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# **CASE STUDY**

# **Plant Disease Detection**

#### 1. Problem Statement

The objective of this project is to develop a robust and efficient system for the classification of plant diseases using image processing and machine learning techniques. The system aims to identify and categorize different types of plant diseases from images of affected plant parts, primarily leaves. By leveraging advanced algorithms and a comprehensive dataset, the system should provide accurate and timely diagnoses to assist farmers and agricultural professionals in making informed decisions for disease management and crop protection.

#### 2. Solution Overview

Agriculture is a cornerstone of the global economy, playing a critical role in supplying essential resources including food, raw materials, and employment opportunities. This sector supports millions of livelihoods and contributes significantly to national and international markets. However, the impact of plant diseases represents a formidable challenge to agricultural productivity. Plant diseases can severely diminish crop yields, degrade the quality of produce, and ultimately lead to significant economic losses for farmers and agricultural enterprises. The consequences of these diseases extend beyond immediate financial impacts, potentially affecting food availability and leading to broader food security concerns.

Early and accurate detection of plant diseases is therefore paramount for mitigating these adverse effects and promoting sustainable agricultural practices. Timely identification of disease outbreaks enables farmers to implement targeted interventions, such as appropriate treatments or preventative measures, which can prevent the spread of diseases and preserve crop health. This proactive approach not only helps to safeguard the quality and quantity of agricultural outputs but also supports long-term food security by reducing the risk of crop failures and ensuring the stability of food supplies. Advancements in diagnostic technologies and disease monitoring are critical in enhancing our ability to address these challenges effectively and maintain a resilient agricultural sector.

# **FLOWCHART START** LOAD PLANT DISEASE **DETECTION DATASET PREPROCESSING** (DATA AUGUMENTATION) **BUILD CNN MODEL COMPILE & TRAIN THE MODEL** MODEL EVALUATION MODEL DEPLOYMENT UPLOAD AN IMAGE OF LEAF PLANT DISEASE CLASSIFIER **DISPLAYS PREDICTED RESULT**

Flow chart of our model

**END** 

#### 1. Data Collection

#### **Gathering Data**

Download the dataset from Kaggle with three classes: Healthy, Rust, and Powdery.

Extract and organize the images into separate folders for each class (Healthy, Rust, Powdery).

#### Labeling Data

Verify that each image is correctly labeled according to its class.

If the dataset is not pre-labeled, manually label the images using a tool like Label Img or through scripts.

## 2. Data Preprocessing

#### **Image Augmentation**

Implement data augmentation techniques such as rotation, flipping, zooming, and shifting to increase dataset variability. Use libraries like *Keras' ImageDataGenerator* for augmentation.

#### Resizing and Normalization

Resize all images to a uniform size (e.g., 128x128 or 256x256 pixels) for consistency. Normalize pixel values to a range of [0, 1] to improve model training.

# 3. Building the Model

#### CNN Architecture

Design a Convolutional Neural Network (CNN) using Keras and TensorFlow.

#### Typical architecture

- Input Layer
- Several Convolutional Layers (e.g., Conv2D)
- Activation Functions (e.g., ReLU)
- Pooling Layers (e.g., MaxPooling2D)
- Fully Connected Layers (Dense)
- Output Layer with softmax activation for multi-class classification.

#### Compilation

Compile the model using an optimizer like Adam.

Use categorical crossentropy as the loss function for image multi-class classification.

Define metrics such as accuracy to evaluate model performance.

# 4. Training the Model

#### Loading Data:

Use ImageDataGenerator to load and preprocess images on-the-fly.

Implement real-time data augmentation during training.

#### Model Training:

Split the dataset into training and validation sets.

Train the model using the training set while validating its performance on the validation set.

Monitor metrics and adjust hyperparameters to prevent overfitting.

# 5. Evaluating the Model

#### **Validation**

Assess the model's accuracy, loss, and other performance metrics on the validation set.

Ensure that the model generalizes well to new data and is not overfitting.

# 6. Deployment

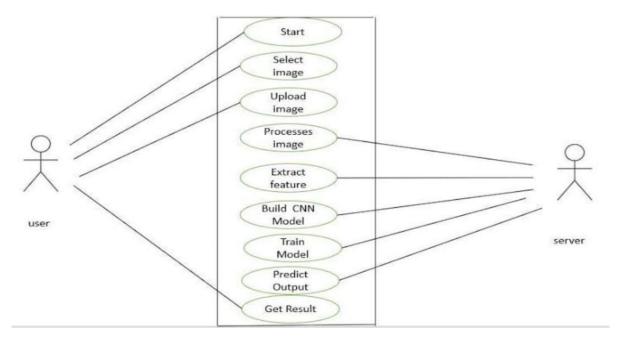
#### Saving the Model:

Save the trained model using model.save('model.h5') to a file for future use.

#### Flask API:

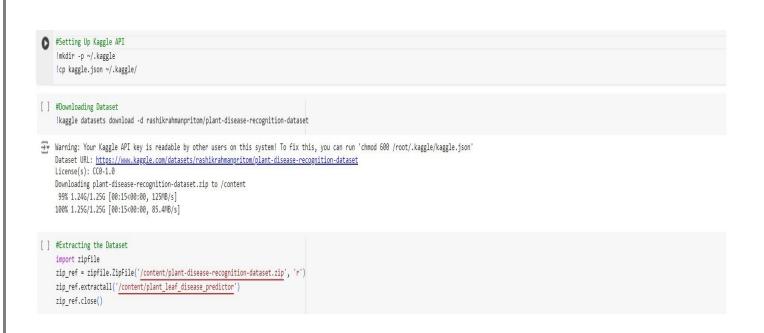
- ✓ Set up a Flask web application.
- ✓ Create an endpoint for users to upload plant images.
- ✓ Load the saved model within the Flask app.
- ✓ Implement preprocessing steps (resizing, normalization) for the uploaded image.
- ✓ Use the model to predict the plant's health or disease status and return the results to the user.

# **Use-case diagram**



Use-case diagram of our model

# 7. Source Code



```
♠ #Count of images in each subdirectory
      import os
      def count_files_and_folders(directory):
           num_files = 0
           num_folders = 0
           for entry in os.listdir(directory):
                 entry_path = os.path.join(directory, entry)
                 if os.path.isfile(entry_path):
                      num_files += 1
                 elif os.path.isdir(entry_path):
                      num_folders += 1
           return num_files, num_folders
      ch = 1
     while(True):
        if ch < 7 :
           directory = input('Directory name :')
           files_count, folders_count = count_files_and_folders(directory)
           print(f'Number of files {directory}: {files_count}')
           ch = ch + 1
         # print(f'Number of folders: {folders_count}')
Directory name :/content/plant_leaf_disease_predictor/Train/Train/Healthy
     Number of files /content/plant_leaf_disease_predictor/Train/Train/Realthy: 458
Directory name :/content/plant_leaf_disease_predictor/Train/Train/Powdery:
Number of files /content/plant_leaf_disease_predictor/Train/Train/Powdery: 430
Directory name :/content/plant_leaf_disease_predictor/Train/Train/Rust
Number of files /content/plant_leaf_disease_predictor/Train/Train/Rust: 434
     Directory name :/content/plant_leaf_disease_predictor/Test/Test/Healthy
```

Number of files /content/plant\_leaf\_disease\_predictor/Test/Test/Healthy: 50 Directory name:/content/plant\_leaf\_disease\_predictor/Test/Test/Powdery Number of files /content/plant\_leaf\_disease\_predictor/Test/Test/Powdery: 50 Directory name:/content/plant\_leaf\_disease\_predictor/Test/Test/Rust Number of files /content/plant\_leaf\_disease\_predictor/Test/Test/Rust: 50

```
[ ] # Displaying Sample Images
              import matplotlib.pyplot as plt
              from PIL import Image
              # Define image paths
              image\_path\_healthy = '\_/content/plant\_leaf\_disease\_predictor/Train/Train/Healthy/800edef467d27c15.jpg' = '\_/content/plant\_leaf\_disease\_predictor/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Train/Tra
              image_path_rust = '/content/plant_leaf_disease_predictor/Train/Train/Rust/80f09587dfc7988e.jpg
              image_path_powdery = '/content/plant_leaf_disease_predictor/Train/Train/Powdery/8299723bc94df5a8.jpg'
              # Open the images
              img healthy = Image.open(image path healthy)
              img_rust = Image.open(image_path_rust)
              img_powdery = Image.open(image_path_powdery)
              # Create a figure with 3 subplots (side by side)
              fig, axs = plt.subplots(1, 3, figsize=(18, 6))
              # Display the healthy leaf image
               axs[0].imshow(img_healthy)
              axs[0].axis('off') # Hide axes
              axs[0].set_title('Healthy Leaf')
              # Display the rust leaf image
              axs[1].imshow(img_rust)
              axs[1].axis('off') # Hide axes
              axs[1].set_title('Rust Leaf')
              # Display the powdery leaf image
               axs[2].imshow(img_powdery)
               axs[2].axis('off') # Hide axes
              axs[2].set_title('Powdery Leaf')
              # Show the plot
              plt.show()
```







#### Sample images from dataset

Found 1322 images belonging to 3 classes. Found 150 images belonging to 3 classes.

```
#Install or upgrade TensorFlow only
|pip install tensorFlow --upgrade

import tensorFlow version:", tf.__version_)

# Keras is now part of TensorFlow
keras_version = tf.keras._version_
print("Keras version:", keras_version)

Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (1.4.0)
Requirement already satisfied: asturparse>-1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (1.6.3)
Requirement already satisfied: asturparse>-1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (1.6.3)
Requirement already satisfied: gastl=0.5.0,1=0.5.1,1=0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.4.3.25)
Requirement already satisfied: gastl=0.5.0,1=0.5.1,1=0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (0.6.0)
Requirement already satisfied: https://doi.ol/10/python3.10/dist-packages (from tensorFlow) (0.2.0)
Requirement already satisfied: https://doi.ol/10/python3.10/dist-packages (from tensorFlow) (0.4.0)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (0.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (0.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.4.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.4.1)
Requirement already satisfied: sizv=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.3.0)
Requirement already satisfied: sizv=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.4.0)
Requirement already satisfied: sizv=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.4.0)
Requirement already satisfied: tensorFlow /usr/local/lib/python3.10/dist-packages (from tensorFlow) (2.4.0)
Requirement already satisfied: tensorFlow>1.1.0 in /usr/local/lib/python3.10/dist-packages (from
```

```
[ ] from keras.models import Sequential
  from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

model = Sequential()
  model.add(Conv2D(32, (3, 3), input_shape=(225, 225, 3), activation='relu'))
  model.add(MaxPooling2D(pool_size=(2, 2)))
  model.add(Conv2D(64, (3, 3), activation='relu'))
  model.add(MaxPooling2D(pool_size=(2, 2)))
  model.add(MaxPooling2D(pool_size=(2, 2)))
  model.add(Dense(64, activation='relu'))
  model.add(Dense(64, activation='softmax'))
```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base\_conv.py:107: UserWarning: Do not pass an `input\_shape`/`input\_dim` argument to a layer. When using Sequential models, prefer using an `Inpu super().\_\_init\_\_(activity\_regularizer=activity\_regularizer, \*\*kwargs)

#### [ ] model.summary()

#### → Model: "sequential"

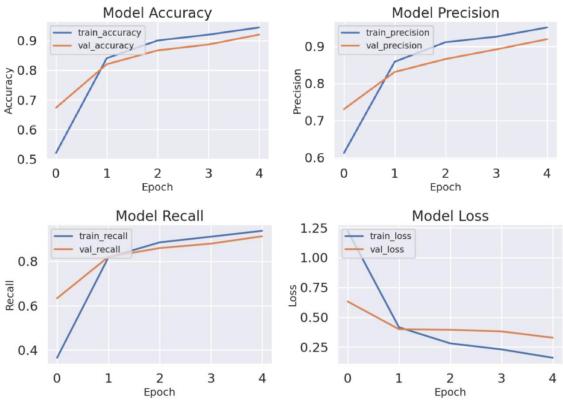
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 223, 223, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
flatten (Flatten)	(None, 186624)	0
dense (Dense)	(None, 64)	11,944,000
dense_1 (Dense)	(None, 3)	195

Total params: 11,963,587 (45.64 MB) Trainable params: 11,963,587 (45.64 MB) Non-trainable params: 0 (0.00 B)

```
[] # Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy', 'precision', 'recall'])
```

₹ Epoch 1/5 /usr/local/lib/python3.10/dist-packages/keras/src/trainers/data\_adapters/py\_dataset\_adapter.py:121: UserWarning: Your `PyDataset` class should call `super().\_init\_(\*\*kwargs)` in its constructor. `\*\*kwargs` can incl self.\_warn\_if\_super\_not\_called() 42/42 -- 111s 2s/step - accuracy: 0.4076 - loss: 1.9102 - precision: 0.4520 - recall: 0.2297 - val\_accuracy: 0.6733 - val\_loss: 0.6316 - val\_precision: 0.7308 - val\_recall: 0.6333 Epoch 2/5 42/42 -- 91s 2s/step - accuracy: 0.8180 - loss: 0.4649 - precision: 0.8435 - recall: 0.7854 - val\_accuracy: 0.8200 - val\_loss: 0.3993 - val\_precision: 0.8311 - val\_recall: 0.8200 Epoch 3/5 42/42 -- 140s 2s/step - accuracy: 0.9017 - loss: 0.2860 - precision: 0.9080 - recall: 0.8868 - val\_accuracy: 0.8667 - val\_loss: 0.3943 - val\_precision: 0.8658 - val\_recall: 0.8600 Epoch 4/5 42/42 -86s 2s/step - accuracy: 0.9288 - loss: 0.2214 - precision: 0.9348 - recall: 0.9190 - val\_accuracy: 0.8867 - val\_loss: 0.3810 - val\_precision: 0.8919 - val\_recall: 0.8800 Epoch 5/5 — 144s 2s/step - accuracy: 0.9556 - loss: 0.1408 - precision: 0.9627 - recall: 0.9489 - val\_accuracy: 0.9200 - val\_loss: 0.3280 - val\_precision: 0.9195 - val\_recall: 0.9133

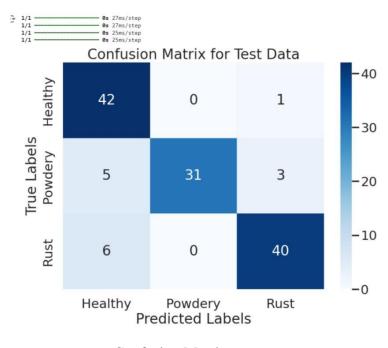
```
from matplotlib import pyplot as plt
 from matplotlib.pyplot import figure
 import seaborn as sns
# Set up seaborn for styling
sns.set_theme()
sns.set_context("poster")
 # Create a figure to plot all metrics
figure(figsize=(14, 10), dpi=100)
# Plot accuracy
plt.subplot(2, 2, 1)
plt.plot(history.history['accuracy'], label='train_accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch',fontsize=18)
plt.ylabel('Accuracy',fontsize=18)
plt.legend(loc='upper left',fontsize=15)
# Plot precision
if 'precision' in history.history:
plt.subplot(2, 2, 2)
plt.plot(history.history['precision'], label='train_precision')
        plt.plot(history.history['val_precision'], label='val_precision')
       plt.title('Model Precision')
plt.xlabel('Epoch', fontsize=18)
plt.ylabel('Precision', fontsize=18)
plt.legend(loc='upper left', fontsize=15)
 # Plot recall
 if 'recall' in history.history:
  plt.subplot(2, 2, 3)
  plt.plot(history.history['recall'], label='train_recall')
       plt.plt(history.history['val_recall'], label='val_recall')
plt.title('Model Recall')
plt.xlabel('Epoch',fontsize=18)
plt.ylabel('Recall',fontsize=18)
        plt.legend(loc='upper left',fontsize=15)
  # Flot loss
plt.subplot(2, 2, 4)
plt.plot(history.history['loss'], label='train_loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.title('Model loss')
plt.xlabel('Epoch',fontsize=18)
plt.ylabel('loss',fontsize=18)
plt.legend(loc='upper left',fontsize=15)
  plt.tight_layout()
  plt.show()
                                                      Model Accuracy
                                                                                                                                                                                                                 Model Precision
                                       train_accuracy
                                                                                                                                                                                                   train_precision
       0.9
                                        val_accuracy
                                                                                                                                                                  0.9
                                                                                                                                                                                                    val precision
                                                                                                                                                                  0.8
```



Plots of Performance Metrics

```
[ ] # Saving the Model
     model.save("model.h5")
🕁 WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.sa
     from \ tensorflow.keras.preprocessing.image \ import \ load\_img, \ img\_to\_array
     import numpy as np
     # Function to preprocess the image
     def preprocess_image(image_path, target_size=(225, 225)):
   img = load_img(image_path, target_size=target_size)
         x = img_to_array(img)
         x = x.astype('float32') / 255.
         x = np.expand_dims(x, axis=0)
         return x
     # Load and preprocess the image
     image_path = '/content/plant_leaf_disease_predictor/Validation/Validation/Powdery/9b6a318cc5721d73.jpg'
     x = preprocess_image(image_path)
     # Make predictions
     predictions = model.predict(x)
     predicted_class = np.argmax(predictions[0])
     # 'train_generator' is defined and has the class indices
     labels = train_generator.class_indices
     labels = \{v: \ k \ \text{for} \ k, \ v \ \text{in labels.items}()\} \ \# \ \text{Invert the dictionary to map indices to labels}
     predicted_label = labels[predicted_class]
     # Output the predicted label
     print(f'Predicted Label: {predicted_label}')
<u>→</u> 1/1 —
                             - 1s 817ms/step
     Predicted Label: Powdery
```

```
import numpy as np
    from sklearn.metrics import confusion matrix
    import matplotlib.pyplot as plt
    import seaborn as sns
    # Generate predictions and true labels for the entire test dataset
    def get_all_predictions_and_labels(generator):
        num_samples = generator.samples
        num_batches = num_samples // generator.batch_size
        all_predictions = []
        all_true_labels = []
        for in range(num batches):
            images, labels = generator.__next__()
            predictions = model.predict(images)
            all_predictions.extend(np.argmax(predictions, axis=-1))
            all_true_labels.extend(np.argmax(labels, axis=-1))
        return np.array(all_true_labels), np.array(all_predictions)
    # Get all predictions and true labels
    true_labels, predicted_labels = get_all_predictions_and_labels(validation_generator)
    # Compute the confusion matrix
    cm = confusion_matrix(true_labels, predicted_labels)
    # Create a figure to plot the confusion matrix
    plt.figure(figsize=(10, 7))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=train_generator.class_indices.keys(),
                y \verb|ticklabels=train_generator.class_indices.keys())|
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix for Test Data')
    plt.show()
```



**Confusion Matrix** 

### 8. Conclusion

The implementation of early and precise disease detection technologies in agriculture is poised to transform the way farmers manage crop health. To support this transformation, we designed a web application for plant leaf disease detection. This proactive tool helps significantly reduce crop losses by identifying diseases early, allowing for timely and efficient interventions. Furthermore, by minimizing the need for excessive pesticide use, the application promotes a healthier environment and safer food production. Early detection and precise treatment ensure that crops remain healthy, which is vital for maximizing yields and maintaining the quality of agricultural produce.

Moreover, integrating these innovative solutions into agricultural practices supports sustainability and contributes to broader food security and economic stability. By reducing reliance on harmful chemicals, farmers can adopt more eco-friendly practices, preserving soil health and biodiversity. This project aims to address key challenges in plant disease management by providing farmers with the tools needed to maintain productive crops, ultimately supporting the agricultural community. By achieving these goals, the initiative not only revolutionizes how plant diseases are managed but also fortifies the agricultural sector's resilience against future challenges. This holistic approach ensures that farming remains a viable and sustainable livelihood, securing food supplies for communities worldwide.

# 9. Outputs

We see the interface of our website as:

# **Plant Disease Classifier**

Upload an image to classify it as Healthy, Powdery, or Rust.

Choose file No file chosen

Upload and Classify

Home page

# Plant Disease Classifier - Result



Prediction: Rust

Healthy: 0.09, Powdery: 0.00, Rust: 0.91

Result of Prediction as Rust

Plant Disease Classifier - Result



Prediction: Healthy

Healthy: 0.96, Powdery: 0.00, Rust: 0.04

Result of Prediction as Healthy

# Plant Disease Classifier - Result



Prediction: Powdery

Healthy: 0.02, Powdery: 0.96, Rust: 0.02

Result of Prediction as Powdery