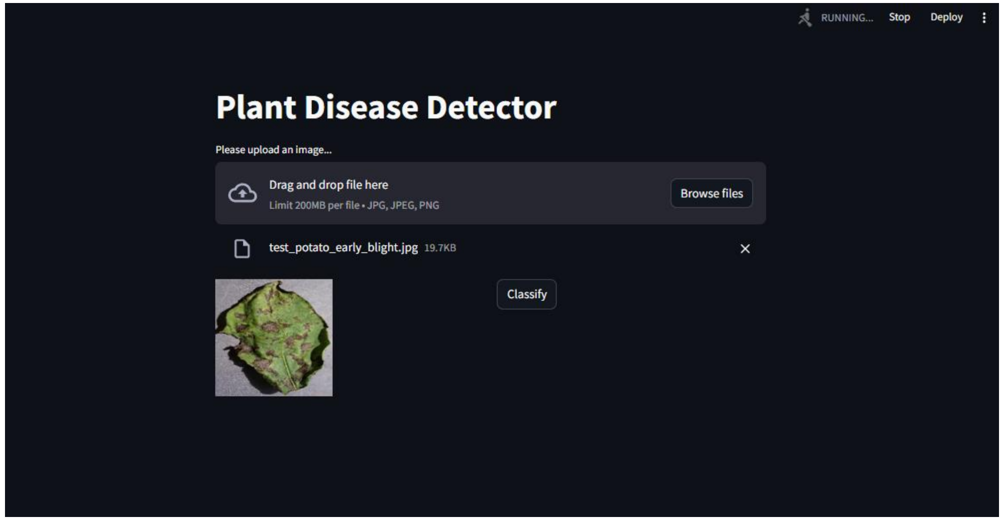
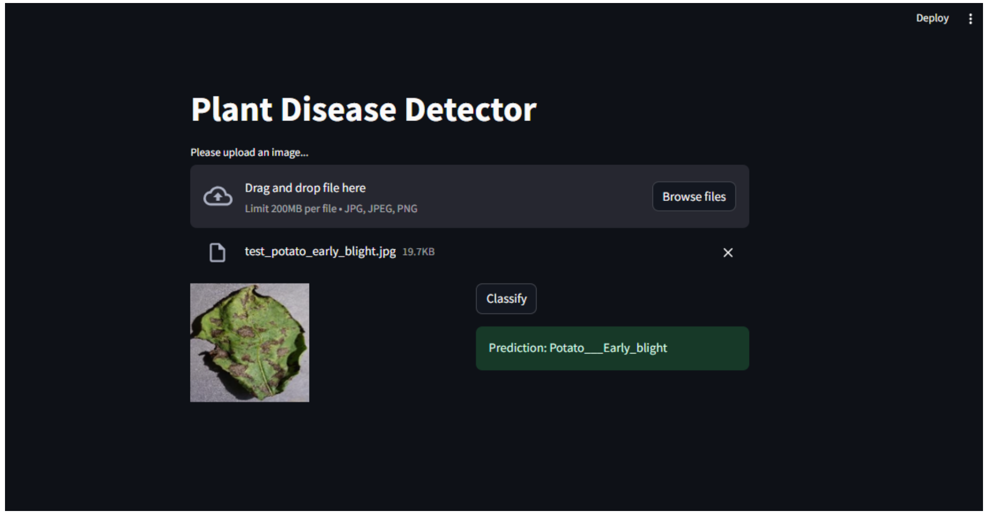
Deployment

*We built an intuitive web application using **Streamlit**. Using the trained model as an engine saved in the HDF5(.h5) format and is loaded by the Streamlit application. This is currently an on-premises solution.*

How it Works:

- A user visits the web app.
- They drag and drop or upload an image of a plant leaf.
- The app preprocesses the image and feeds it to our trained model.
- The model's prediction is displayed on the screen.





Future Work

While our model is highly accurate on the test data, there are clear paths for improvement and real-world application which will be the *next step*.

Data Diversity

Incorporate more images from real-world field conditions

Real-Time Capabilities

Optimize the model using TensorFlow for deployment on edge devices like smartphones, enabling offline use directly in the field.

Broader Integration

- Create a REST API (e.g., Flask, FastAPI) for programmatic access.
- Combine our AI with drones and IoT sensors for automated, large-scale field monitoring and early warning systems.

References

- *The persistent threat of emerging plant disease pandemics to global food security – PNAS, accessed April 10, 2025* Link
- *Plant Disease: A Growing Threat to Global Food Security – MDPI, accessed Apr 10, 2025* Link
- *The Impact of Plant Diseases – Safefood, accessed April 10, 2025* Link
- *Plant health and its effects on food safety and security in a One Health framework: four case studies – PubMed, accessed April 10, 2025* Link
- *Special Issue : The Impact of Plant Disease on Food Security – MDPI, accessed April 10, 2025* Link

Thank you!

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