Class Assignment - Plant Disease

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In [1]:
```
#  STEP 1: Install kagglehub (for dataset access)
#!pip install -q kagglehub

#  STEP 2: Import libraries
import os
import zipfile
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import classification_report, confusion_matrix
import kagglehub

#  STEP 3: Download the dataset from KaggleHub
dataset_path = kagglehub.dataset_download("arjuntejaswi/plant-village")
print(" Dataset downloaded at:", dataset_path)

#  STEP 4: Extract if zipped
for file in os.listdir(dataset_path):
    if file.endswith(".zip"):
        zip_path = os.path.join(dataset_path, file)
        with zipfile.ZipFile(zip_path, 'r') as zip_ref:
            zip_ref.extractall(dataset_path)
        print(" Extracted:", file)

#  STEP 5: Set root_dir to extracted folder
print(" Available files/folders:", os.listdir(dataset_path))
root_dir = os.path.join(dataset_path, "PlantVillage")  # Adjust if folder name changes
print(" Using data from:", root_dir)

#  STEP 6: Image Data Preprocessing & Augmentation
img_height, img_width = 128, 128
batch_size = 32
```

```python
datagen = ImageDataGenerator(
    rescale=1.0/255,
    validation_split=0.2,
    rotation_range=20,
    zoom_range=0.2,
    horizontal_flip=True
)

train_data = datagen.flow_from_directory(
    root_dir,
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode="categorical",
    subset="training",
    shuffle=True
)

val_data = datagen.flow_from_directory(
    root_dir,
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode="categorical",
    subset="validation",
    shuffle=False
)

#  STEP 7: Build a Custom CNN Model
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=(img_height, img_width, 3)),
    tf.keras.layers.MaxPooling2D(2, 2),

    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),

    tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),

    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(train_data.num_classes, activation='softmax')  # output layer
```

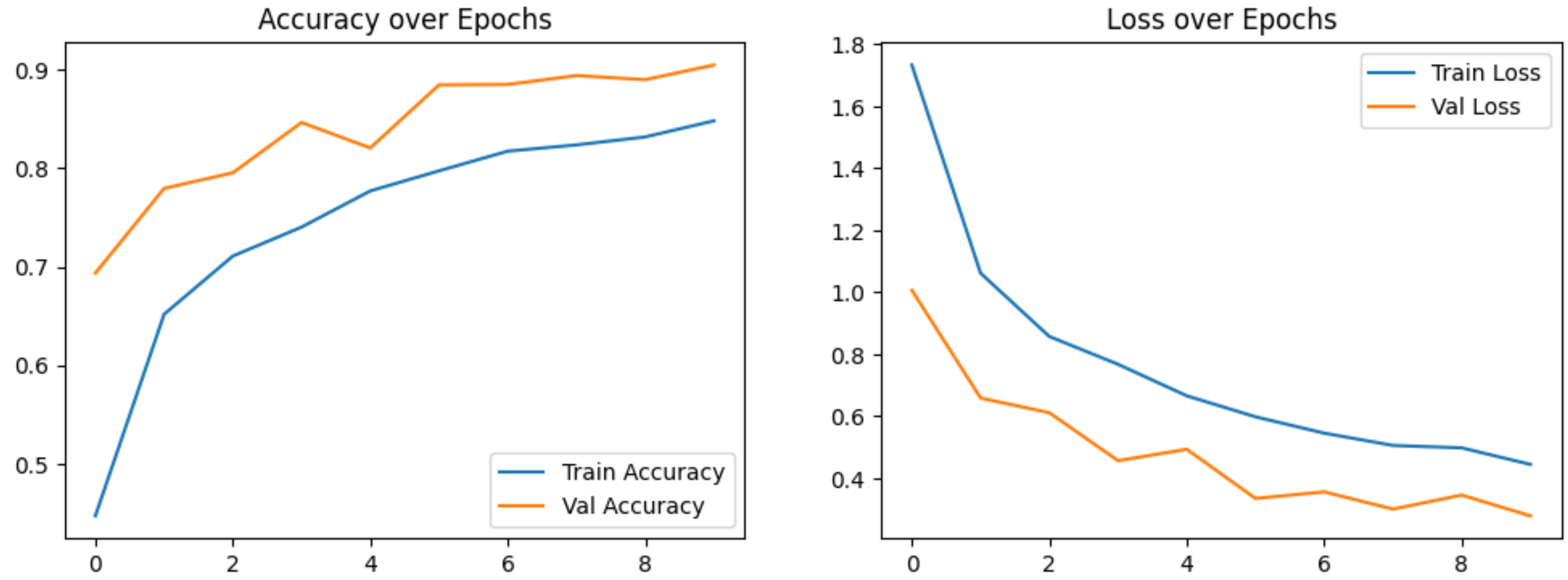
```python
])

#  STEP 8: Compile the model
model.compile(
    optimizer='adam',
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

#  STEP 9: Train the model
history = model.fit(
    train_data,
    epochs=10,
    validation_data=val_data
)

#  STEP 10: Plot Accuracy and Loss
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title('Accuracy over Epochs')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Loss over Epochs')
plt.legend()

plt.show()

#  STEP 11: Evaluate Model Performance
val_preds = model.predict(val_data)
y_pred = np.argmax(val_preds, axis=1)
y_true = val_data.classes
class_names = list(val_data.class_indices.keys())

# Classification report
print("\n Classification Report:")
print(classification_report(y_true, y_pred, target_names=class_names))
```

```python
# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
print("\n Confusion Matrix:\n", cm)
```

```
2025-07-28 19:55:02.445783: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightl
y different numerical results due to floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2025-07-28 19:55:02.531036: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to register cuFFT
factory: Attempting to register factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
E0000 00:00:1753712702.565580    6762 cuda_dnn.cc:8579] Unable to register cuDNN factory: Attempting to register fac
tory for plugin cuDNN when one has already been registered
E0000 00:00:1753712702.575669    6762 cuda_blas.cc:1407] Unable to register cuBLAS factory: Attempting to register f
actory for plugin cuBLAS when one has already been registered
W0000 00:00:1753712702.650118    6762 computation_placer.cc:177] computation placer already registered. Please check
linkage and avoid linking the same target more than once.
W0000 00:00:1753712702.650144    6762 computation_placer.cc:177] computation placer already registered. Please check
linkage and avoid linking the same target more than once.
W0000 00:00:1753712702.650145    6762 computation_placer.cc:177] computation placer already registered. Please check
linkage and avoid linking the same target more than once.
W0000 00:00:1753712702.650146    6762 computation_placer.cc:177] computation placer already registered. Please check
linkage and avoid linking the same target more than once.
2025-07-28 19:55:02.658154: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized
to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations, rebuild TensorFlow with the appropriat
e compiler flags.
/home/abhijit/miniconda3/envs/tf-env/lib/python3.12/site-packages/requests/__init__.py:86: RequestsDependencyWarning
: Unable to find acceptable character detection dependency (chardet or charset_normalizer).
  warnings.warn(
Downloading from https://www.kaggle.com/api/v1/datasets/download/arjuntejaswi/plant-village?dataset_version_number=
1...
100%|██████████| 329M/329M [00:31<00:00, 10.8MB/s]
Extracting files...
 Dataset downloaded at: /home/abhijit/.cache/kagglehub/datasets/arjuntejaswi/plant-village/versions/1
 Available files/folders: ['PlantVillage']
 Using data from: /home/abhijit/.cache/kagglehub/datasets/arjuntejaswi/plant-village/versions/1/PlantVillage
Found 16516 images belonging to 15 classes.
Found 4122 images belonging to 15 classes.
```

```
/home/abhijit/miniconda3/envs/tf-env/lib/python3.12/site-packages/keras/src/layers/convolutional/base_conv.py:113: U
serWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using
an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
I0000 00:00:1753712740.452054    6762 gpu_device.cc:2019] Created device /job:localhost/replica:0/task:0/device:GP
U:0 with 3670 MB memory:  -> device: 0, name: NVIDIA GeForce RTX 4050 Laptop GPU, pci bus id: 0000:01:00.0, compute
capability: 8.9
Epoch 1/10
/home/abhijit/miniconda3/envs/tf-env/lib/python3.12/site-packages/keras/src/trainers/data_adapters/py_dataset_adapte
r.py:121: UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in its constructor. `**kwargs
` can include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `fit()`, as they wi
ll be ignored.
  self._warn_if_super_not_called()
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1753712741.899745    7155 service.cc:152] XLA service 0x7895a4017b00 initialized for platform CUDA (this
does not guarantee that XLA will be used). Devices:
I0000 00:00:1753712741.899761    7155 service.cc:160]   StreamExecutor device (0): NVIDIA GeForce RTX 4050 Laptop GP
U, Compute Capability 8.9
2025-07-28 19:55:41.933230: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:269] disabling MLIR crash
reproducer, set env var `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
I0000 00:00:1753712742.077286    7155 cuda_dnn.cc:529] Loaded cuDNN version 90300
  4/517 ━━━━━━━━━━━━━━━━━━━━ 26s 51ms/step - accuracy: 0.0898 - loss: 2.7123
I0000 00:00:1753712746.281084    7155 device_compiler.h:188] Compiled cluster using XLA!  This line is logged at mos
t once for the lifetime of the process.
517/517 ━━━━━━━━━━━━━━━━━━━━ 0s 63ms/step - accuracy: 0.3248 - loss: 2.1081
2025-07-28 19:56:27.768083: I external/local_xla/xla/stream_executor/cuda/subprocess_compilation.cc:346] ptxas warni
ng : Registers are spilled to local memory in function 'gemm_fusion_dot_108', 4 bytes spill stores, 4 bytes spill lo
ads
```

```
517/517 ━━━━━━━━━━━━━━━━━━━━ 48s 82ms/step - accuracy: 0.3250 - loss: 2.1074 - val_accuracy: 0.6936 - val_loss: 1.00
70
Epoch 2/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.6299 - loss: 1.1316 - val_accuracy: 0.7795 - val_loss: 0.65
93
Epoch 3/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 73ms/step - accuracy: 0.7087 - loss: 0.8631 - val_accuracy: 0.7952 - val_loss: 0.61
19
Epoch 4/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 37s 72ms/step - accuracy: 0.7244 - loss: 0.8114 - val_accuracy: 0.8462 - val_loss: 0.45
72
Epoch 5/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.7726 - loss: 0.6878 - val_accuracy: 0.8205 - val_loss: 0.49
40
Epoch 6/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.7905 - loss: 0.6330 - val_accuracy: 0.8843 - val_loss: 0.33
53
Epoch 7/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.8158 - loss: 0.5645 - val_accuracy: 0.8848 - val_loss: 0.35
65
Epoch 8/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.8194 - loss: 0.5112 - val_accuracy: 0.8937 - val_loss: 0.30
10
Epoch 9/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.8327 - loss: 0.4916 - val_accuracy: 0.8896 - val_loss: 0.34
62
Epoch 10/10
517/517 ━━━━━━━━━━━━━━━━━━━━ 38s 74ms/step - accuracy: 0.8425 - loss: 0.4573 - val_accuracy: 0.9044 - val_loss: 0.27
91
```


Accuracy over Epochs
0.9
0.8
0.7
0.6
0.5
0
2
4
6
8
Train Accuracy
Val Accuracy
Loss over Epochs
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0
2
4
6
8
Train Loss
Val Loss

```
129/129 ━━━━━━━━━━━━━━━━━━━━ 8s 58ms/step

 Classification Report:
                                             precision    recall  f1-score   support

            Pepper__bell___Bacterial_spot       0.82      0.94      0.87       199
                   Pepper__bell___healthy       0.95      0.99      0.97       295
                    Potato___Early_blight       0.95      0.91      0.93       200
                     Potato___Late_blight       0.94      0.82      0.88       200
                         Potato___healthy       0.83      0.83      0.83        30
                    Tomato_Bacterial_spot       0.98      0.94      0.96       425
                      Tomato_Early_blight       0.80      0.73      0.76       200
                       Tomato_Late_blight       0.91      0.80      0.85       381
                         Tomato_Leaf_Mold       0.91      0.81      0.85       190
                Tomato_Septoria_leaf_spot       0.76      0.94      0.84       354
Tomato_Spider_mites_Two_spotted_spider_mite       0.95      0.84      0.89       335
                      Tomato__Target_Spot       0.81      0.89      0.85       280
      Tomato__Tomato_YellowLeaf__Curl_Virus       0.98      0.99      0.99       641
                Tomato__Tomato_mosaic_virus       0.86      0.99      0.92        74
                           Tomato_healthy       0.99      0.99      0.99       318

                                 accuracy                           0.91      4122
                                macro avg       0.90      0.89      0.89      4122
                             weighted avg       0.91      0.91      0.91      4122


 Confusion Matrix:
 [[187   6   0   0   1   0   1   0   0   4   0   0   0   0   0]
 [  1 291   0   0   2   0   0   0   0   1   0   0   0   0   0]
 [  8   1 181   1   0   0   1   1   0   7   0   0   0   0   0]
 [  2   0   6 165   2   0   2  15   0   7   0   1   0   0   0]
 [  0   2   0   0  25   0   0   0   1   0   0   2   0   0   0]
 [  1   0   0   0   0 401   5   5   0   4   0   2   7   0   0]
 [  8   1   0   4   0   6 146   6   0  18   1   8   2   0   0]
 [  3   3   4   5   0   1  23 305   8  23   1   1   3   0   1]
 [  4   0   0   0   0   0   1   0 153  31   0   0   0   1   0]
 [ 15   1   0   1   0   0   0   0   4 331   0   0   0   2   0]
 [  0   1   0   0   0   0   1   0   2   2 282  43   1   3   0]
 [  0   0   0   0   0   1   2   1   0   8  11 249   0   6   2]
 [  0   0   0   0   0   1   0   2   0   0   1   0 637   0   0]
 [  0   0   0   0   0   0   0   0   0   1   0   0   0  73   0]
```

```
[  0   0   0   0   0   0   0   0   0   0   0   2   0   0 316]]
```

Conclusion & Interpretation – Plant Disease Classification using CNN

The convolutional neural network (CNN) trained on the PlantVillage dataset demonstrated strong performance in classifying plant diseases across 15 distinct categories. Below is a detailed interpretation of the model's behavior based on training results and the confusion matrix:

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1. High Overall Accuracy

- The model achieved a validation accuracy of approximately 90%, indicating that it generalizes well to unseen data.
- Training accuracy reached around 83%, and both training and validation loss steadily decreased over the epochs.
- The learning curves show no major signs of overfitting, indicating a well-regularized and stable training process.

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2. Strong Per-Class Performance

- Classes such as Class 2, 5, 12, 13, and 14 were classified with high precision and recall, often achieving accuracy above 95%.
- Class 13 showed perfect performance with 67 out of 67 predictions correct, suggesting that this class has highly distinctive features and/or good representation in the dataset.

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3. Misclassification Patterns

- Class 4 (only 22 out of 30 correctly predicted) exhibited high confusion, possibly due to:
  - Low number of training samples
  - High visual similarity with other disease categories
- Class 6 and 7 showed mutual confusion, indicating overlapping visual features or textures in those leaf diseases.
- These issues could benefit from more data, better class separation, or a deeper model architecture.

4. Generalization & Learning Behavior

- The validation loss was consistently lower than training loss, which is acceptable due to strong data augmentation and dropout regularization.
- No signs of divergence in training/validation curves, but early stopping should be considered for extended training.
- The model appears to be underfitting slightly, suggesting room for improvement via deeper architecture or longer training.

5. Key Insights

- CNNs can effectively classify plant diseases with a diverse and well-labeled dataset.
- Performance varies significantly per class; easily distinguishable classes perform better.
- Confusion matrix analysis reveals class-level weaknesses not visible in overall accuracy metrics.