KRISHI SAHAAYAK

AI-DRIVEN CROP DISEASE PROTECTION AND DETECTION

Project Overview

Problem Statement:

- Crop diseases pose a major threat to the global agricultural industry, impacting food security, environmental sustainability, and farmers' livelihoods.
- Traditional methods for detecting and managing crop diseases are slow, reliant on human experience, and often lead to inaccurate diagnoses.
- Consequences include reduced yields, increased costs, and environmental damage due to overuse of pesticides and fertilizers.

Objective:

- Leverage AI technologies like Machine Learning, Computer Vision, and Predictive Analytics to enable early detection and targeted treatment of crop diseases.
- Provide real-time insights to empower farmers to make informed decisions, reduce losses, and ensure sustainable agricultural practices.

Project Goals and Impact

AI Solution:

- Early Detection: Use AI models to identify diseases at early stages through image analysis and data insights, reducing delays in diagnosis.
- Predictive Analytics: Predict disease outbreaks and potential breakdowns, allowing proactive intervention.
- Resource Optimization: Prescribe precise treatments for crops, minimizing the use of pesticides and fertilizers, reducing costs and environmental harm.

Impact:

- Enhanced Crop Yields: Timely and accurate disease management leads to higher productivity.
- Sustainability: Reduced chemical usage contributes to better soil and water health.
- Profitability: Efficient resource usage improves the farmer's bottom line, fostering long-term agricultural sustainability.

Proposed Solution Approach

1. Data Collection:

- Image Capture: Utilize drone imagery, satellite images, and smartphone cameras to capture high-quality images of crops.
- Sensor Data: Gather data from environmental sensors (e.g., soil and climate parameters) to support recommendation models.
- Historical Data: Use historical disease occurrence and weather data to train AI models for accurate predictions.

2. Data Processing:

- Preprocessing: Clean and preprocess image data (e.g., resizing, normalization) and sensor data (e.g., removing noise).
- Feature Extraction: Extract key features such as color patterns, leaf structure, and other visual indicators of diseases.

3. AI Model Development:

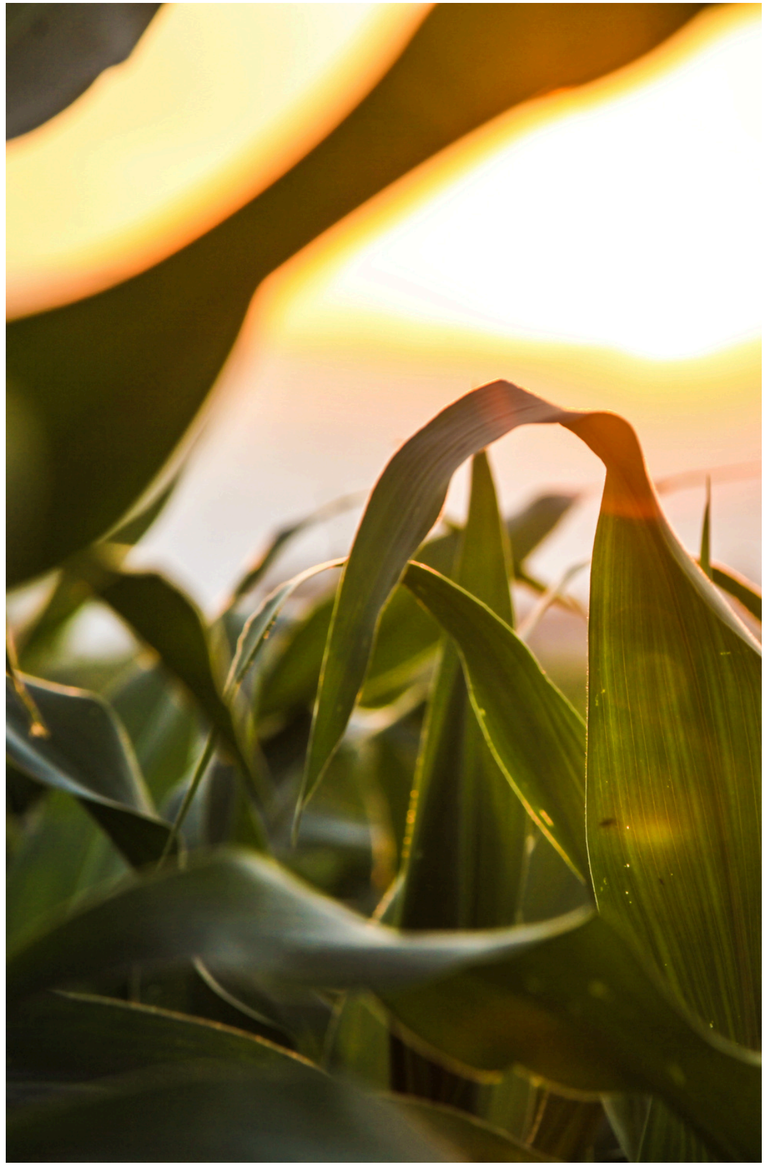
- Machine Learning & Deep Learning:
  - Convolutional Neural Networks (CNNs) for image classification to detect specific diseases.
  - Comparing various Classification models like SVC, Gaussian Naive Bayes, Random Forest, etc. for analyzing sensor and environmental data and giving Crop Recommendations.
- Training: Train the AI models using large datasets of crop images with labeled diseases and environmental data.
- Validation: Test the model for accuracy, precision, and recall to ensure reliable results.

4. Real-Time Monitoring and Disease Prediction:

- Real-Time Detection: Implement AI-powered tools for continuous monitoring of crop health.
- Predictive Analytics: Use historical data and environmental factors to predict potential disease outbreaks.

5. Deployment and Adoption:

- Farmer-Friendly Interface: Develop easy-to-use mobile or web applications that provide farmers with disease detection, predictions, and treatment recommendations.
- Continuous Learning: Models adapt and improve over time as more data is collected, ensuring sustained accuracy and relevance.



Causes of Disease

Environmental Factors:

- **Temperature & Humidity:** Excessive moisture or high humidity can promote fungal and bacterial growth, while extreme temperatures can weaken crops and make them more susceptible to diseases.
- **Soil Health**: Poor soil quality, lack of nutrients, or improper pH levels can stress crops, making them more vulnerable to infections.
- **Climate Change:** Shifts in climate patterns, like increased rainfall or extreme temperatures, can create conditions that favor the spread of certain diseases.

Pathogens:

- **Fungi:** Responsible for diseases like rust, blight, and powdery mildew. Fungal infections thrive in moist, warm environments.
- **Bacteria:** Lead to diseases like bacterial wilt, leaf spot, and blight. These often spread via water, insects, or infected tools.
- **Viruses:** Affect crops like tomatoes, potatoes, and cucumbers, often transmitted by insects like aphids.

Pests:

Insects such as aphids, beetles, and caterpillars can damage crops directly or act as vectors for diseases, spreading bacteria and fungi.

Cure and Precautions

Cure (Treatment Methods):

- **Chemical Control:** Use of fungicides, bactericides, and pesticides to treat crops affected by pathogens. However, this can be harmful to the environment if overused.
- **Biological Control:** Introducing natural predators (e.g., ladybugs to control aphids) or using beneficial microbes to combat harmful pathogens.
- **Crop Rotation:** Rotate crops to avoid the build-up of soil-borne pathogens and prevent the recurrence of disease in the same location.
- **Soil Treatment:** Improving soil health through organic matter, proper irrigation, and pH adjustment to reduce susceptibility to disease.

Precautions (Preventive Measures):

- **Regular Monitoring:** Implement regular field inspections using AI-powered tools to detect early signs of disease.
- **Proper Spacing & Ventilation:** Ensure crops are spaced properly to reduce humidity levels and improve airflow, preventing fungal growth.
- **Clean Equipment:** Disinfect tools, machinery, and water systems to prevent spreading diseases between crops.
- **Integrated Pest Management (IPM):** Combine biological, cultural, and mechanical methods to manage pests and diseases in an eco-friendly manner.

Meet Our Team

Sanchit Mishra

BACKEND

Crop Disease Detection Model [CNN] using Tensorflow

INTEGRATION with FRONTEND [FLASK]

Ridhi Jolly

BACKEND

Crop Recommendation Model
[SVC, Gaussian Naive Bayes, Random Forest, etc.]

Abhay Kumar Saini

FRONTEND

UI for Recommendation Model [HTML/CSS/JS]

PPT
REPORT

Samarth Maheshwari

FRONTEND

UI for Disease Detection Model [HTML/CSS/JS]

INTEGRATION with BACKEND [FLASK]

Work Done

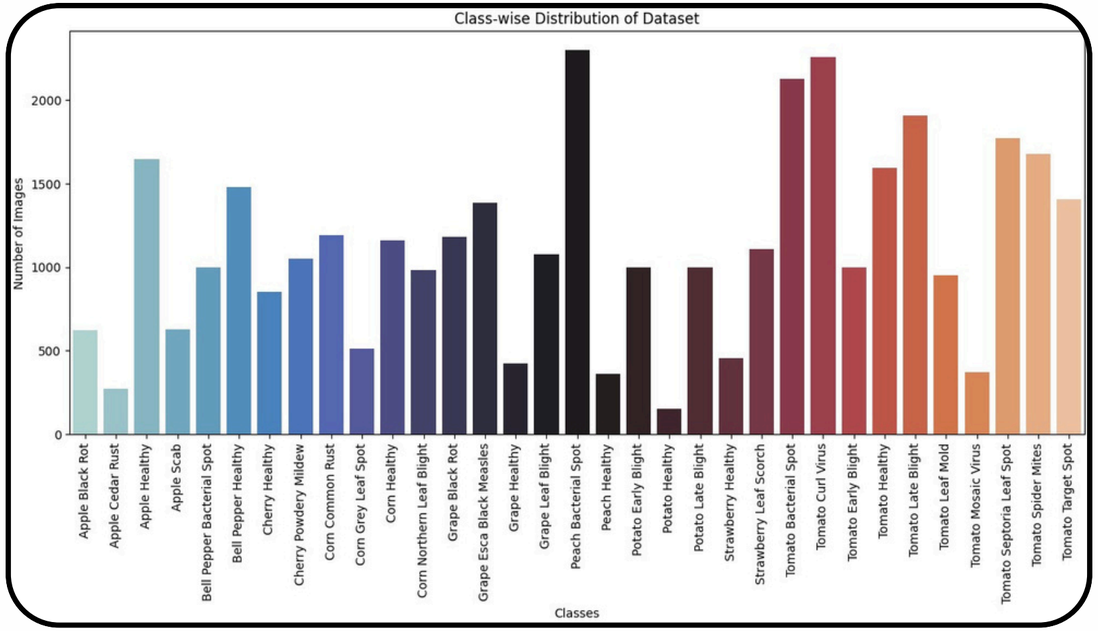
Model	Accuracy
Logistic_Regression	0.963636
Naive Bayes	0.995455
Decision_Tree	0.986364
Extra_Tree	0.895455
SVC	0.968182
K_Neighbors	0.959091
Random_Forest	0.995455
Gradient_Boosting	0.981818
Ada_Boost	0.145455
Bagging	0.984091

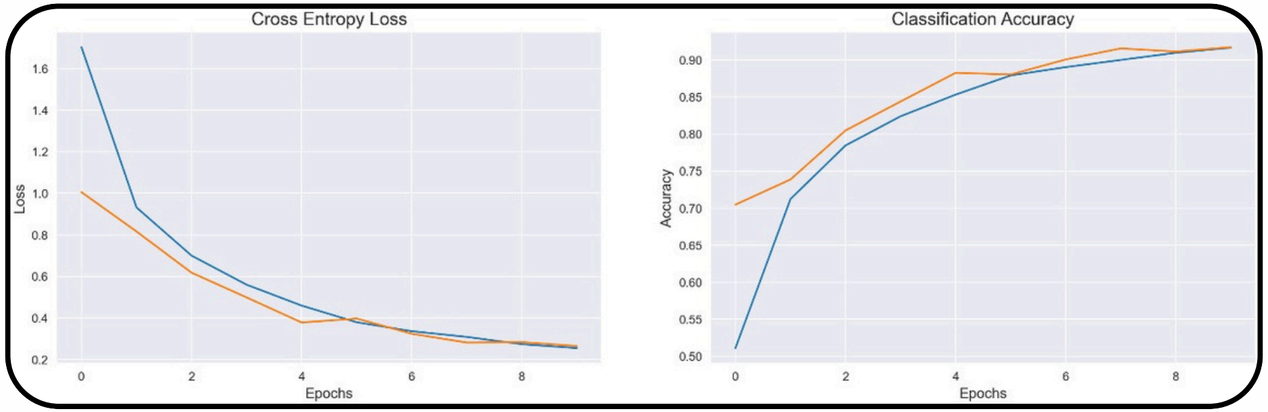
```
splitfolders.ratio('./CropDisease/',output='./Dataset Split/', seed=40, ratio=(0.7,0.2,0.1))

train_path = './Dataset Split/train'
val_path = './Dataset Split/val'
test_path = './Dataset Split/test'
```

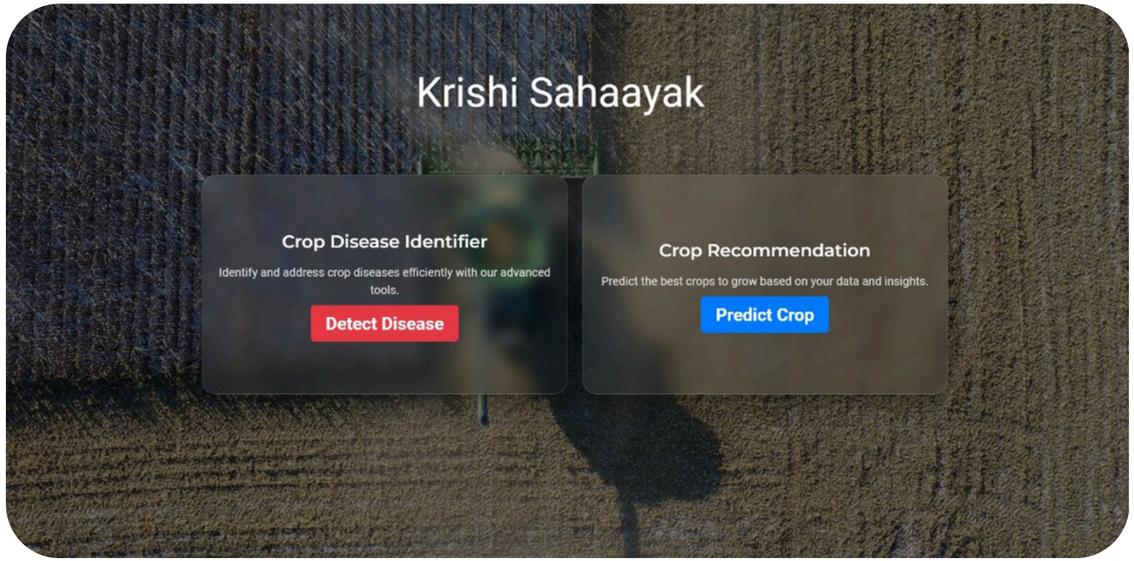
```
# Directory paths
batch_size = 64
image_size = (256, 256)

datagen = ImageDataGenerator(rescale=1./255, rotation_range=140, brightness_range=[0.4,1.0], horizontal_flip=True, vertical_flip=True)

train_data = datagen.flow_from_directory(train_path, target_size=image_size, batch_size=batch_size, class_mode='sparse')
val_data = datagen.flow_from_directory(val_path, target_size=image_size, batch_size=batch_size, class_mode='sparse')
test_data = datagen.flow_from_directory(test_path, target_size=image_size, batch_size=batch_size, class_mode='sparse')
```

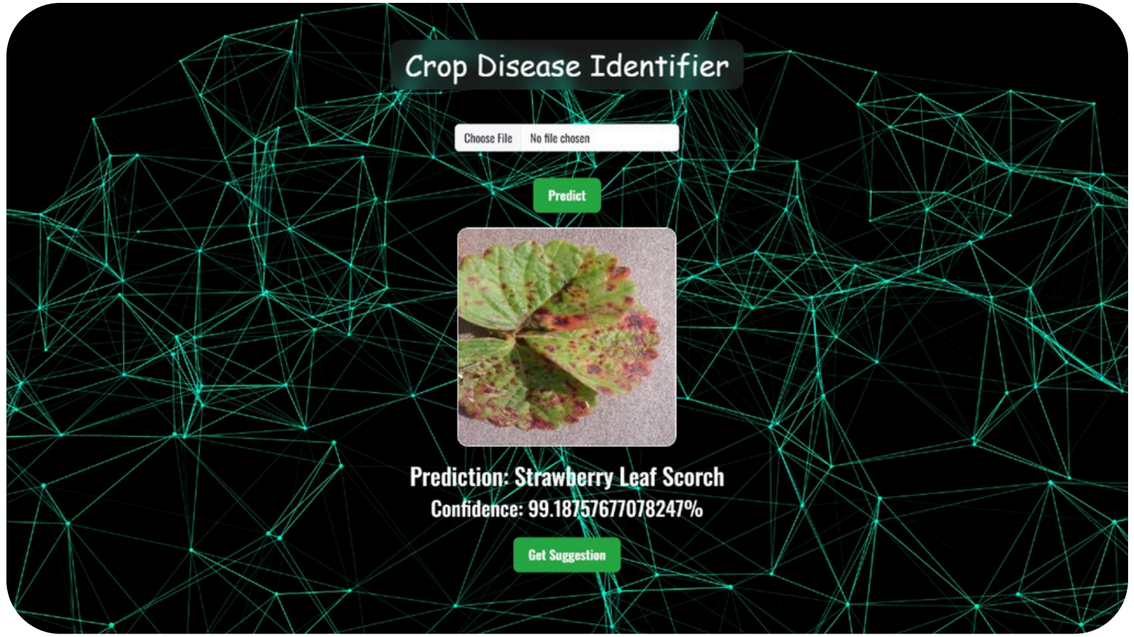
```
Found 26858 images belonging to 33 classes.
Found 8039 images belonging to 33 classes.
Found 4107 images belonging to 33 classes.
```

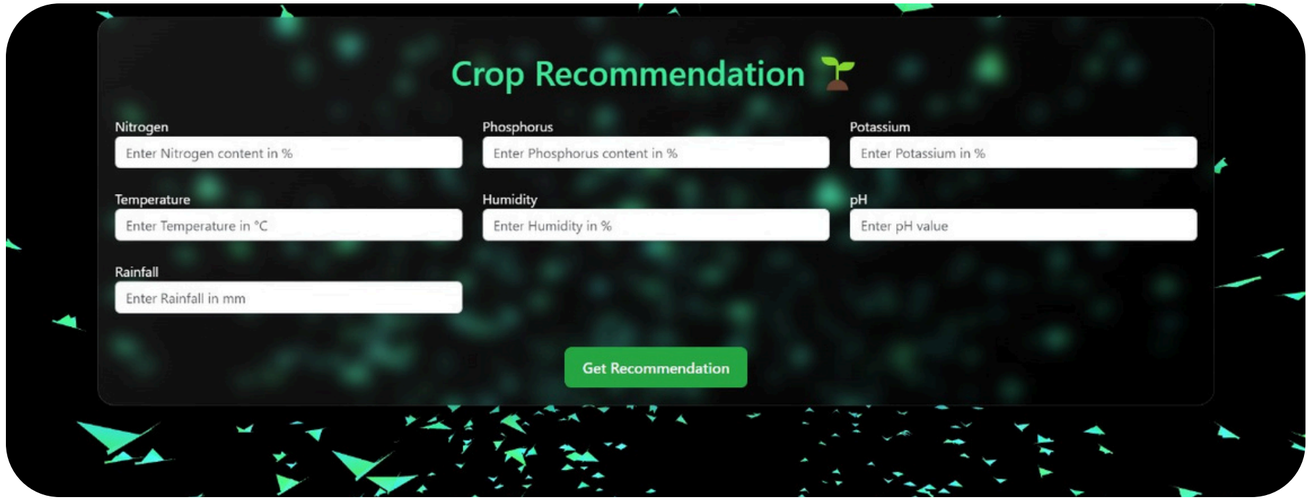
```
Epoch 4/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 865s 2s/step - accuracy: 0.8179 - loss: 0.5786 - val_accuracy: 0.8439 - val_loss: 0.4989
Epoch 5/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 652s 2s/step - accuracy: 0.8513 - loss: 0.4621 - val_accuracy: 0.8826 - val_loss: 0.3782
Epoch 6/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 615s 1s/step - accuracy: 0.8779 - loss: 0.3827 - val_accuracy: 0.8803 - val_loss: 0.3973
Epoch 7/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 613s 1s/step - accuracy: 0.8904 - loss: 0.3341 - val_accuracy: 0.9006 - val_loss: 0.3241
Epoch 8/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 614s 1s/step - accuracy: 0.8981 - loss: 0.3105 - val_accuracy: 0.9155 - val_loss: 0.2818
Epoch 9/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 613s 1s/step - accuracy: 0.9075 - loss: 0.2737 - val_accuracy: 0.9113 - val_loss: 0.2839
Epoch 10/10
420/420 ━━━━━━━━━━━━━━━━━━━━ 1124s 3s/step - accuracy: 0.9213 - loss: 0.2357 - val_accuracy: 0.9173 - val_loss: 0.2650
```

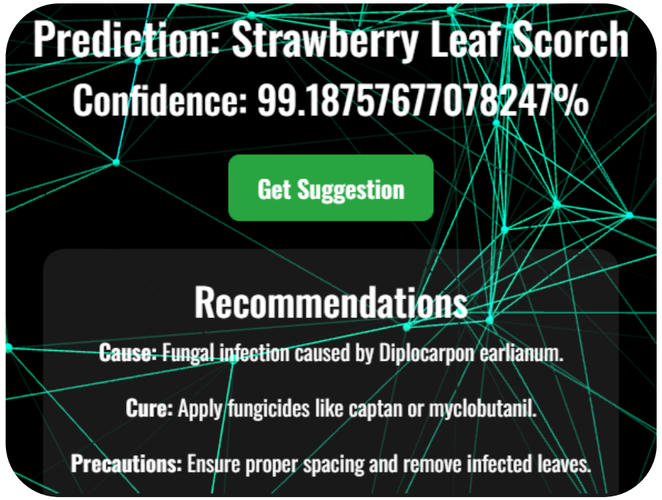

Class-wise Distribution of Dataset
Number of Images
0
500
1000
1500
2000
Apple Black Rot
Apple Cedar Rust
Apple Healthy
Apple Scab
Bell Pepper Bacterial Spot
Bell Pepper Healthy
Cherry Healthy
Cherry Powdery Mildew
Corn Common Rust
Corn Grey Leaf Spot
Corn Healthy
Corn Northern Leaf Blight
Grape Black Rot
Grape Esca Black Measles
Grape Healthy
Grape Leaf Blight
Peach Bacterial Spot
Peach Healthy
Potato Early Blight
Potato Healthy
Potato Late Blight
Strawberry Healthy
Strawberry Leaf Scorch
Tomato Bacterial Spot
Tomato Curl Virus
Tomato Early Blight
Tomato Healthy
Tomato Late Blight
Tomato Leaf Mold
Tomato Mosaic Virus
Tomato Septoria Leaf Spot
Tomato Spider Mites
Tomato Target Spot
Classes


Cross Entropy Loss
Loss
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
0
2
4
6
8
Epochs
Classification Accuracy
Accuracy
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0
2
4
6
8
Epochs


Krishi Sahaayak
Crop Disease Identifier
Identify and address crop diseases efficiently with our advanced tools.
Detect Disease
Crop Recommendation
Predict the best crops to grow based on your data and insights.
Predict Crop


Crop Disease Identifier
Choose File
No file chosen
Predict
Prediction: Strawberry Leaf Scorch
Confidence: 99.18757677078247%
Get Suggestion


Crop Recommendation
Nitrogen
Enter Nitrogen content in %
Phosphorus
Enter Phosphorus content in %
Potassium
Enter Potassium in %
Temperature
Enter Temperature in °C
Humidity
Enter Humidity in %
pH
Enter pH value
Rainfall
Enter Rainfall in mm
Get Recommendation


Prediction: Strawberry Leaf Scorch
Confidence: 99.18757677078247%
Get Suggestion
Recommendations
Cause: Fungal infection caused by Diplocarpon earlianum.
Cure: Apply fungicides like captan or myclobutanil.
Precautions: Ensure proper spacing and remove infected leaves.


Thank You
KRISHI SAHAAYAK